Title
Component-Specific Developmental Trajectories of ERP Indices of Cognitive Control in Early Childhood

Author
Peters, Amanda

Publication Date
2023

Peer reviewed|Thesis/dissertation

UNIVERSITY OF CALIFORNIA, MERCED

Component-Specific Developmental Trajectories of ERP Indices of Cognitive Control in Early Childhood

A Thesis submitted in partial satisfaction of the requirements for the degree of Master of Arts

in

Psychological Sciences

by

Amanda Peters

Committee in charge:

Professor Elif Isbell, Chair
Professor Heather Bortfeld
Professor Sarah Depaoli

2023

The thesis of Amanda Peters is approved, and it is acceptable in quality and form for publication on microfilm and electronically:

Heather Bortfeld

Sarah Depaoli

Elif Isbell, Chair

University of California, Merced

2023

Table of Contents

List of Tables

List of Figures

Acknowledgements

Thank you to Dr. Elif Isbell for your support and guidance throughout both my undergraduate and graduate journey. You have been fundamental in advancing my progress as a scholar and my passion for ERP research. I greatly appreciate all of the work you have put into reading my drafts and motivating me to improve my writing on each iteration. I look forward to continuing to work together as I complete my PhD.

Thank you to Dr. Heather Bortfeld for all of the advice and encouragement me you have offered me. Your presence at UC Merced is greatly appreciated as my interests in developmental cognitive neuroscience continue to grow. I am excited to continue working together as I progress through graduate school.

Thank you to Dr. Sarah Depaoli for the significant part you have played in increasing my interests in statistics and my desire to continue learning about and improving my statistical analysis skills. I am thankful for the feedback you gave me as I worked on the complex analyses in my thesis.

Thank you to Dr. Selin Zeytinoglu for the advice and guidance you offered me as I learned about longitudinal data analyses. Your feedback was instrumental in helping me to complete the analyses in my thesis.

Thank you to Dr. Esther M. Leerkes for your encouragement and for allowing me to use your dataset. I have greatly enjoyed working with you on this project.

Thank you to my fellow graduate students, my lab-mates and friends Nancy and Dylan, and the psychological sciences department at UC Merced. I appreciate the feedback and support you have all given me over the past two years.

And finally: thank you to my family and to Jacob for the unconditional support you have given me throughout the years. You all have helped me stay motivated since the beginning of my graduate school journey.

Funding: This work was supported by the Eunice Kennedy Shriver National Institute of Child Health and Human Development (NICHD; Grant 5R01HD071957) and the National Institute of Mental Health (NIMH; Grant F32-MH127869 awarded to Selin Zeytinoglu). The contents are the sole responsibility of the authors and do not necessarily reflect the views of the NICHD or NIMH.

Abstract

Component-Specific Developmental Trajectories of ERP Indices of Cognitive Control in Early Childhood

by Amanda Peters for the partial satisfaction of the requirements for the degree of Master of Arts in Psychological Sciences University of California, Merced 2023
Dr. Elif Isbell, Chair

Early childhood is characterized by robust developmental changes in cognitive control; however, our understanding of intra-individual change in neural indices of cognitive control during this period remains limited. Here, we examined developmental changes in event-related potential (ERP) indices of cognitive control from preschool through first grade, in a large and diverse sample of children (N = 257). We recorded ERPs during a visual Go/No-Go task. N2 and P3b mean amplitudes were extracted from the observed waveforms (Go and No-Go) and the difference wave (No-Go minus Go, or Δ). Latent growth curve modeling revealed that while N2 Go and No-Go amplitudes showed no linear change, P3b Go and No-Go amplitudes displayed linear decreases in magnitude (became less positive) over time. ΔN2 amplitude demonstrated a linear increase in magnitude (became more negative) over time whereas ΔP3b amplitude was more positive in kindergarten compared to preschool. Younger age in preschool predicted greater rates of change in ΔN2 amplitude, and higher maternal education predicted larger initial P3b Go and No-Go amplitudes in preschool. Our findings suggest that observed waveforms and difference waves are not interchangeable for indexing neurodevelopment, and the developmental trajectories of different ERP indices of cognitive control are component-specific in early childhood.

Introduction

Cognitive control (executive function) skills support goal-directed behaviors, especially in the face of distractions or irrelevant behavior choices (Cohen, 2017; Gratton et al., 2018). The development of these skills in early childhood is essential for school readiness and academic success (Schmitt et al., 2017). In contrast, cognitive control difficulties are implicated in various neurodevelopmental disorders, including attention-deficit/hyperactivity disorder and obsessive-compulsive disorder (Yang et al., 2022). Given the educational and clinical significance of early cognitive control development, many studies have investigated the neural underpinnings of cognitive control (for a review, see Fiske & Holmboe, 2019).

In particular, the event-related potential (ERP) technique has commonly been used to examine neural indices of cognitive control given its ability to capture the rapid temporal dynamics of cognitive control (Gratton et al., 2018). Further, the ERP technique is non-invasive and child-friendly, making this neuroimaging method well-suited for developmental research (Coch & Gullick, 2011). However, the developmental ERP literature primarily consists of cross-sectional studies, limiting our understanding of the longitudinal characteristics of ERP components across childhood. Thus, the overarching goal of this study was to delineate the potentially distinct developmental trajectories of two widely studied neural indices of cognitive control, namely the ERP components N2 and P3b, across early childhood – a period of critical importance for cognitive control development.

Development of cognitive control in early childhood

According to the developmental model of cognitive control proposed by Munakata and colleagues (2012), three key transitions occur in early childhood that support improvements in cognitive control skills. Specifically, children transition from perseverating on habits to engaging control in response to environmental demands, from reactive to proactive control, and from externally-driven to self-directed control. These developmental transitions are paralleled by improvements in accuracy and increases in response speed across various cognitive control tasks (Reilly et al., 2022; Schmitt et al., 2017; Willoughby et al., 2012). Taken together, cognitive control develops substantially during preschool and the early school-aged years.

In addition to these behavioral changes, there are marked structural and functional changes in brain regions subserving cognitive control during this period (for a review, see Fiske & Holmboe, 2019). Notable structural changes within the prefrontal and posterior cortices occur in addition to the maturation of white matter microstructure in tracts connecting these regions (Goddings et al., 2021; Houston et al., 2013). Additionally, with age, there are changes in the activation patterns of frontal and posterior regions as well as the strengthening of frontoparietal functional connectivity (Buss et al., 2014; Fiske & Holmboe, 2019). Given the pronounced development of brain regions supporting cognitive control across early childhood, it is plausible that this maturation would be paralleled by developmental changes in ERP indices of cognitive control.

ERP components N2 and P3b

Two of the most commonly studied ERP indices of cognitive control are the N2 and P3b components. The N2 is a negative deflection in the ERP waveform that is commonly observed during competing response tasks. The N2 is generally found to be enhanced (more negative) for infrequently presented trials that elicit competing response representations compared to frequently presented trials that elicit more automatic responses (Folstein & Van Petten, 2007; Hoyniak, 2017). Investigators have interpreted the N2 as indexing response inhibition (e.g., Bokura et al., 2001). However, there is evidence that the N2 is larger for infrequent responses, regardless of whether a motor response is inhibited, leading others to argue that the N2 may reflect the monitoring of conflict between competing response representations (e.g., Botvinick et al., 2001). The N2 occurs over frontal electrodes around 200-300 ms post stimulus in adults (Bokura et al., 2001; Folstein & Van Petten, 2007). In children, N2 is typically observed around 250-500 ms post stimulus, and can have a broader scalp distribution over the anterior and central electrodes (Abdul Rahman et al., 2017; Lahat et al., 2010). ERP work combined with source localization techniques have identified the anterior cingulate, ventral and dorsal prefrontal, and orbitofrontal cortices as N2 generators in children and adults (Bokura et al., 2001; Lahat et al., 2010; Lamm et al., 2006).

The P3b is a positive deflection in the ERP waveform that tends to be elicited during tasks in which participants must discriminate between and respond differently to frequent and rare stimuli (Polich, 2011). The hallmark of the P3b is that its amplitude tends to be larger (more positive) for infrequent compared to frequent stimuli (Polich, 2011). In terms of its functional significance, the P3b is considered to reflect context updating and information processing associated with attentional and memory mechanisms (Polich, 2011). The P3b is maximal over posterior electrodes and occurs around 300-600 ms post stimulus in adults (Kappenman et al., 2021; Polich, 2011) and around 300-700 ms post stimulus in children (Abdul Rahman et al., 2017; Riggins & Scott, 2020; St John et al., 2019). Neural generators of the P3b have been identified as the inferior temporal and posterior parietal cortices (Bledowski et al., 2004; Polich, 2011). Given that N2 and P3b differ in the cognitive processes they are considered to reflect, as well as in their timing, scalp distribution, and neural generators, these components may display distinct developmental trajectories in childhood.

