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Original Research

Long-Term Orchestral String Learning and Event-Related Potentials of Inhibitory Control in Children From Disadvantaged Communities

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Abstract

Background: Children from low socioeconomic status (SES) backgrounds are at increased risk for delays in executive function (EF), particularly inhibitory control and attentional regulation. Orchestral string music training is a complex multisensory activity that repeatedly engages executive control systems, yet its neurophysiological mechanisms remain insufficiently understood. In this study we examined whether prolonged string training is associated with enhanced neural dynamics underlying inhibitory control in socioeconomically disadvantaged children. **Methods**: We re-analyzed 32-channel electroencephalography (EEG) data from an auditory Go/NoGo task in 20 children aged 9–12 years (11 with $\geq$4 years of orchestral string training; 9 controls). Event-related potentials (ERPs) were extracted using a data-driven vincentization pipeline. Group differences were assessed using mixed-model ANOVAs and topographic analyses. **Results**: Musically trained children showed significantly larger NoGo-related ERP amplitudes across N1–N2, P300, N400, and late positive components, with maximal effects over right frontocentral and temporoparietal regions (median Cohen's $f = 0.78$, median $p = 0.005$, median upper bound Bayesian Factor = 24.17). These neural differences emerged despite comparable behavioral performance between groups. **Conclusions**: Findings suggest that orchestral string training is associated with more efficient recruitment of inhibitory–attentional networks in children facing socioeconomic adversity. These effects align with enhanced fronto-parietal integration and neural efficiency principles, consistent with Adaptive Resonance Theory and Parieto-Frontal Integration Theory frameworks, supporting its potential as a scalable intervention for executive function development.

Keywords: executive function; inhibitory control; attention regulation; event-related potentials; electroencephalography; auditory processing; music training; neuroplasticity; child development; socioeconomic factors

1. Introduction

Executive functions (EFs) regulate perception, action, and cognition, with the response inhibition and attentional regulation system [1] forming a central core responsible for the suppression of prepotent responses, filtering irrelevant input, and the stabilization of goal-directed behavior under conditions of uncertainty [2]. Developmental challenges in inhibitory control predict poorer academic achievement, increased health risk, and long-term societal burden [3,4]. These vulnerabilities are disproportionately observed in children from low socioeconomic status (SES) backgrounds, where reduced environmental enrichment may constrain maturation of the widely distributed network supporting inhibitory coordinated activity across prefrontal and parietal cortices, basal ganglia, thalamus, and cerebellum [5]. Identifying ecologically valid cognitive support which may be functionally interdependent [6][1] with changes in neural inhibitory circuitry is therefore a public health priority within developmental integrative neuroscience [7]. ([1]Throughout this paper, terms referring to relationships between musical training and changes in the neural substrates (i.e., strengthening, enhancement) reflect associative rather than causal interpretations. Although our statements do not intend causal and strict determinism, they satisfy functional interdependence (i.e., psychophysical parallelism) as defined by Bunge [6; pages 91–97].)

The present study explored whether prolonged orchestral string training is associated with enhanced neural dynamics underlying inhibitory control in children from socioeconomically disadvantaged communities. We report a retrospective re-analysis of neural correlates of auditory attention regulation and response inhibition, as measured through a Go/NoGo paradigm [8], in two groups of middle-school children from low-SES backgrounds. One group had long-term exposure to socially based orchestral string training, whereas the comparison group had no formal music training. Two objectives guided the investigation.

Although orchestral string music training is a complex, multisensory activity repeatedly engaging inhibitory and attentional control processes [9,10,11], its neural mechanisms remain underexplored. Therefore, our first objective was to quantify neural correlates of response inhibition and attentional control associated with orchestral string training using the Go/NoGo paradigm. Orchestral string performance embeds demands conceptually analogous to Go/NoGo tasks within a socially coordinated auditory–motor context. Musicians must selectively initiate (Go) or suppress (NoGo) motor responses based on rapidly changing sensory cues. Repeated rehearsal therefore constitutes high-frequency, ecologically grounded engagement of inhibitory and attentional systems [12].

To assess neural differences associated with this training experience, we employed event-related potentials (ERPs), which provide temporally precise indices of cognitive processing. Indeed, music-based interventions are often correlated with robust neurophysiological changes in low SES children, even when behavioral effects are modest or even undetected, supporting ERPs as sensitive markers of training-associated plasticity in this population [7]. However, ERP findings are frequently interpreted in a component-wise manner, limiting systems-level integration. Therefore, our second objective was to offer a synthesis of potential ERP differences associated with long-term music training within a framework of functional interdependence [6] integrating Adaptive Resonance Theory (ART) [13,14] and the Parieto-Frontal Integration Theory (P-FIT) [15].

ART provides a framework of coordination between attention, inhibition, and learning across hierarchical neural networks. According to this model, cognition emerges from dynamic resonance between bottom-up sensory input and top-down expectations mediated by competitive inhibitory circuits. On-center/off-surround dynamics amplify task-relevant representations while suppressing competing signals, whereas mismatches trigger orienting responses and inhibitory reset. Within this framework, early negativities such as the N100 index attentional amplification and template matching, the N200 relates to orienting-related disinhibition during response suppression, the P300 indexes attentional reset and context updating, and late positive deflections (LP) is associated with sustained top-down control.

The functional relationships proposed by ART can be complemented by the neural efficiency perspective. Similarly to ART, P-FIT [15] posits that top-down executive control of action is regulated by parietal areas (including the angular and supramarginal gyri) first interacting with the dorsolateral prefrontal cortex to assess task demands, and subsequently with other frontal areas (i.e., anterior cingulate) to select the best response and inhibit competing ones. Accordingly, higher levels of cognitive processing are often associated with more efficient communication within such distributed frontoparietal networks. Thus, from a P-FIT perspective, repeated recruitment of frontal–parietal circuits during orchestral string training may be a correlate of strengthened inhibitory–attentional network efficiency.

Integrating ART and P-FIT, we hypothesized that, relative to their non-trained counterparts, string-trained children would exhibit neural correlates of more efficient auditory inhibitory processing during NoGo trials. This effect could be interpreted as an associated marker of enhanced early ERP activity (N100–N200, and P300), which may support signal detection and stimulus evaluation. At the same time, it is well established that individuals with low SES usually engage in late/delayed selection and EF control [4]. We predicted that, as a result of prolonged string training, the processing supporting executive control and associated with late (LP) components over frontal and parietal regions, would be completed (resolved) earlier in the string-trained group than in the untrained group.

Convergence between ERP differences and predictions derived from ART and P-FIT would provide systems-level support for orchestral string training as a possible naturalistic, cost-effective, and scalable intervention for optimal development of inhibitory control.

2. Methods

2.1 Study Design

This study employed a quasi-experimental laboratory design based on retrospective secondary analysis of a database consolidated from previous electroencephalography (EEG) studies [16,17,18,19]. The objective was to evaluate neural correlates of inhibitory control under ecologically valid community-based orchestral training conditions. The design emphasized internal comparison (music-trained vs. non-trained children drawn from the same low socioeconomic stratum) [20] rather than inclusion of an external comparison group (higher-SES group), thereby isolating poverty and socioeconomic disadvantage as a shared environmental factor. Hence, a restriction to a single SES level was used in this study.

The intervention derived from OrKidstra, a community-based orchestral string program developed to promote executive-function development in children from socioeconomically disadvantaged backgrounds. Previous reports from this dataset examined Go-trial effects; the present analysis focuses exclusively on NoGo-related inhibitory processes.

2.2 Participants

2.2.1 Eligibility Criteria

Inclusion criteria were: (1) EEG data quality (sufficient NoGo trials); (2) Normal hearing; (3) Age between 9 and 12 years; (4) Residence in low-SES inner-city neighborhoods of Ottawa, Canada; (5) For the intervention group, participation in the OrKidstra string ensemble program for at least one academic year. Exclusion criteria were: (1) History of neurodevelopmental disorder or cognitive learning disability; (2) Non-fluency in English; (3) Clinically significant auditory impairment. Neurodevelopmental conditions were excluded to reduce heterogeneity and isolate socioeconomic effects.

2.2.2 Recruitment and Group Allocation

An initial pool of participants was drawn from a consolidated laboratory database (N = 26). Children were categorized into: (i) Music Training group (MT): intensive orchestral string training (three weekly rehearsals plus weekend ensemble sessions); (ii) Non-Music group (NM): limited-to-no formal music training.

As mentioned earlier, we operated a restriction on SES level. Socioeconomic status (SES) was assessed using an updated and adapted version of the Hollingshead Index [21], a survey designed to measure an individual or family's SES based on a four-factor index including parental income, parental occupation, parental education level and residential quality (score range: 6–88). All participating families were classified at the lowest quartile. Mean SES was 24.64 (SD = 13.47) and 16.01 (SD = 13.96), respectively, for MT group and NM group (with no significant mean SES difference, i.e., $p = 0.18$). Levene's Test (F = 0.001, $p = 0.978$) confirmed that the within-SES variability was virtually the same. Participants also met Statistics Canada Low-Income Cut-Off (LICO) criteria, which defines poverty status in Canada (https://www.canada.ca/en/employment-social-development/services/foreign-workers/caregiver/financial-ability.html).

Furthermore, to partially counteract some of the issues introduced by restricting sampling within a poor population (i.e., selection bias), we attempted to make the two groups as comparable as possible. Groups were age-matched (±6 months) and sex-balanced (7 females, 6 males per group).

2.3 Intervention

The OrKidstra program provides structured ensemble-based orchestral string instruction integrated within a social-development framework. Training consisted of three after-school rehearsals per week and weekend ensemble sessions throughout the academic year. The program specifically serves children from socioeconomically disadvantaged backgrounds.

The NM group did not receive structured ensemble training and had minimal prior musical exposure.

2.4 Psychometric, Questionnaire and Qualitative Baseline Measures

Audiometric screening using a GSI 61 audiometer (Grason-Stadler, Eden Prairie, MN, USA) test confirmed normal hearing between –10 dB and 25 dB HL (i.e., tones between 500 and 4000 Hz in each left and right ear at 20 dB Sound Pressure Level).

Handedness was assessed using the Edinburgh Handedness Inventory [22]

Receptive vocabulary was assessed using the Peabody Picture Vocabulary Test [23].

Behavioral and emotional functioning were evaluated using the Strengths and Difficulties Questionnaire [24].

Parents completed additional questionnaires including:

- Brief Music Experience Questionnaire (BMEQ) [25];
- Depression Anxiety Stress Scales (DASS-21) [26];
- Perceived Stress Scale [27];
- Ruminative Responses Scale [28].

These measures were used for a comprehensive characterization and screening of initial groups' baseline level for cool (cognitive) and hot (emotional regulation) EFs.

Qualitative information was also collected regarding extracurricular activities outside school and whether they included musical components. Response for these variables was rather low due to unavailability of extra disposable income in these families.