Development of N2 and P3b

Several researchers have successfully adapted the classic visual Go/No-Go task to elicit N2 and P3b in children (e.g., Lahat et al., 2010; Ruberry et al., 2017). Generally, in this task, participants are instructed to respond to frequently presented targets (Go) and withhold responses to rare non-targets (No-Go), and enhanced amplitudes are typically observed for the No-Go compared to Go trials (e.g., Lahat et al., 2010; St. John et al., 2019). ERPs elicited during Go/No-Go tasks can be quantified using observed waveforms (Go and No-Go) or the difference wave (No-Go minus Go, or Δ). Observed waveforms consist of a mixture of underlying brain components, reflecting underlying neurophysiology, whereas difference waves eliminate concurrent neural processes across conditions, reflecting experimental effects on ERP components (Luck, 2014). Given that observed waveforms and difference waves diverge in the neural activity that they reflect, they may show different developmental trajectories.

Cross-sectional studies using visual Go/No-Go tasks have reported somewhat contradictory results regarding age-related changes in N2 amplitudes extracted from both observed waveforms and difference waves. N2 No-Go amplitude has been found to linearly decrease in magnitude (become less negative) with age (Hoyniak, 2017; Lo, 2018), while N2 Go amplitude has been found to show no change across childhood and adolescence (Hoyniak, 2017). Correlational studies have reported that P3b Go and No-Go amplitudes show no change with age (St. John et al., 2019; Willner et al., 2015). Studies examining ΔN2 amplitude have reported both increases and decreases across development (Cragg et al., 2009; Jonkman, 2006). It is unclear how ΔP3b amplitude changes with age as P3b amplitudes have primarily been examined using observed waveforms. The somewhat inconsistent findings reported in previous research may stem from differences in age groups of interest, task characteristics across studies (e.g., task paradigm, types and frequency of visual stimuli, task difficulty), and whether ERP components are quantified with observed waveforms or difference waves.

Individual differences in cognitive control development

Beyond the need for delineating average change in different ERP indices of cognitive control in early childhood, it is also important to examine what factors may contribute to individual differences in these trajectories. Although age-related differences in ERP indices of cognitive control have been less consistent, children's age has consistently been found to relate to concurrent behavioral measures of cognitive control, such that older children outperform but demonstrate slower rates of growth in cognitive control, compared to younger children (Davidson et al., 2006; Lensing & Elsner, 2018). Although widely studied, gender differences in cognitive control have not been consistent. While there is some evidence that compared to boys, girls demonstrate greater accuracy and slower response times during cognitive control tasks (Clark et al., 2013), other studies have reported no gender differences in behavioral performance or N2 and P3b amplitudes (Lahat et al., 2010; St. John et al., 2019; Willner et al., 2015).

Among family-level factors, socioeconomic status (SES) has consistently been found to relate to cognitive control in early childhood (Merz et al., 2018; Ursache & Noble, 2016). However, for N2 and P3b amplitudes, findings have been less consistent. While some studies reported smaller N2 and P3b amplitudes in children from lower compared to higher SES backgrounds (Kishiyama et al., 2009; St. John et al., 2019), others did not find SES-related disparities (Rubbery et al., 2017). It remains to be investigated to what extent these child- and family-level characteristics contribute to the neurodevelopment of cognitive control in early childhood.

Current study

In the current study, we examined developmental changes in neural indices of cognitive control, specifically, ERP components N2 and P3b, in early childhood. ERPs were recorded during a visual Go/No-Go task from a large sample of children (N = 257) from diverse socioeconomic and racial/ethnic backgrounds across 3 time points: preschool, kindergarten, and first grade. N2 and P3b mean amplitudes were extracted from observed waveforms (Go and No-Go) *and* the difference wave (No-Go minus Go). We used latent growth curve modeling to delineate the longitudinal characteristics of N2 and P3b amplitudes.

Based on previous research demonstrating that N2 and P3b differ in the cognitive processes they are considered to reflect, and in their timing, scalp distribution, and neural generators, we expected N2 and P3b amplitudes to demonstrate unique developmental trajectories. Further, given that observed waveforms reflect underlying neurophysiology, whereas difference waves reflect experimental effects on ERP components (Luck, 2014), we predicted that amplitudes extracted from observed waveforms and difference waves would display distinct developmental trajectories.

After characterizing the developmental trajectories of N2 and P3b amplitudes, we examined whether child- and family-level sociodemographic characteristics related to the initial starting values and rates of change in N2 and P3b amplitudes. Specifically, we examined links between age, gender, and family SES, and N2 and P3b amplitudes. Previous inconsistent findings precluded us from having *a priori* hypotheses regarding the links between these sociodemographic factors and the longitudinal characteristics of N2 and P3b amplitudes.

Method

Participants

Participants were part of a longitudinal study examining school readiness and early academic success. The initial sample consisted of 278 children (55% girls) between the ages of 3.75 and 5.83 years (Mean = 4.70, *SD* = 0.39) who were recruited from daycare centers, public establishments, and via participant referral in the Southeastern United States. The study consisted of three waves of data collection: preschool, kindergarten, and first grade. At the preschool laboratory visit, none of the participants had started kindergarten. The kindergarten laboratory visit took place approximately 1 year after the preschool visit and was proceeded approximately 1 year later by the first grade visit. The present study included children for whom we had usable electroencephalogram (EEG) data for at least one time point ($n = 257$; 54% girls). Children who had ERP data for at least one time point did not differ from children who did not have ERP data at any time point ($n = 21$) in terms of age at the beginning of the study, gender, maternal education, or income-to-needs ratio (all *p*s > .056).

According to parent reports of child race, 59% of children were White, 30% were African American, 9% were multiracial, and 2% were Asian. This sample broadly represented the diversity of the county from which the children were recruited (U.S. Census, 2010). Children who participated in all visits (84%) did not differ from children who participated in only one or two visits in terms of age at the beginning of the study, gender, maternal education, or income-to-needs ratio (all *p*s > .085).

Procedure

Upon arrival to the laboratory, informed written consent was obtained from parents and verbal assent was obtained from the child prior to beginning data collection. Each laboratory visit took approximately 2 hours and consisted of a battery of tasks assessing cognitive, social, and emotional development and academic readiness. At the beginning of the testing session, the child's head circumference was measured, and an appropriately sized EEG net was fitted. During the Go/No-Go task, children were seated in front of a computer monitor; the distance and alignment to the monitor were kept consistent across children. To reduce motor artifacts, children were instructed to sit still during the task. Parents received monetary compensation and children selected a toy at the completion of the visit.

Measures

Demographics. Information about children's age, gender, race and ethnicity, and family SES was obtained via a questionnaire filled out by parents at the preschool time point. Income-to-needs ratio and maternal education were used as measures of family SES. Parents reported monthly family income on an item that consisted of 15 income ranges. The midpoint of each range was used as an estimate of total monthly income, and this value was multiplied by 12 to obtain an estimate of total yearly income. The appropriate poverty threshold was assessed based on U.S. Census Reports for the year in which annual income was earned, the number of individuals living in the home, and the number of children living in the home. Income-to-needs ratio was computed by dividing the annual family income by the poverty threshold. Maternal education level was rated on an ordinal scale ranging from 10 (some high school, no diploma) to 18 (graduate or professional degree). The values approximately correspond to the number of years of schooling. Descriptive statistics for the demographic variables are presented in Table 1.

Cognitive control. A computerized Go/No-Go task (Lahat et al., 2010; see Figure 1 for a schematic of task structure) was used to assess children's cognitive control. The task was presented using E-Prime version 2.0 (PST, Pittsburgh, PA, USA) while EEG data was collected. At the beginning of each trial, a fixation point accompanied by a "ding" sound appeared in the middle of the screen and was shown for 1,500 ms. This was followed by an animal stimulus that was displayed on the screen for 1,500 ms or until a response was made. Task stimuli were colored animal pictures (cow, horse, bear, pig, or dog). Children were instructed to respond by pressing a button as soon as they saw an animal (Go trial), except for when they saw a dog (No-Go trial). Feedback was displayed for 500 ms after each trial. A yellow smiley face followed a correct response, and a red frowning face followed an incorrect response or a response that occurred after the 1,500 ms stimulus window. Before beginning the task, children completed 10 practice trials (6 Go). The practice block was repeated until children responded correctly on at least 9 out of 10 trials. The task itself consisted of 144 trials (75% Go) divided into 4 blocks, with breaks offered between blocks. No-Go trials were preceded by two, three, or four Go trials to avoid predictability.

EEG recording and analyses

EEG was recorded using a 64-channel HydroCel Geodesic Sensor Net, a NetAmps 300 Amplifier, and the NetStation 4.5.4 software (Electrical Geodesics Inc., Eugene, OR, USA). Following an advisory notice released by EGI on anti-alias filter effects on timing, event latencies were re-coded by adding 8 ms to the original event latencies. Prior to data collection, the sensor nets were customized for the study by removing four face electrodes. Electrodes approximating the international 10-20 locations were renamed and clusters were defined around these electrodes (Vanderwert et al., 2016), as shown in Figure 2. EEG data were sampled at 250 Hz and referenced online to a single vertex electrode (Cz). Channel impedances were kept at or below 80 kΩ.

EEG preprocessing and ERP analyses were conducted in MATLAB using customized EEGLAB (Delorme & Makeig, 2004) and ERPLAB (Lopez-Calderon & Luck, 2014) scripts, as well as scripts adapted from the ERP CORE (Kappenman et al., 2021), ICLabel (Pion-Tonachini et al., 2019), and Mass Univariate Toolbox (Groppe et al., 2011).

EEG data were band-pass filtered from 0.1 to 30 Hz with a linear finite impulse response (FIR) filter. Upon initial inspection of the data, electrodes E23, E29 (LM), E47 (RM), and E55 were found to be artifact-laden across participants. These four electrodes were excluded from further processing and not included in the final analyses. Electrodes E1, E5 (FP2), E10 (FP1), and E17 were used only for the detection of ocular movements. For the remaining 52 electrodes, bad electrodes were detected with the *pop_clean_rawdata* function in EEGLAB and replaced using spherical interpolation. After interpolation, the EEG data were re-referenced to the average.

Next, recording periods with no event codes (defined as no events for 5000 ms or longer, with 2500 ms before and 2500 ms after any codes) were removed. Data segments with extreme artifacts were rejected from the continuous data with the ERPLAB moving window peak-to-peak threshold algorithm (across a 500 ms window, moving at 250 ms increments, with a +/- 300 μV threshold) applied to all electrodes except E1, E5, E10, and E17. ICA was then conducted on all electrodes. The computed ICA weights were then applied to the preprocessed data files (after interpolation and re-referencing). For the removal of eye components, we used the ICLabel classifier (Pion-Tonachini et al., 2019). Each independent component that was associated with the "eye" label with at least 80% probability and associated with the "brain" label with less than 5% probability was selected as an "eye component". Only the first 3 "eye" components listed for each participant were removed to prevent losing too much non-artifactual activity.

After the removal of the eye components, the EEG data were epoched offline between 200 ms prior to and 1000 ms after stimulus onset, using the first 200 ms as the pre-stimulus baseline period. Artifact rejection was run on a sample group of channels (E1, E5, E10, E12, E17, E20, E28, E42, E50, E60) with a simple voltage threshold of 200 μV to determine channels that might cause large amounts of ERP data loss. Channels that caused at least 10% of ERP trials to be rejected and had a rejection percentage of at least 3.29 *SD* (Tabachnick & Fidell, 2007) above the within-participant mean were marked as bad. The channels marked as bad for each participant were excluded from artifact detection and data analyses. The final artifact rejection step was run on all channels of interest, shown in Figure 2, using a simple voltage threshold of 200 μV for all participants.

To reduce the number of factors used in the statistical analyses, electrode clusters were used instead of single electrodes (Luck & Gaspelin, 2017). Given that larger N2 amplitudes for the No-Go versus Go trials have been observed over the anterior right (Lahat et al., 2010) and left hemispheres (Abdul Rahman et al., 2017), we created frontal and central electrode clusters separately for the right hemisphere (F4 and C4 clusters) and left hemisphere (F3 and C3 clusters). Larger P3b amplitudes in children have been reported over midline posterior electrodes (St. John et al., 2019; Willner et al., 2015), but hemisphere differences have also been found, with larger P3b amplitudes observed over parietal right and midline electrodes compared to the left hemisphere (Abdul Rahman et al., 2017). Therefore, we created posterior electrode clusters separately for the midline region (PM and OM clusters), right hemisphere (P4 cluster), and left hemisphere (P3 cluster). For the electrodes included in each cluster, see Figure 2.

An initial data quality check was done via visual inspection of the individual ERP plots, for each participant at each time point. ERP data of children were excluded if there were not clear visual evoked potentials (visual P1 and N1, for the frequent, i.e., Go trials) in the PM and OM clusters. Only correct trials were included in the analyses. ERP data of children who did not have at least 10 artifact-free trials per probe type were excluded from analyses. For information on exclusion criteria, see Table 2.

Based on previous research using similar paradigms with a similar age group, we planned to measure the N2 component between 250-450 ms post stimulus onset (Lahat et al., 2010; Ruberry et al., 2017) and the P3b component between 300-600 ms poststimulus onset (Abdul Rahman et al., 2017; Ruberry et al., 2017; St. John et al., 2019). The Mass Univariate ERP Toolbox (Groppe et al., 2011) was used to check the appropriateness of the ERP measurement time windows we selected *a priori*, as well as to examine the scalp distribution of the N2 and P3b. As recommended, to isolate the experimental effects, difference waves were used in these analyses (Groppe et al., 2011). Specifically, we used the t-max permutation, conducting repeated-measures two-tailed permutation tests for the difference waves (No-Go minus Go) at every time point at each selected channel cluster (F3, F4, C3, C4, P3, P4, PM, OM) from 200 to 800 ms post stimulus (i.e., 1208 comparisons), while controlling for the family-wise error rate. Separate permutation tests were performed for the preschool, kindergarten, and first grade ERPs. The mass univariate analyses supported the use of the time windows selected for N2 and P3b *a priori*. Additionally, based on the results from the permutation tests (see Figure 3 for raster diagrams), we collapsed across the F4 and C4 clusters and used a single right frontocentral cluster in subsequent analyses of N2. We also collapsed across the PM and OM clusters and used a single midline posterior cluster in subsequent analyses of P3b (see Figure 4 for channels included in the final clusters).

After selection of the channel clusters to be used in the analyses, two more exclusion criteria were applied separately for N2 and P3b and for preschool, kindergarten, and first grade ERP data before the statistical analyses were conducted. First, we conducted visual inspection of the individual average ERP plots across participants for the clusters of interest to identify any cases in which data quality was poor (e.g., excessive drift in observed waveforms). These ERP data were excluded from the final analyses. Second, an objective data quality measure, namely the analytic standardized measurement error (aSME; Luck et al., 2021), was computed for Go and No-Go mean amplitude, using a window of 250-450 ms for N2 and 300-600 ms for P3b. An aSME outlier was defined as a value at least +/- 3.29 *SD* (Tabachnick & Fidell, 2007) or more extreme than the between-participant mean for each component at preschool, kindergarten, and first grade. Given that higher aSME values indicate lower measurement precision and worse data quality, ERP data were excluded from the final analyses if there was an aSME outlier for either the Go or No-Go condition. Counts for all exclusion criteria are provided in Table 2.

The final analyses included ERP mean amplitudes extracted from observed waveforms (Go and No-Go) and the difference wave (denoted as Δ), between 250-450 ms over the right frontocentral cluster for N2, and 300-600 ms over the midline posterior cluster for P3b.

Analytic strategy

To examine the average trajectories of N2 Go, N2 No-Go, ΔN2, P3b Go, P3b No-Go, and ΔP3b across preschool, kindergarten, and first grade, we conducted an unconditional latent growth curve model for each outcome separately. The latent intercept factor, representing outcome values at the first data collection point (preschool), was estimated by constraining the paths of each data collection point to 1. The latent slope factor, representing the linear change in the outcome across the three data collection points, was estimated by constraining the paths for preschool, kindergarten, and first grade to 0, 1, and 2, respectively. The intercept and slope were allowed to covary. Bonferroni correction was applied per ERP component to control for the family-wise error rate[1]. Poor fit between an unconditional model and the observed data was addressed by conducting post-hoc pairwise comparisons, applying Bonferroni correction to control for the type I error rate.

To evaluate whether the trajectories of the outcomes of interest varied as a function of sociodemographic factors, we examined whether age at the beginning of the study, gender, maternal education, and income-to-needs ratio predicted the intercept and slope of each outcome. These factors were added as time-invariant covariates to the unconditional models that provided good fit to the observed data. Maternal education and income-to-needs ratio were significantly correlated, $r = .49$, $p < .001$, thus, we allowed these variables to covary in the conditional models. Bonferroni correction was applied per ERP component to control for the family-wise error rate[2].

Missing data were handled using full information maximum likelihood (FIML) estimation to reduce potential bias in the parameter estimates (Enders & Bandalos, 2001). Model fit was evaluated using a combination of fit indices, including χ^2, CFI ($\geq .90$), and RMSEA ($\leq .06$; Hu & Bentler, 1999). All data analyses were done in R (Version 4.2; R Core Team, 2022) and RStudio (Version 7.2; RStudio Team, 2022) using the *lavaan* package (Version 0.6; Rosseel, 2012).

[1]Given that observed waveform and difference wave amplitudes were extracted using the same cluster of electrodes per ERP component as well as the relatively high multicollinearity among the amplitude measures per ERP component (see Table 4 for bivariate correlations), we used a stringent multiple comparison correction method.