2.5 Experimental Procedure

Go/NoGo Paradigm

Selective attention and response inhibition were assessed using an auditory Go/NoGo paradigm [29]. Stimuli consisted of pure tones (1100 Hz; 2000 Hz), 100 ms duration, presented with a jittered interstimulus interval of 1000–1400 ms. The task comprised 400 trials (four blocks of 100 trials: 70% Go, 30% NoGo). Participants pressed a response button with their dominant hand to Go stimuli and withheld responses to NoGo stimuli. Forty practice trials preceded testing.

2.6 EEG Data Acquisition

EEG was recorded using a 32-channel actiCAP system (Brain Products GmbH, Gilching, Germany) arranged according to the International 10–20 system (26 scalp electrodes analyzed). Signals were amplified using a Neuroscan SynAmps RT system (Compumedics Neuroscan, Charlotte, NC, USA) (±200 µV range) and digitized at 1000 Hz. Offline filters were set at 0.15–100 Hz. Impedances were maintained below 5 kΩ. Horizontal eye movements were monitored using bipolar electrodes positioned at the outer canthi. Pre-recording resting EEG spectral distributions were visually inspected and fell within normative pediatric frequency ranges.

2.7 EEG Preprocessing

Data were re-referenced to common average. Epochs were extracted from –200 ms to 1000 ms relative to stimulus onset and baseline corrected using the prestimulus interval. Artifact rejection criteria included removal of trials exceeding ±100 µV at non-ocular electrodes. Ocular artifacts were corrected using principal component analysis and the BESA Surrogate Model ($R^2 > 0.90$). The threshold for maximum allowed trial artifact rejection rates was 10% for NoGo in both groups.

Final Sample and Baseline Comparability

Following EEG artifact and trial rejection, the final analyzable sample was reduced to 20 participants, comprising 11 MT participants (5 F, 6 M) and 9 NM (5 F, 4 M). The mean number of accepted EEG NoGo trials were 94% (SD = 8%) and 92% (SD = 14%) for MT and NM groups, respectively ($t(18) = 0.41$; $p = 0.69$). A non-parametric comparison between included and excluded participants across demographic and psychometric variables (Bonferroni-adjusted threshold $p < 0.002$) revealed no significant group differences (detailed report: https://doi.org/10.5281/zenodo.18109032).

2.8 Analysis

2.8.1 ERP Component Identification

To avoid adult-centric peak assignment assumptions common in developmental ERP research [30], a data-driven binning pipeline was implemented. Using EEGLAB 2026.0.0 (Swartz Center for Computational Neuroscience, University of California, San Diego, CA, USA) [31], each 1200-point epoch was segmented into 120 bins of 10 ms. Furthermore, vincentized quantile binning [32] was applied to preserve distributional shape and mitigate small-sample bias [33]. Given its shape-preservation property, vincentized quantile binning minimizes the effects of distortions of individual differences in the distributions of averaged ERP peak mid-points, thereby producing more reliable and consistent average tracings for valid component extraction [34].

Component windows were defined using pooled data across groups and electrodes. Specifically, automated peak detection (BESA 7.1 algorithm, BESA GmbH, Gräfelfing, Germany) identified four reproducible components: N100–N200 (median 60 ms; range 20–270 ms); P300 (median 317 ms; range 260–460 ms); N400 (median 450 ms; range 370–750 ms); Late Positivity (LP) (median 720 ms; range 550–845 ms).

N100 and N200 were collapsed due to limited morphological separability in pediatric samples [35,36,37].

For further component windows validation, we repeated the same peak finder procedure on the average binned ERPs of each individual participant within each group. Bootstrap permutation correlation analyses showed high consistency between group and individuals correlations for MT group (r = 0.83; 95% CI: 0.73–0.96) and for NM group (r = 0.80; 95% CI: 0.69–0.93).

2.8.2 Statistical Analysis

Data were reduced to participant-level summaries by computing mean binned amplitudes within pre-defined component windows per electrode. For each electrode, separate mixed (between-subjects and repeated measures) ANOVAs, with Group (MT vs NM) X ERP Component (N100–200 vs. P300 vs. N400 vs. LP), group as a between-subjects factor and ERP component as a repeated measures variable. Type III sums of squares were used to ensure robustness to unequal cell sizes. Within-subjects effects were adjusted using the Greenhouse-Geisser correction. Our key analysis was on focused contrasts [38] examining interaction between Group X Component and, in case of no interaction, the main effect of Group.

To assess acceptability of our sample size, we conducted an a priori analysis of statistical power (using G*Power version 3.1.9.7 [39]), assuming Power = 0.95, and ANOVA design (Repeated measures, within-between interaction model, with 2 groups and 4 repeated measurements). For computation estimations, we selected an effect size of f(v) = 0.50, following the lower bound threshold of large effect sizes recommended by the standard Cohen's guidelines [40], the chosen effect size value was within the 99% confidence interval of effect sizes estimated from a rapid scoping survey of previous Go/NoGo ERP literature (see **Supplementary Material**). On these assumptions, the result of our power test indicated a minimum required sample of N = 12, smaller than our actual total sample.

Sensitivity analysis for new diagnostic tests [41] assuming a prevalence of 100% Low SES and high sensitivity commensurate with a high statistical effect as defined by the Common Language Effect Size CLES approach. This analysis gave an estimate of N = 24, which is not too far off our total sample size.

2.8.3 Statistical Indices

Following recommendations by Benjamin & Berger [42], results are reported with p values (threshold $p < 0.05$), effect size (Cohen's f, i.e., f(v)), estimated upper bound Bayesian factor (BFB, computed as $1 / - e\ \mathrm{p} \log p$) and associated upper bound of posterior probability (PrU) of the alternative hypothesis (H1), all interpreted as converging evidence of the strength of the findings [42]. Notably, the PrU is the inverse of the probability of the null hypothesis (H0) and therefore can be readily used to estimate also the upper bound of the posterior probability of false positives (as 1 – PrU) [42].