[2] Prior to applying this correction method, younger age at preschool related to larger (more negative) ΔN2 amplitudes in preschool ($p = .037$). All other relations between sociodemographic factors and the intercepts and slopes did not change in terms of significance when Bonferroni correction was applied.

Results

Preliminary analyses

Descriptive statistics for all study variables are reported in Table 1. Bivariate correlations among sociodemographic factors and the outcomes of interest are reported in Tables 3 and 4. Skewness and kurtosis were within the limits of moderate normality (+/- 3); however, first grade ΔP3b kurtosis was 3.05. Scores at or more extreme than +/- 3.29 *SD* were considered univariate outliers (Tabachnick & Fidell, 2007). The following outliers were identified: 2 children for kindergarten N2, 3 children for preschool P3b, and 2 children for first grade P3b[3]. All analyses were conducted with children's original scores as well as with outliers set to missing. The direction and strength of the results remained consistent across the analyses. The subsequent results reported here include all children to reflect the true range of scores. The grand average ERP plots for the No-Go versus Go conditions over the right frontocentral cluster and the midline posterior cluster are shown in Figures 5 and 6, respectively.

Developmental trajectories of N2 amplitude

The unconditional models examining the trajectories of N2 Go, N2 No-Go, and ΔN2 amplitudes demonstrated good fit to the data (see Table 5 for fit indices). Results suggested that N2 Go and No-Go amplitudes showed no significant linear change whereas ΔN2 amplitude linearly increased in magnitude (became more negative) across time (see Table 6 for model estimates). Specifically, the initial average value of N2 Go amplitude during preschool was -4.61 µV which did not change across time. The initial average value of N2 No-Go amplitude was -7.42 µV and also did not change across time. Finally, the initial average value of ΔN2 amplitude was -2.81 µV, which declined 0.53 µV on average across each time point. There was significant variability in the initial levels of all three outcomes, however, there were no significant individual differences in the rate of linear change.

Next, we examined whether sociodemographic factors were associated with the intercepts and slopes. The conditional models demonstrated good fit to the data (see Table 5 for fit indices). None of the sociodemographic factors were associated with the intercepts or slopes of N2 Go or No-Go amplitudes (all ps > .090). None of the sociodemographic factors were associated with the intercept of ΔN2 amplitude (all ps > .037). Initial age predicted the slope of ΔN2 amplitude ($b = 1.08$, $p = .004$). That is, for children who were younger in preschool, on average, ΔN2 amplitude became more negative at a faster rate over time, compared to older children. Gender, maternal education, and income-to-needs ratio did not predict the slope of ΔN2 amplitude (all ps > .179; see Table 7 for model estimates).

Developmental trajectories of P3b amplitude

The unconditional models examining the trajectories of P3b Go and No-Go amplitudes resulted in negatively estimated slope variances, producing non-positive definite covariance matrices for the latent growth factors. As recommended by Chen and colleagues (2001), for each model, we conducted a Wald test for the null hypothesis that

---

[3] Outliers were identified per ERP component using mean amplitude values extracted from the difference wave. When conducting analyses without outliers, the same cases were excluded for all other ERP measures (i.e., Go and No-Go amplitudes) to keep the final analytic sample consistent across statistical models per ERP component.

the slope variance is zero versus the alternative that it is smaller than zero. The statistically non-significant Wald test results ($W(1) = 0.000121$, $p = .995$ for P3b Go and $W(1) = 0.0484$, $p = .900$ for P3b No-Go amplitudes) suggested that negative slope variance estimates may be due to sampling fluctuations rather than model misspecification. As suggested, we fixed the slope variances to zero (Chen et al., 2001). These models demonstrated good fit to the data (see Table 5 for fit indices). Results suggested that P3b Go and No-Go amplitudes linearly decreased in magnitude (became less positive) across time (see Table 6 for model estimates). Specifically, the initial average value of P3b Go amplitude during preschool was 16.38 μV, which on average declined 1.53 μV across each time point. The initial average value of P3b No-Go amplitude was 21.67 μV, which declined 1.27 μV on average across each time point. There was significant variability in the initial levels of both outcomes.

The unconditional model examining the trajectory of ΔP3b amplitude demonstrated poor fit to the data (see Table 5 for fit indices). Poor model fit may be due to the non-linear trend of ΔP3b mean amplitude (see Table 1 for descriptive statistics). Model estimates are provided in Table 7. Given that we only had data from three time points, we could not test for non-linear growth models. To address the poor model fit, we conducted post-hoc pairwise comparisons across data collection time points (see Table 8 for pairwise comparison results). Results demonstrated a significant difference in ΔP3b amplitude only between preschool and kindergarten such that larger (more positive) ΔP3b amplitudes were observed in kindergarten ($p = .011$).

Following the approach used in Verstaen et al. (2020), in instances where we set the slope variances to zero, we did not include slope covariates. Thus, we only examined whether the sociodemographic factors predicted the intercepts of P3b Go and No-Go amplitudes. The conditional models demonstrated good fit to the data (see Table 5 for fit indices). Maternal education predicted the intercept of P3b Go ($b = 0.60$, $p = .004$) and P3b No-Go amplitudes ($b = 0.82$, $p = .004$). Specifically, on average, higher maternal education predicted larger (more positive) P3b Go and No-Go amplitudes during preschool. Age, gender, and income-to-needs ratio did not predict the intercepts of P3b Go or No-Go amplitudes (all *p*s > .166; see Table 7 for model estimates). Given the poor fit of the unconditional model for ΔP3b amplitude, we did not conduct a conditional growth model.

Discussion

The current study aimed to delineate the longitudinal characteristics of two commonly studied neural indices of cognitive control, ERP components N2 and P3b, from preschool through first grade. We found that for both N2 and P3b, observed waveforms and difference waves displayed disparate developmental trajectories. Further, the developmental trajectories of ERP amplitudes extracted from both observed waveforms and difference waves were component specific. Similarly, the links between children's sociodemographic characteristics and ERP amplitudes partly depended on whether observed waveforms or the difference wave was used and the ERP component of interest. Together, these findings emphasize that observed waveforms and difference waves are not interchangeable for indexing neurodevelopment and different neural indices of cognitive control have distinct developmental trajectories in early childhood.

Observed waveforms versus difference waves

In line with our expectations, our results demonstrated that both N2 and P3b amplitudes displayed unique developmental trajectories depending on whether observed waveforms or difference waves were used. We found that N2 amplitudes extracted from observed waveforms displayed no linear change as children transitioned from preschool to first grade. Previous meta-analyses have reported that N2 No-Go amplitude linearly decreases in magnitude (becomes less negative) across childhood and adolescence (Hoyniak, 2017; Lo, 2018). However, the studies included in these meta-analyses varied based on task characteristics and examined age-related changes in N2 amplitudes across a wider developmental period, specifically, from ages 2-12 years (Hoyniak, 2017) and 3-17 years (Lo, 2018). To speculate, the lack of change we observed in N2 Go and No-Go amplitudes may suggest that the underlying neurophysiology reflected by these waveforms displays more robust changes later in development.

In contrast, we found that N2 amplitude extracted from the difference wave linearly increased in magnitude (became more negative) over time. Difference waves isolate task-specific neural activity, reflecting experimental effects on ERP components (Luck, 2014). Thus, compared to N2 observed waveforms, ΔN2 is a closer estimate of neural processes involved in cognitive control. Developmental changes in ΔN2 amplitude may coincide with the substantial neurodevelopment of cognitive control as well as behavioral improvements in cognitive control during preschool and the early school-aged years (Fiske & Holmboe, 2019; Goddings et al., 2021; Willoughby et al., 2012).

While previous correlational studies have reported no age-related differences in P3b Go and No-Go amplitudes (St. John et al., 2019; Willner et al., 2015), in our longitudinal study, we found that P3b Go and No-Go amplitudes linearly decreased in magnitude (became less positive) over time. There are several plausible explanations for this finding. Developmental changes in P3b amplitudes extracted from observed waveforms may reflect a combination of maturational changes occurring throughout the brain that affect the magnitude of ERPs recorded at the scalp, such as changes in synaptic density, myelination, and cerebral blood flow (Coch & Gullick, 2011).

Contrary to P3b Go and No-Go amplitudes, which displayed linear decreases in amplitude over time, our results suggested that ΔP3b amplitude may show a nonlinear trajectory of change. Specifically, we found that ΔP3b amplitude was larger (more positive) in kindergarten compared to preschool only. Behavioral studies have reported unique effects of kindergarten on the growth of cognitive control skills, over and above the effect of age (Kim et al., 2020). Thus, it is possible that the transition to kindergarten may also contribute to ΔP3b development. Interestingly, we did not observe a difference in ΔP3b amplitudes between preschool and first grade nor between kindergarten and first grade. The lack of linear change observed in ΔP3b amplitude emphasizes the importance that future studies use more than three time points to explore potential nonlinear trajectories of ERP amplitudes. Overall, our findings indicate that observed waveforms and difference waves may capture different aspects of neurodevelopment.

Component-specific developmental trajectories

In addition to developmental differences based on whether observed waveforms or difference waves were used, we also found component-specific differences in the developmental trajectories of ERP amplitudes, which is consistent with our predictions. Specifically, for both observed waveforms and the difference wave, N2 amplitudes displayed different trajectories of change, compared to P3b amplitudes. When extracting amplitudes from observed waveforms, we found that N2 amplitudes displayed no linear change whereas P3b amplitudes linearly decreased in magnitude (became less positive) over time. The anterior cingulate, ventral prefrontal, and orbitofrontal cortices are proposed neural generators of N2 observed waveforms (Lahat et al., 2010; Lamm et al., 2006), whereas inferior temporal and posterior parietal cortices are suggested neural generators of P3b observed waveforms (Bledowski et al., 2004; Polich, 2011). These regions have been found to show different patterns of structural and functional brain development across childhood (Fiske & Holmboe, 2019; Houston et al., 2013). Thus, it is possible that the underlying neurophysiology reflected by N2 and P3b observed waveforms demonstrated disparate developmental trajectories given the distinct developmental changes observed in the proposed neural generators of N2 and P3b observed waveforms.

Similarly, the developmental trajectories of amplitudes extracted from the difference wave were component specific. We found that ΔN2 amplitude linearly increased in magnitude (became more negative) over time while ΔP3b amplitude was larger (more positive) in kindergarten compared to preschool only. The N2 and P3b components differ in their timing and in the cognitive processes they are thought to reflect, which may have contributed to the component-specific longitudinal trajectories observed in the current study. In line with this, it has been suggested that different developmental trajectories of ERP components may stem from differences in the complexity of the cognitive processes the components reflect and the development of brain structures and functions involved in the components (Coch & Gullick, 2011; Taylor & Baldeweg, 2002). Taken together, these findings demonstrate that the development of different ERP indices of cognitive control are not uniform in early childhood.

Links between sociodemographic factors and ERP amplitudes

Another aim of the present study was to examine whether children's sociodemographic characteristics contributed to individual differences in N2 and P3b development. We found that age at the beginning of the study did not relate to the longitudinal characteristics of N2 or P3b amplitudes extracted from observed waveforms. However, for children who were younger in preschool, ΔN2 amplitude became more negative at a faster rate over time, compared to children who were older in preschool. To speculate, greater rates of change in brain development and plasticity observed in younger compared to older children across the transition from preschool to formal schooling (Tooley et al., 2021) may have contributed to the greater rate of change in ΔN2 amplitude across this period. Similarly, previous behavioral studies that have reported greater rates of improvement in cognitive control in younger compared to older children (Lensing & Elsner, 2018). Gender did not relate to any of the ERP measures which is consistent with previous studies that reported no gender differences in N2 or P3b amplitudes (Lahat et al., 2010; Willner et al., 2015).

Additionally, we found that income-to-needs ratio did not relate to the initial starting value or rate of change of any of the ERP measures. This finding is consistent with Ruberry et al. (2017)'s findings that family income did not relate to N2 or P3b amplitudes extracted from observed waveforms or difference waves in 4.5-5.5-year-olds. However, there is evidence that higher SES, based on parental education and family income, relates to larger N2 amplitudes in 7-12-year-olds (Kishiyama et al., 2009). Thus, it is possible that the contributions of family SES on N2 development may become more apparent later in childhood.

We also found that maternal education was associated with P3b but not N2 amplitudes. Specifically, higher maternal education was related to larger (more positive) P3b Go and No-Go amplitudes during preschool. Contrary to our findings, income-to-needs ratio, but not parental education, has been found to predict P3b Go and No-Go amplitudes in 4.5-5.5-year-olds (St. John et al., 2019). Our findings suggest that compared to family income, maternal education may more strongly contribute to the underlying neurophysiology reflected by P3b observed waveforms. This interpretation is similar to the argument that compared to family income, parental education is a stronger predictor of children's cognitive and academic development (Davis-Kean et al., 2021).

Because of the model constraints placed on slope variance estimates, we were unable to examine relations between the sociodemographic factors and the rate of change in P3b Go and No-Go amplitudes. Additionally, given that our results suggested that ΔP3b amplitude may display a nonlinear trajectory of change, we were unable to examine the associations between sociodemographic characterisitcs and linear change in ΔP3b amplitude. Future work is needed to examine how these factors contribute to P3b development across childhood. Nevertheless, our findings suggest that the contributions of child- and family-level sociodemographic characteristics on neurodevelopment may depend on whether observed waveforms or difference waves are used and the ERP component of interest.

Limitations and future directions

One limitation of our study is that the findings may be limited in their generalizability to other task paradigms. Task characteristics such as types of stimuli, task complexity, and modality (e.g., visual or auditory) can greatly moderate the magnitude of ERP amplitudes (Lo, 2018; Riggins & Scott, 2020). In addition, even if an ERP component exhibits the same polarity and timing as ERP components elicited during similar experiments, these components may not necessarily reflect the same underlying neural processes (Luck, 2014). It is possible that N2 and P3b elicited during different experiments display developmental trajectories that differ from the trajectories observed in the current study. Future research is needed to assess how task characteristics may modulate the development of ERP components.

Another limitation of our study is the inability to test for potential nonlinear developmental trajectories of ERP amplitudes. Although our results suggested that ΔP3b amplitude may demonstrate a nonlinear rate of change from preschool to first grade, we were unable to include nonlinear growth factors in the latent growth curve models given that we only had three data collection points. The transition to formal schooling encompasses major qualitative changes in children's environments, such as greater expectations for social and self-regulation skills, increased demands on children's ability to control attention, and an emphasis on academic achievement (Bassok et al., 2016). It is plausible that the rate of change in neural indices of cognitive control is not constant across this period. Longitudinal behavioral studies examining early childhood provide evidence for nonlinear growth rates in children's cognitive control skills (Reilly et al., 2022; Willoughby et al., 2012). Thus, longitudinal ERP studies that utilize more than three time points are necessary to provide a more comprehensive understanding of the development of ERP indices of cognitive control across childhood.

Conclusion

In summary, our study contributed to the characterization of the developmental trajectories of N2 and P3b, two commonly-studied neural indices of cognitive control, in early childhood. The disparate developmental trajectories of amplitudes extracted from observed waveforms versus difference waves suggest that observed waveforms and difference waves capture unique aspects of neurodevelopment and cannot be used interchangeably. Further, for both observed waveforms and difference waves, the longitudinal characteristics of ERP amplitudes were component-specific, which suggests that different ERP indices of cognitive control do not develop in a uniform manner in early childhood.

The methodological- and component-specific differences in developmental trajectories reported here may have important clinical implications. ERP amplitudes have consistently been found to be implicated in various neurodevelopmental disorders; however, there are inconsistencies in the direction of the effects which may stem from variability across studies in terms of task characteristics and whether observed waveforms or difference waves were used (Downes et al., 2017; Lo, 2018; Riggins & Scott, 2020). Distinguishing between the development of ERPs extracted from observed waveforms versus difference waves could help to inform how neurodevelopmental disorders manifest. In sum, our study is among the first to examine the longitudinal characteristics of ERP indices of cognitive control in early childhood in a large and socioeconomically and racially/ethnically diverse sample of children. Our findings highlight the importance of longitudinal ERP studies in order to better understand the nuances of the neurodevelopment of cognitive control in early childhood.

References

Abdul Rahman, A., Carroll, D. J., Espy, K. A., & Wiebe, S. A. (2017). Neural Correlates of Response Inhibition in Early Childhood: Evidence From a Go/No-Go Task. *Developmental Neuropsychology*, *42*(5), 336–350. https://doi.org/10.1080/87565641.2017.1355917

Bassok, D., Latham, S., & Rorem, A. (2016). Is Kindergarten the New First Grade? *AERA Open*, *2*(1), 2332858415616358.