False Discovery Rate (FDR) [43] correction across electrodes and components was applied for multiple comparisons in the contrast analysis (see Table 1). In particular, we used the Benjamini–Yekutieli procedure, which controls the FDR under arbitrary dependence assumptions and adjusts for the bias introduced by spatial multicollinearity among EEG electrodes.

2.9 Visualization and Data Availability

Topographical scalp maps were generated in R using eegUtils [44] within a Shiny-based application interface [45]. All processed ERP datasets, bin definitions, and statistical outputs are available at: https://doi.org/10.5281/zenodo.18109032.

3. Results

3.1 Behavioral Outcomes

After FDR correction, no significant between-group differences were observed in reaction time (RT), accuracy or response differences (misses and false alarms) on the Go and NoGo (correct rejection) trials, receptive vocabulary (Peabody Picture Vocabulary Test Fourth Edition), behavioral functioning (Strengths and Difficulties Questionnaire), or sex or group X sex interactions. In particular,

Table 1. Table of electrode main effects and interaction Contrasts, NoGo Trials.

Electrode	F(2,39)	FDRp	BFB Group	PrU	η^2	f(v)	Mean critical μV difference
Fz	8.01	0.0317	3.36	0.77	0.29	0.64	1.29
C4	**11.90**	**0.0088**	**8.80**	**0.90**	**0.38**	**0.78**	**0.66**
CP6	**12.06**	**0.0088**	**8.80**	**0.90**	**0.38**	**0.79**	**0.90**
T8	**12.12**	**0.0088**	**8.80**	**0.90**	**0.38**	**0.79**	**0.34**
TP9	**9.69**	**0.0180**	**5.08**	**0.84**	**0.33**	**0.70**	**2.75**
P8	20.26	0.0016	36.49	**0**.97	0.51	1.02	0.54
Group X Component							
F7	29.89	0.00001	3195.36	1.00	0.61	1.24	1.29
F3	4.39	0.02923	3.56	0.78	0.18	0.47	0.61
F8	**26.42**	**0.00001**	**3195.36**	**1.00**	**0.58**	**1.16**	**2.14**
FC5	7.09	0.00474	14.50	0.94	0.27	0.60	0.88
FC1	13.02	0.00016	259.47	1.00	0.40	0.82	1.16
FC2	42.33	0.00001	3195.36	1.00	0.68	1.47	1.82
FT10	8.22	0.00248	24.71	0.96	0.30	0.65	0.66
C3	11.02	0.00042	113.60	0.99	0.36	0.75	0.80
C4	**7.16**	**0.00474**	**14.50**	**0.94**	**0.27**	**0.61**	0.66
CP5	4.99	0.01905	4.88	0.83	0.20	0.51	0.70
CP6	**11.74**	**0.00029**	**156.26**	**0.99**	**0.38**	**0.78**	**0.90**
T7	78.89	0.00001	3195.36	1.00	0.80	2.01	1.47
T8	**6.11**	**0.00849**	**9.08**	**0.90**	**0.24**	**0.56**	0.34
TP9	**39.46**	**0.00001**	**3195.36**	**1.00**	**0.67**	**1.42**	2.75
TP10	6.89	0.00507	13.73	0.93	0.26	0.59	0.73
Pz	16.46	0.00004	970.95	1.00	0.46	0.92	1.02
P4	40.45	0.00001	3195.36	1.00	0.67	1.44	1.54

Note. After mean False Discovery Rate (FDR) correction, threshold significance is $p < 0.05$. "FDRp" stands for "FDR-corrected *p* values". Bolded values represent contrasts that yielded significance for both main and interaction effects. BFB, Bayes Factor Bound; PrU, upper bound of posterior probability.

Electrodes are listed in the following scalp distribution order: Lobe, Lateral to central, Left to Right.

mean NoGo accuracy (correct rejection) rates were 86.88% (SD = 9.39) and 84.81% (SD = 13.49), for MT and NM groups, respectively.

3.2 Electrophysiological Findings

To enhance clarity, findings are presented by ERP component and organized by electrode distribution in Figs. 1,2,3. The specific coefficients for the ANOVA contrasts are detailed in Table 1.

3.2.1 PN-P120

Focused analysis showed that PN and P120 were not statistically distinguishable or different in the two groups, topographical visualizations show more clearly that these waveform complexes followed the same pattern of frontally distributed, negative amplitudes.

3.2.2 N1–N2

Across bilateral frontal (F7, Fz, F8), bilateral central (C3, C4), and frontotemporal (FT10) and temporal (T7) electrodes, the MT group showed significantly larger N100–N200 amplitudes than the NM group, the effects were robust and showed large sizes (Cohen's f up to 1.47; η^2 up to 0.68) (see Table 1 for specific results). However, in parietal electrodes, the NM group showed larger N200 amplitudes than the MT group. Key electrodes associated with these findings are shown in Figs. 1,2.

3.2.3 P3 and N4

The MT group showed significantly larger P3 than the NM group in central, centro-parietal and parietal electrodes effects were strongest in the right side at C4, CP6, P8 (see key examples in Fig. 2) and fronto-temporally in the left side at FT9. Although not a main focus of our analysis, N4 also showed large effects for the NM group as compared to the MT group in right frontal, central and parietal electrodes with especially noticeable effect at P8 (see Fig. 2).