Bledowski, C., Prvulovic, D., Hoechstetter, K., Scherg, M., Wibral, M., Goebel, R., & Linden, D. E. J. (2004). Localizing P300 Generators in Visual Target and Distractor Processing: A Combined Event-Related Potential and Functional Magnetic Resonance Imaging Study. *The Journal of Neuroscience, 24*(42), 9353-9360. https://doi.org/10.1523/JNEUROSCI.1897-04.2004

Bokura, H., Yamaguchi, S., & Kobayashi, S. (2001). Electrophysiological correlates for response inhibition in a Go/NoGo task. *Clinical Neurophysiology*, *112*(12), 2224–2232. https://doi.org/10.1016/S1388-2457(01)00691-5

Botvinick, M. M., Braver, T. S., Barch, D. M., Carter, C. S., & Cohen, J. D. (2001). Conflict monitoring and cognitive control. *Psychological Review*, *108*(3), 624. https://doi.org/10.1037/0033-295X.108.3.624

Buss, A. T., Fox, N., Boas, D. A., & Spencer, J. P. (2014). Probing the early development of visual working memory capacity with functional near-infrared spectroscopy. *NeuroImage, 85*, 314-325. https://doi.org/10.1016/j.neuroimage.2013.05.034

Chen, F., Bollen, K. A., Paxton, P., Curran, P. J., & Kirby, J. B. (2001). Improper solutions in structural equation models: Causes, consequences, and strategies. *Sociological Methods & Research, 29*(4), 468-508. https://doi.org/10.1177/0049124101029004003

Clark, C. A. C., Sheffield, T. D., Chevalier, N., Nelson, J. M., Wiebe, S. A., & Espy, K. A. (2013). Charting early trajectories of executive control with the shape school. *Developmental Psychology*, *49*(8), 1481–1493. https://doi.org/10.1037/a0030578

Coch, D., & Gullick, M. M., (2011). Event-related potentials and development. In S. Luck & E. Kappenman (Eds.), *The Oxford handbook of event-related potential components*. (pp. 475-511). Oxford University Press.

Cohen, J. D. (2017). Cognitive control: Core constructs and current considerations. In T. Egner (Ed.), *The Wiley Handbook of Cognitive Control* (pp. 1–28). John Wiley & Sons, Ltd. https://doi.org/10.1002/9781118920497.ch1

Cragg, L., Fox, A., Nation, K., Reid, C., & Anderson, M. (2009). Neural correlates of successful and partial inhibitions in children: An ERP study. *Developmental Psychobiology*, *51*(7), 533–543. https://doi.org/10.1002/dev.20391

Davidson, M. C., Amso, D., Anderson, L. C., & Diamond, A. (2006). Development of cognitive control and executive functions from 4 to 13 years: Evidence from manipulations of memory, inhibition, and task switching. *Neuropsychologia, 44*(11), 2037-2078. https://doi.org/10.1016/j.neuropsychologia.2006.02.006

Davis-Kean, P. E., Tighe, L. A., & Waters, N. E. (2021). The Role of Parent Educational Attainment in Parenting and Children's Development. *Current Directions in Psychological Science*, *30*(2), 186–192.

Delorme, A., & Makeig, S. (2004). EEGLAB: An open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. Journal of Neuroscience Methods, 134(1), 9–21. https://doi.org/10.1016/j.jneumeth.2003.10.009.

Downes, M., Bathelt, J., & De Haan, M. (2017). Event-related potential measures of executive functioning from preschool to adolescence. *Developmental Medicine & Child Neurology*, *59*(6), 581–590. https://doi.org/10.1111/dmcn.13395

Enders, C. K., & Bandalos, D. (2001). The relative performance of full information maximum likelihood estimation for missing data in structural equation models. *Structural Equation Modeling: A Multidisciplinary Journal*, *8*(3), 430–457. https://doi.org/10.1207/S15328007SEM0803_5

Fiske, A., & Holmboe, K. (2019). Neural substrates of early executive function development. *Developmental Review*, *52*, 42–62. https://doi.org/10.1016/j.dr.2019.100866

Folstein, J. R., & Van Petten, C. (2007). Influence of cognitive control and mismatch on the N2 component of the ERP: A review. *Psychophysiology*, *0*(0). https://doi.org/10.1111/j.1469-8986.2007.00602.x

Goddings, A., Roalf, D., Lebel, C., & Tamnes, C. K. (2021). Development of white matter microstructure and executive functions during childhood and adolescence: A review of diffusion MRI studies. *Developmental Cognitive Neuroscience, 51*, 12. https://doi.org/10.1016/j.dcn.2021.101008

Gratton, G., Cooper, P., Fabiani, M., Carter, C. S., & Karayanidis, F. (2018). Dynamics of cognitive control: Theoretical bases, paradigms, and a view for the future. *Psychophysiology, 55*(3), 1-29. https://doi.org/10.1111/psyp.13016

Groppe, D. M., Urbach, T. P., & Kutas, M. (2011). Mass univariate analysis of event-related brain potentials/fields I: A critical tutorial review: Mass univariate analysis of ERPs/ERFs I: Review. *Psychophysiology*, *48*(12), 1711–1725. https://doi.org/10.1111/j.1469-8986.2011.01273.x

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, *6*(1), 1–55. https://doi.org/10.1080/10705519909540118

Houston, S. M., Herting, M. M., & Sowell, E. R. (2013). The neurobiology of childhood structural brain development: Conception through adulthood. In S. L. Andersen & D. S. Pine (Eds.), *The Neurobiology of Childhood* (Vol. 16, pp. 3–17). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-662-45758-0_265

Hoyniak, C. (2017). Changes in the NoGo N2 Event-Related Potential Component Across Childhood: A Systematic Review and Meta-Analysis. *Developmental Neuropsychology*, *42*(1), 1–24. https://doi.org/10.1080/87565641.2016.1247162

Jonkman, L. M. (2006). The development of preparation, conflict monitoring and inhibition from early childhood to young adulthood; a Go/Nogo ERP study. *Brain Research*, *1097*(1), 181–193. https://doi.org/10.1016/j.brainres.2006.04.064

Kappenman, E. S., Farrens, J. L., Zhang, W., Stewart, A. X., & Luck, S. J. (2021). ERP CORE: An open resource for human event-related potential research. *NeuroImage, 225*. doi:10.1016/j.neuroimage.2020.117465

Kim, M. H., Ahmed, S. F., & Morrison, F. J. (2021). The effects of kindergarten and first grade schooling on executive function and academic skill development: Evidence from a school cutoff design. *Frontiers in Psychology, 11*, 13. https://doi.org/10.3389/fpsyg.2020.607973

Kishiyama, M. M., Boyce, W. T., Jimenez, A. M., Perry, L. M., & Knight, R. T. (06/2009). Socioeconomic Disparities Affect Prefrontal Function in Children. *Journal of Cognitive Neuroscience*, *21*(6), 1106–1115.

Lahat, A., Todd, R., Mahy, C., Lau, K., & Zelazo, P. (2010). Neurophysiological correlates of executive function: A comparison of european-canadian and chinese-canadian 5-year-olds. *Frontiers in Human Neuroscience*, *3*. https://doi.org/10.3389/neuro.09.072.2009

Lamm, C., Zelazo, P. D., & Lewis, M. D. (2006). Neural correlates of cognitive control in childhood and adolescence: Disentangling the contributions of age and executive function. *Neuropsychologia, 44*(11), 2139–2148. https://doi.org/10.1016/j.neuropsychologia.2005.10.013

Lensing, N., & Elsner, B. (2018). Development of hot and cool executive functions in middle childhood: Three-year growth curves of decision making and working memory updating. *Journal of Experimental Child Psychology, 173*, 187-204. https://doi.org/10.1016/j.jecp.2018.04.002

Lo, S. L. (2018). A meta-analytic review of the event-related potentials (ERN and N2) in childhood and adolescence: Providing a developmental perspective on the conflict monitoring theory. *Developmental Review*, *48*, 82–112. https://doi.org/10.1016/j.dr.2018.03.005

Lopez-Calderon, J., & Luck, S. J. (2014). ERPLAB: An open-source toolbox for the analysis of event-related potentials. Frontiers in Human Neuroscience, 8, 213. https://doi.org/10.3389/fnhum.2014.00213.

Luck, S. J. (2014). *An introduction to the event-related potential technique, second edition*. MIT Press.

Luck, S. J., & Gaspelin, N. (2017). How to get statistically significant effects in any ERP experiment (and why you shouldn't). Psychophysiology, 54(1), 146–157.

Luck, S. J., Stewart, A. X., Simmons, A. M., & Rhemtulla, M. (2021). Standardized measurement error: A universal metric of data quality for averaged event-related potentials. *Psychophysiology*, *58*(6). https://doi.org/10.1111/psyp.13793

Merz, E. C., Wiltshire, C. A., & Noble, K. G. (2019). Socioeconomic inequality and the developing brain: Spotlight on language and executive function. *Child Development Perspectives, 13*(1), 15-20. https://doi.org/10.1111/cdep.12305

Munakata, Y., Snyder, H. R., & Chatham, C. H. (2012). Developing cognitive control: Three key transitions. *Current Directions in Psychological Science, 21*(2), 71-77. https://doi.org/10.1177/0963721412436807

Pion-Tonachini, L., Kreutz-Delgado, K., & Makeig, S. (2019). ICLabel: An automated electroencephalographic independent component classifier, dataset, and website. *NeuroImage*, *198*, 181–197. doi.org/10.1016/j.neuroimage.2019.05.026

Polich, J. (2011). Neuropsychology of P300. In S. Luck & E. Kappenman (Eds.), *The Oxford handbook of event-related potential components*. (pp. 159-188). Oxford University Press.

R Core Team (2022). R: A language and environment for statistical computing (Version 4.2). [Computer software]. R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/.

Reilly, S. E., Downer, J. T., & Grimm, K. J. (2022). Developmental trajectories of executive functions from preschool to kindergarten. *Developmental Science*, *25*(5). https://doi.org/10.1111/desc.13236

Riggins, T., & Scott, L. S. (2020). P300 development from infancy to adolescence. *Psychophysiology*, *57*(7). https://doi.org/10.1111/psyp.13346

Rosseel, Y. (2012). Lavaan: An R package for structural equation modeling and more. *Journal of Statistical Software*, *48*(2), 1–36. https://doi.org/10.18637/jss.v048.i02

RStudio Team (2022). RStudio: Integrated Development Environment for R (Version 7.2). [Computer software]. RStudio, PBC, Boston, MA. http://www.rstudio.com/.

Ruberry, E. J., Lengua, L. J., Crocker, L. H., Bruce, J., Upshaw, M. B., & Sommerville, J. A. (2017). Income, neural executive processes, and preschool children's executive control. *Development and Psychopathology*, *29*(1), 143–154. https://doi.org/10.1017/S095457941600002X

Schmitt, S. A., Geldhof, G. J., Purpura, D. J., Duncan, R., & McClelland, M. M. (2017). Examining the relations between executive function, math, and literacy during the transition to kindergarten: A multi-analytic approach. *Journal of Educational Psychology*, *109*(8), 1120-1140. https://doi.org/10.1037/edu0000193

St. John, A. M., Finch, K., & Tarullo, A. R. (2019). Socioeconomic status and neural processing of a go/no-go task in preschoolers: An assessment of the P3b. *Developmental Cognitive Neuroscience*, *38*, 100677. https://doi.org/10.1016/j.dcn.2019.100677

Tabachnick, B. G., & Fidell, L. S. (2007). Using multivariate statistics. Boston, MA: Pearson/Allyn & Bacon.

Taylor, M. J., & Baldeweg, T. (2002). Application of EEG, ERP and intracranial recordings to the investigation of cognitive functions in children. *Developmental Science*, *5*(3), 318–334. https://doi.org/10.1111/1467-7687.00372

Tooley, U. A., Bassett, D. S., & Mackey, A. P. (2021). Environmental influences on the pace of brain development. *Nature Reviews. Neuroscience*, *22*(6), 372–384.

Ursache, A., & Noble, K. G. (2016). Neurocognitive development in socioeconomic context: Multiple mechanisms and implications for measuring socioeconomic status: SES and neurocognitive function. *Psychophysiology*, *53*(1), 71–82. https://doi.org/10.1111/psyp.12547

U.S. Census Bureau. (2010). Profile of General Population and Housing Characteristics. Retrieved from https://factfinder.census.gov/faces/tableservices/jsf/pages/productview.xhtml?pxml:id=DEC_10_SF1_SF1DP1&prodType=table

Vanderwert, R. E., Zeanah, C. H., Fox, N. A., & Nelson, C. A. (2016). Normalization of EEG activity among previously institutionalized children placed into foster care: A 12-year follow-up of the Bucharest Early Intervention Project. *Developmental Cognitive Neuroscience*, 17, 68–75. https://doi.org/10.1016/j.dcn.2015.12.004

Verstaen, A., Haase, C. M., Lwi, S. J., & Levenson, R. W. (2020). Age-related changes in emotional behavior: Evidence from a 13-year longitudinal study of long-term married couples. *Emotion, 20*(2), 149-163. https://doi.org/10.1037/emo0000551

Willner, C. J., Gatzke-Kopp, L. M., Bierman, K. L., Greenberg, M. T., & Segalowitz, S. J. (2015). Relevance of a neurophysiological marker of attention allocation for children's learning-related behaviors and academic performance. *Developmental Psychology*, *51*(8), 1148–1162. https://doi.org/10.1037/a0039311

Willoughby, M. T., Wirth, R. J., Blair, C. B., & Family Life Project Investigators. (2012). Executive function in early childhood: Longitudinal measurement invariance and developmental change. *Psychological Assessment*, *24*(2), 418–431. https://doi.org/10.1037/a0025779

Yang, Y., Shields, G. S., Zhang, Y., Wu, H., Chen, H., & Romer, A. L. (2022). Child executive function and future externalizing and internalizing problems: A meta-analysis of prospective longitudinal studies. *Clinical Psychology Review, 97*, 1-17. https://doi.org/10.1016/j.cpr.2022.102194

Table 1
Descriptive Statistics

Variables	n	Mean	*SD*	Min	Max
Demographics					
Age in years (Pre)	256	4.70	0.39	3.75	5.83
Maternal education	256	15.34	2.24	10	18
Income-to-needs	251	2.14	1.44	0.10	6.40
N2 Go Amplitude (μV)					
Preschool	209	-4.66	3.03	-13.62	1.37
Kindergarten	200	-4.45	2.68	-11.84	2.34
First Grade	204	-4.29	2.84	-12.78	5.60
N2 No-Go Amplitude (μV)					
Preschool	209	-7.45	4.19	-18.21	4.46
Kindergarten	200	-7.94	3.95	-16.67	3.07
First Grade	204	-8.09	3.93	-25.95	1.27
ΔN2 Amplitude (μV)					
Preschool	209	-2.79	3.57	-12.53	7.23
Kindergarten	200	-3.49	3.49	-18.45	4.84
First Grade	204	-3.80	3.28	-14.18	5.42
P3b Go Amplitude (μV)					
Preschool	212	16.93	7.65	-0.03	36.90
Kindergarten	201	14.74	7.10	-6.24	39.63
First Grade	209	13.69	7.49	-9.22	35.38
P3b No-Go Amplitude (μV)					
Preschool	212	21.84	10.72	-1.33	50.01
Kindergarten	201	20.97	9.85	-3.57	48.65
First Grade	209	19.10	9.97	-8.44	52.44
ΔP3b Amplitude (μV)					
Preschool	212	4.92	7.31	-19.76	39.81
Kindergarten	201	6.24	6.15	-6.94	25.24
First Grade	209	5.41	6.65	-27.96	30.06

Note. Δ: No-Go minus Go difference wave; Pre: preschool; Maternal education: years of education. Mean maternal education of 15.34 corresponds to slightly below a bachelor's degree (coded as 16); μV: microvolts.

Table 2

ERP Data Exclusion Criteria and Counts

Initial ERP data	Description	Count
Preschool		250
Kindergarten		234
First Grade		237
Exclusion Criterion		
Equipment error	EEG data were unusable due to a malfunction in the EEG equipment	
Preschool		6
Kindergarten		6
First Grade		0
Trial numbers	ERP data were excluded if a participant had less than 10 correct Go trials and/or less than 10 correct No-Go trials	
Preschool		16
Kindergarten		10
First Grade		6
PM and OM data quality check	Visual inspection of the posterior electrode clusters (PM and OM) of each individual ERP plot was done to identify and exclude cases in which no visual evoked potentials were present for the frequent Go trials	
Preschool		8
Kindergarten		8
First Grade		5
Data quality check for the N2 channel cluster used in the final analyses	Visual inspection of the right frontocentral cluster for each individual ERP plot was done to identify and exclude cases in which data quality was poor (e.g., excessive drift)	
Preschool		7
Kindergarten		7
First Grade		8
Data quality check for the P3b channel cluster used in the final analyses	Visual inspection of the midline posterior cluster for each individual ERP plot was done to identify and exclude cases in which data quality was poor (e.g., excessive drift)	
Preschool		4
Kindergarten		5
First Grade		4

aSME outliers for N2 measures	ERP data for the N2 component was excluded if the aSME value for either the Go or No-Go condition was at or more extreme than +/- 3.29 *SD* of the between-participant mean as it indicates poor data quality	
Preschool		4
Kindergarten		3
First Grade		8
aSME outliers for P3b measures	ERP data for the P3b component was excluded if the aSME for either the Go or No-Go condition was at or more extreme than +/- 3.29 *SD* of the between-participant mean as it indicates poor data quality	
Preschool		4
Kindergarten		4
First Grade		7
Usable ERP data included in final analyses		
Usable N2 data	Number of participants for whom we had usable N2 data after the exclusion criteria was applied	
Preschool		209
Kindergarten		200
First Grade		204
Usable P3b data	Number of participants for whom we had usable P3b data after the exclusion criteria was applied	
Preschool		212
Kindergarten		201
First Grade		209

Note. This table provides a description and count for each ERP data exclusion criterion, listed in chronological order of how they were applied during data processing and analysis. PM: parietal midline channel cluster. OM: occipital midline channel cluster. aSME: analytic standardized measurement error.