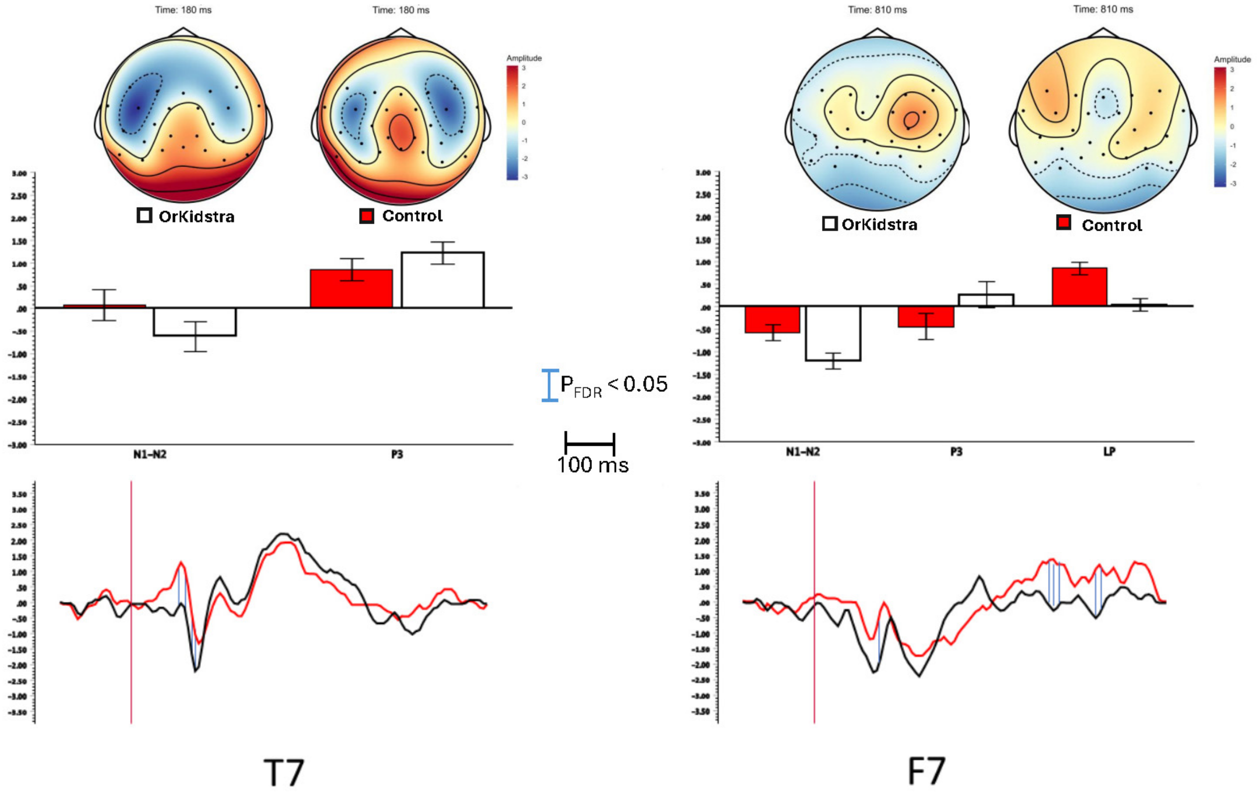

Fig. 1. NoGo trials – Selected best examples of Frontal and Temporal scalp electrodes. Bar graphs display mean ERP amplitudes (μV) within defined time windows (F7, T7) for each frontal and temporal electrode cluster by group. Error bars represent standard errors. Specifically, blue lines indicate the minimal critical μV significant difference for simultaneous F-based focused contrasts, with *p*-value corrected with FDR (see Methods for details). Line graphs depict estimated marginal means across participants, allowing visualization of the temporal emergence of statistically significant Group differences. Negative deflections correspond to N-components; positive deflections correspond to P-components. Negative values represent increased cortical negativity; positive values represent increased positivity. ERP, event-related potential; FDR, false discovery rate.

3.2.4 LP

The LP showed a mixed pattern of findings, strong effects (η^2 up to 0.67; f up to 1.44) were revealed bilaterally in fronto-temporal, temporal, and central clusters of electrodes especially at C4 (see Fig. 3) where the MT group had much larger LP positive amplitudes than the NM group. However, this outcome shifts in the opposite direction (NM > MT) in fronto-central (i.e., prefrontal) electrodes, especially FC5, and frontal electrodes bilaterally (see Fig. 1 and Fig. 3).

4. Discussion

In summary, orchestral string music training was associated with enhanced neural responses across multiple ERP components (N100–N200, P300, N400, and LP) within frontal and temporoparietal networks. In contrast, the earliest stimulus-locked components (PN and P120) were unreliable or did not differ between groups, indicating that group differences emerged primarily at later stages of processing. The music-trained (MT) group showed stronger early frontal N100–N200 responses, reduced posterior N200 and N400, larger parietal P300, and earlier-resolving LPs centrally. The non-musician (NM) group exhibited weaker early frontal recruitment, larger posterior N200, smaller P300, and more sustained LP activity resolving later over posterior regions. These findings indicate systematic differences in the timing and spatial distribution of neural recruitment.

Despite comparable behavioral performance, neural activity differed substantially, consistent with a possible correlated pattern of neural efficiency. The MT group engaged frontal inhibitory networks earlier and more robustly, possibly in association with enhanced conflict detection and with more efficient evaluative processing. This shift toward earlier, frontally mediated control processes did not translate into behavioral differences, perhaps in part reflecting task insensitivity, since tone selection might be too simple or easy of a manipulation to be able to distinguish the two groups. Additionally, the results warrant the conclusion that four years of string training might not be sufficient yet for the possible re-organization at neural level to translate into enhancement of behavioral performance.

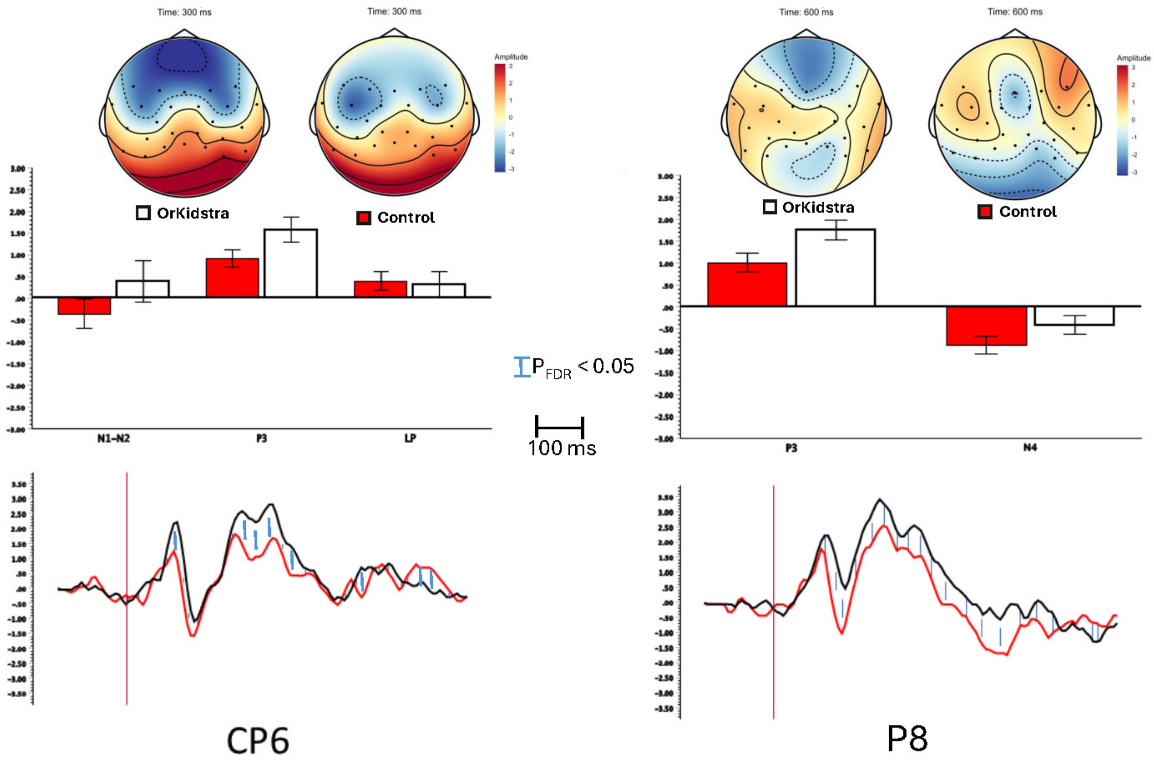

Fig. 2. NoGo trials – Selected best examples of Central, and Parietal scalp electrodes. Bar graphs display mean ERP amplitudes (µV) within defined time windows (CP6, P8) for each centro-parietal and parietal electrode cluster by group. Line graphs visualize group-specific waveform progression across time windows, highlighting where statistically significant amplitude divergences occur. Specifically, blue lines indicate the minimal critical µV significant difference for simultaneous F-based focused contrasts, with *p*-value corrected with FDR (see Methods for details). Negative deflections correspond to N-components; positive deflections correspond to P-components. Negative values represent increased cortical negativity; positive values represent increased positivity.

To contextualize these findings within established neurocognitive frameworks, ERP components were interpreted using integrated Adaptive Resonance Theory (ART) and Parieto-Frontal Integration Theory (P-FIT) accounts. Table 2 (Ref. [12,13,14,15,19,46,47,48,49,50,51,52,53,54,55,56,57]) provides a summary of our proposed synthesis. The observed ERP profile aligns with ART's hierarchical resonance dynamics while also reflecting a possible association with efficient fronto-parietal integration as described by P-FIT.

According to our interpretation, early components (PN, N100, P120) could primarily reflect sensory encoding and attentional gating mechanisms. Although PN and P120 did not differ between groups, the larger and frontally distributed N100 in MT participants may indicate neural correlates of enhanced stimulus encoding and of more efficient propagation of auditory information from temporal to frontal regions [47,48]. Within ART, this pattern is consistent with a possible scenario of more precise top-down template matching, while in P-FIT terms it could reflect improved coordination between posterior sensory regions and frontal control systems.

Mid-latency components (N200, P300) could index conflict monitoring, inhibitory control, and attentional updating. The larger frontal N200 observed in MT participants is consistent with enhanced mismatch detection and inhibitory processing [48,49,51,52,53], while the increased parietal P300 may reflect more efficient working memory updating and attentional–motor integration [14,54,55]. Within ART, these effects are assumed to correspond to faster mismatch signaling and efficient resetting of short-term memory representations via F1–F2 interactions [46]. A P-FIT perspective is compatible with the interpretation that these processes may also reflect optimized information transfer across fronto-parietal networks supporting executive control.

Later components (N400/LP) could reflect higher-order integration and meaning-related processing. The larger LP responses previously observed in MT participants [19] suggest the interpretation of enhanced large-scale integration across temporal, parietal, and frontal regions. Within ART, these effects are consistent with distributed template pre-activation and hierarchical meaning integration [56,57], whereas in P-FIT they are associated with more efficient global network coordination supporting semantic processing and cognitive flexibility.

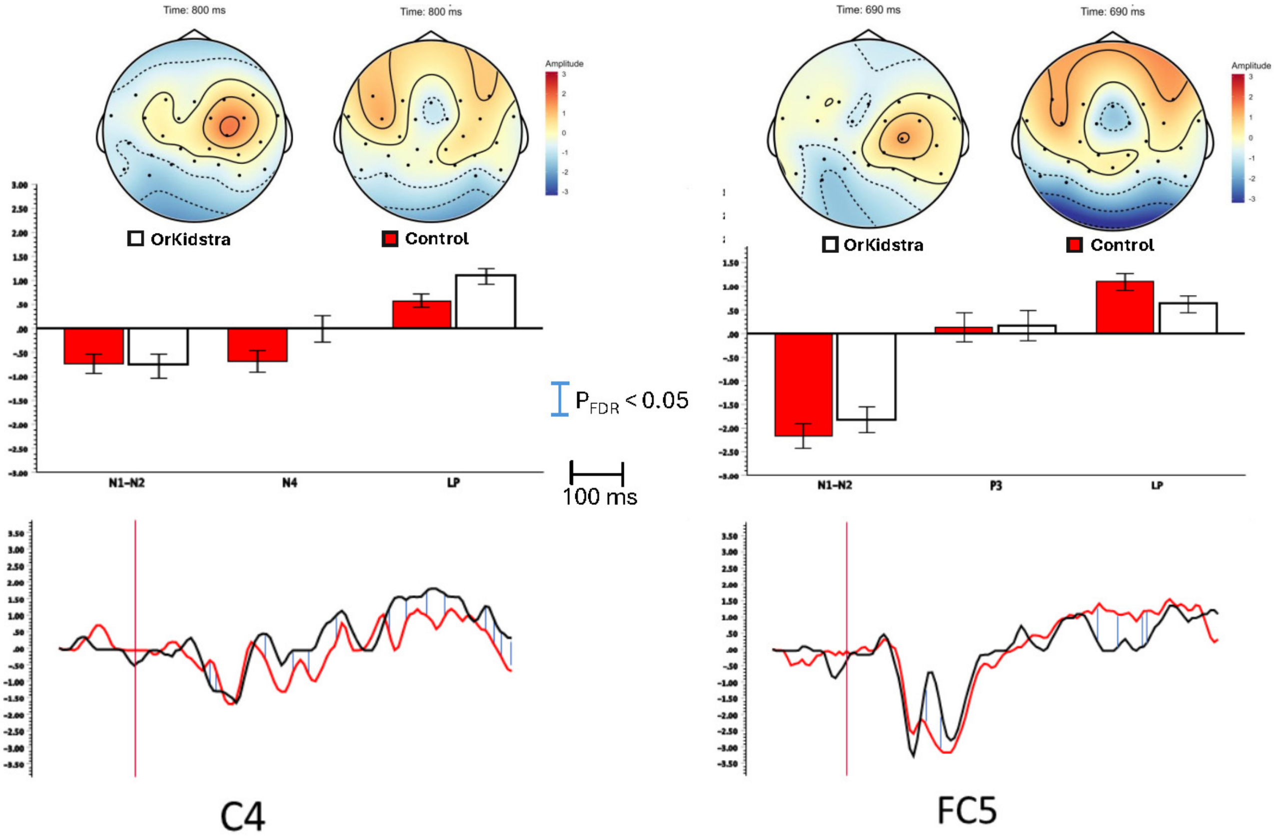

Fig. 3. NoGo trials – Selected examples of Fronto-Central and Central scalp electrodes. Bar graphs display mean ERP amplitudes (µV) within defined time windows (C4, FC5) for each Fronto-central and central electrode cluster by group. Line graphs visualize group-specific waveform progression across time windows, highlighting where statistically significant amplitude divergences occur. Specifically, vertical blue lines across indicate the minimal critical mean µV significant difference for simultaneous F-based focused contrasts, with *p*-value corrected with FDR (see Methods for details). Negative deflections correspond to N-components; positive deflections correspond to P-components. Negative values represent increased cortical negativity; positive values represent increased positivity.

Enhanced mismatch-related (N200, P3a) and response-related (P3b) activity in the MT group would also be consistent with developmental models of executive function, which emphasize coordinated interactions among sensory, salience, and fronto-motor networks. Long-term string training may, therefore, have positive associations with goal-directed behavior due to the possibility that it may strengthen predictive coding mechanisms and facilitate flexible reconfiguration of large-scale networks supporting goal-directed behavior.

These findings situate themselves in the context of prior work demonstrating enhanced neural responses following orchestral and string-based music training [9,10,11,58,59]. In addition, here we attempted to embed the findings within a unified mechanistic framework. By jointly applying ART and P-FIT, the results suggest that music training might be associated with enhancement of both local resonance dynamics and distributed network efficiency, providing a coherent account of possible experience-dependent plasticity associated with music training.

Response inhibition, commonly assessed using Go/NoGo paradigms, is a core component of executive control. The present findings extend this literature by embedding electrophysiological evidence within a computationally explicit framework, suggesting that orchestral string training may represent a scalable and ecologically valid intervention targeting executive function. However, music training is inherently multifaceted, engaging sustained practice, cognitive control, social coordination, and affective regulation, and the relative contribution of these components remains to be determined, as we did not address many of these possible confounds.

Although age and baseline cognitive abilities were controlled, additional covariates such as parental education and extracurricular engagement were not directly measured. Contextual factors suggest limited influence of these variables: participants were drawn from underserved communities with restricted access to enrichment opportunities and disposable income, and the present music program represented their primary (or only) structured extracurricular activity. Prior studies report small effects of such variables

Table 2. Interpretation of ERP components within Adaptive Resonance Theory (ART) and Parieto-Frontal Integration Theory (P-FIT).

Component	ART mechanism/network process (refs)	Group effect (MT vs. NM)	Functional interpretation (ART–P-FIT integration)
PN	Early selective attention via top-down template priming and resonant STM states in on-centre/off-surround networks [15,46]; response-specific resonance [47]	Larger in MT (topographic maps), not significant	Trend toward more efficient attentional priming and template formation; may reflect the correlate of improved early frontal–posterior coordination supporting preparatory attention
N100	Stimulus-specific template encoding and matching in early sensory STM [48]; cross-modal template comparison [49]	Larger, frontally distributed in MT	Possible association with enhanced sensory encoding and transmission from temporal to frontal regions, consistent with more efficient bottom-up/top-down integration
P120	Suppression of F1 activity during mismatch without trace formation [50]	No reliable group differences	Possible association with early mismatch-related gating preserved across groups; likely precedes higher-order fronto-parietal integration processes [51]
N200	Disinhibition of orienting subsystem producing nonspecific arousal at F2 during mismatch [46]	Larger frontal N2 in MT	Possible association with enhanced conflict detection and inhibitory control; reflects stronger prefrontal engagement within fronto-parietal networks [51,52,53]
P300 (P3a/P3b)	Parallel F2 outputs: attentional reorientation (P3a) and motor preparation (P3b) [12,13,14,46]	Larger parietal P3 in MT	Possible correlates of more efficient working memory updating and attentional–motor integration; reflects optimized fronto-parietal information transfer [53,54]
P300 lateralization	Hemispheric specialization within distributed auditory–attentional networks [55]	Greater right-hemispheric bias in MT	Possible index of increased functional specialization within large-scale networks supporting auditory–spatial attention
N400 / LP	Distributed template pre-activation and meaning integration across hierarchical STM levels [56]; PDP modeling [57]	Larger LP in MT (previously reported [19])	Possible correlates of enhanced higher-order integration across temporal–parietal–frontal regions, supporting semantic processing and cognitive flexibility

Note.

PN, Processing Negativity; STM, short-term memory; MT, music-trained; NM, non-musicians; LP, late positivity; PDP, parallel distributed processing; ART, Adaptive Resonance Theory; P-FIT, Parieto-Frontal Integration Theory.

($f(v) \approx 0.10$), whereas the present study yielded substantially larger effects (median $f(v) = 0.78$). Bayesian analyses further indicated strong evidence against the null hypothesis (median BFB = 24.17), making it unlikely that unmeasured background factors alone can account for the observed neural differences.

Still, several limitations warrant consideration. The specificity of string training limits generalization to other instruments or pedagogical approaches, and behavioral measures were not sufficiently granular to map specific executive subcomponents onto neural indices. Future studies should incorporate broader cognitive assessments, diverse training modalities, and more heterogeneous samples, including neurodivergent populations. Longitudinal and randomized controlled designs will be essential to establish causality and reduce potential selection biases.

Despite these limitations, the present findings provide a bridge between theoretical models and real-world data, advancing a possible account of how group-based musical training shapes executive networks. These insights have translational relevance, particularly for populations at risk of executive dysfunction, including children from low socioeconomic backgrounds and neurodivergent individuals. Community-based music programs offer a promising, accessible approach to support the development of neural systems underlying executive control. Future work using larger, well-matched samples, better designs, and multimodal neuroimaging (e.g., MEG, fMRI) will be important to extend and validate these findings.

5. Conclusions

Prolonged (i.e., ≥4 years) orchestral string music training in children from disadvantaged socioeconomic background may be associated with changes in neural recruitment supporting inhibitory control, characterized by earlier and more efficient engagement of frontal and fronto-parietal networks. In principle, these effects are compatible with and can be understood within an integrated ART–P-FIT framework linking local resonance mechanisms with large-scale network efficiency, providing a possible account of music experience-dependent plasticity in executive functions, with implications for both theory and intervention.

Availability of Data and Materials

All data and materials are available at https://doi.org/10.5281/zenodo.18109032.

Author Contributions

Both authors, TH and ADA, designed the study, performed the research, conducted the data diagnostics, power and sensitivity analysis and all ANOVA analyses. Both TH and ADA performed the visualizations and graphics. Both authors wrote the first draft, then further contributed to editorial changes in the manuscript. Both authors contributed to critical revisions of the manuscript for important intellectual content. Both authors read and approved the final manuscript. Both authors have participated fully in the work and agreed to be accountable for all aspects of the work.

Ethics Approval and Consent to Participate

The study was conducted in accordance with the Declaration of Helsinki and complied with the Canadian Tri-Council Policy Statement (https://ethics.gc.ca/eng/policy-politique_tcps2-eptc2_2022.html). Written informed consent was obtained from parents or legal guardians, and assent was obtained from children prior to participation.

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Conflicts of Interest

The authors declare no conflicts of interest. Amedeo D'Angiulli is serving as one of the Guest editors of this journal. We declare that Amedeo D'Angiulli had no involvement in the peer review of this article and has no access to information regarding its peer review. Full responsibility for the editorial process for this article was delegated to Bettina Platt.

Supplementary Material

Supplementary material associated with this article can be found, in the online version, at https://doi.org/10.31083/JIN45659.

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