Table 3

Zero-Order Correlations Among Sociodemographic Factors and Outcome Variables

	1	2	3	4
1. Age (Pre)	--			
2. Gender	-0.10	--		
3. Mat Edu	0.00	-0.04	--	
4. INR	0.09	0.09	**0.49**	--
5. N2 Go Pre	0.06	0.00	-0.04	-0.03
6. N2 Go K	-0.03	0.07	-0.05	0.10
7. N2 Go 1st	-0.08	0.05	0.08	0.04
8. N2 NG Pre	-0.06	-0.02	-0.10	-0.10
9. N2 NG K	-0.04	0.03	-0.13	-0.07
10. N2 NG 1st	0.03	0.05	-0.08	**-0.15**
11. ΔN2 Pre	-0.12	-0.02	-0.09	-0.09
12. ΔN2 K	-0.03	-0.02	-0.11	**-0.16**
13. ΔN2 1st	0.11	0.02	**-0.16**	**-0.21**
14. P3b Go Pre	0.03	-0.03	**0.17**	-0.02
15. P3b Go K	-0.02	-0.10	**0.17**	0.01
16. P3b Go 1st	0.04	-0.07	0.03	-0.04
17. P3b NG Pre	0.03	-0.01	**0.22**	0.03
18. P3b NG K	0.03	-0.11	**0.20**	0.07
19. P3b NG 1st	-0.03	-0.10	0.03	-0.02
20. ΔP3b Pre	0.01	0.01	**0.15**	0.06
21. ΔP3b K	0.08	-0.07	0.13	0.10
22. ΔP3b 1st	-0.10	-0.07	0.01	0.01

Note. Pre: preschool; K: kindergarten; 1^{st}: first grade. Mat Edu: years of maternal education; INR: income-to-needs ratio; Gender: 0 = male, 1 = female. NG: No-Go; Δ: No-Go minus Go difference wave. For N2, more negative values correspond to a larger neural index. For P3, more positive values correspond to a larger neural index. Boldface type indicates $p < .050$.

Table 4

Zero-Order Correlations Among Outcome Variables

	1 N2 Go Pre	2 N2 Go K	3 N2 Go 1st	4 N2 NG Pre	5 N2 NG K	6 N2 NG 1st	7 ΔN2 Pre	8 ΔN2 K	9 ΔN2 1st	10 P3b Go Pre	11 P3b Go K	12 P3b Go 1st	13 P3b NG Pre	14 P3b NG K	15 P3b NG 1st	16 ΔP3b Pre	17 ΔP3b K	18 ΔP3b 1st
1	--																	
2	**0.48**	--																
3	**0.36**	**0.43**	--															
4	**0.55**	**0.27**	**0.24**	--														
5	**0.32**	**0.50**	**0.30**	**0.47**	--													
6	**0.33**	**0.34**	**0.57**	**0.41**	**0.45**	--												
7	**-0.20**	-0.10	-0.02	**0.71**	**0.28**	**0.20**	--											
8	0.00	**-0.20**	0.00	**0.32**	**0.75**	**0.26**	**0.38**	--										
9	0.08	0.04	**-0.18**	**0.27**	**0.28**	**0.70**	**0.26**	**0.30**	--									
10	**-0.50**	**-0.44**	**-0.33**	**-0.43**	**-0.29**	**-0.30**	-0.09	0.00	-0.08	--								
11	**-0.24**	**-0.54**	**-0.34**	**-0.26**	**-0.50**	**-0.36**	-0.10	**-0.14**	-0.13	**0.60**	--							
12	-0.15	**-0.31**	**-0.60**	**-0.22**	**-0.22**	**-0.50**	-0.13	-0.01	-0.11	**0.57**	**0.58**	--						
13	**-0.36**	**-0.40**	**-0.30**	**-0.56**	**-0.38**	**-0.35**	**-0.36**	-0.12	**-0.16**	**0.73**	**0.53**	**0.55**	--					
14	**-0.27**	**-0.42**	**-0.31**	**-0.32**	**-0.60**	**-0.39**	-0.14	**-0.35**	**-0.20**	**0.55**	**0.78**	**0.50**	**0.59**	--				
15	**-0.27**	**-0.31**	**-0.53**	**-0.35**	**-0.34**	**-0.65**	**-0.19**	**-0.16**	**-0.31**	**0.49**	**0.49**	**0.75**	**0.58**	**0.56**	--			
16	0.00	-0.13	-0.10	**-0.38**	**-0.26**	**-0.20**	**-0.45**	**-0.19**	-0.15	0.03	**0.16**	**0.22**	**0.70**	**0.31**	**0.35**	--		
17	**-0.16**	-0.05	-0.12	**-0.22**	**-0.38**	**-0.23**	-0.11	**-0.39**	**-0.18**	**0.20**	0.10	0.14	**0.35**	**0.70**	**0.35**	**0.32**	--	
18	**-0.24**	-0.12	**-0.18**	**-0.30**	**-0.27**	**-0.45**	-0.15	**-0.22**	**-0.38**	0.13	0.08	-0.01	**0.28**	**0.28**	**0.66**	**0.28**	**0.36**	--

Note. Pre: preschool; K: kindergarten; 1st: first grade. NG: No-Go; Δ: No-Go minus Go difference wave. For N2, more negative values correspond to a larger neural index. For P3, more positive values correspond to a larger neural index. Boldface type indicates $p < .050$.

Table 5

Model Fit Indices of Latent Growth Curve Models

	Outcome	Chi-square (df)	CFI	RMSEA (90% CI)
Unconditional Models	N2 Go amplitude	0.01 (1)	1.00	0.00 (0.000 – 0.069)
	N2 No-Go amplitude	1.23 (1)	1.00	0.03 (0.000 – 0.172)
	ΔN2 amplitude	1.01 (1)	1.00	0.01 (0.000 – 0.166)
	P3b Go amplitude[a]	2.18 (2)	1.00	0.02 (0.000 – 0.127)
	P3b No-Go amplitude[a]	1.27 (2)	1.00	0.00 (0.000 – 0.108)
	ΔP3b amplitude	6.56 (1)*	0.88	0.15 (0.057 – 0.262)*
Conditional Models	N2 Go amplitude	6.84 (5)	0.98	0.04 (0.000 – 0.101)
	N2 No-Go amplitude	4.31 (5)	1.00	0.00 (0.000 – 0.081)
	ΔN2 amplitude	1.73 (5)	1.00	0.00 (0.000 – 0.041)
	P3b Go amplitude[a,b]	12.70 (11)	0.99	0.03 (0.000 – 0.072)
	P3b No-Go amplitude[a,b]	15.89 (11)	0.97	0.04 (0.000 – 0.083)

Note. Δ: No-Go minus Go difference wave; CI: confidence interval; [a]Slope variance fixed to [0]. [b]Slope covariates were not included in the model. * $p < .050$.

Table 6

Estimates for Unconditional Latent Growth Curve Models

Outcome	Parameter	b	*b*	*SE*	*p*
N2 Go amplitude	Intercept	-2.09	-4.61	0.20	< .001*
	Slope	0.25	0.19	0.12	.104
	D_i		4.88	1.14	< .001*
	D_s		0.58	0.57	.313
	R_{is}	-0.54	-0.91	0.67	.176
N2 No-Go amplitude	Intercept	-2.52	-7.42	0.27	< .001*
	Slope	-0.43	-0.34	0.16	.033
	D_i		8.69	2.31	< .001*
	D_s		0.62	1.14	.589
	R_{is}	-0.42	-0.98	1.34	.466
ΔN2 amplitude	Intercept	-1.16	-2.81	0.23	< .001*
	Slope	-0.51	-0.53	0.15	< .001*
	D_i		5.89	1.82	.001*
	D_s		1.09	0.91	.232
	R_{is}	-0.60	-1.52	1.09	.161
P3b Go amplitude[a]	Intercept	2.85	16.38	0.49	< .001*
	Slope		-1.53	0.26	< .001*
	D_i		33.02	5.49	< .001*
	D_s		0.00		
	R_{is}				
P3b No-Go amplitude[a]	Intercept	2.67	21.67	0.68	< .001*
	Slope		-1.27	0.35	< .001*
	D_i		65.93	10.56	< .001*
	D_s		0.00		
	R_{is}				
ΔP3b amplitude	Intercept	1.41	5.39	0.46	< .001*
	Slope	0.18	0.19	0.30	.530
	D_i		14.69	7.04	.037
	D_s		1.12	3.60	.757
	R_{is}	-0.27	-1.07	4.25	.801

Note. Δ: No-Go minus Go difference wave; D_i: intercept variance; D_s: slope variance; R_{is}: covariance between intercept and slope. Bonferroni correction was applied to correct for multiple comparisons per ERP component (alpha level = 0.05 / 3 tests). [a]Slope variance fixed to [0]. * $p < 0.017$.

Table 7

Estimates for Conditional Latent Growth Curve Models

Outcome		Intercept				Slope			
	Predictor	b	*b*	*SE*	*p*	b	*b*	*SE*	*p*
N2 Go amplitude	Age (Pre)	0.06	0.32	0.50	.516	-0.23	-0.44	0.31	.149
	Gender	0.04	0.16	0.40	.688	0.04	0.06	0.24	.802
	Mat Edu	-0.11	-0.11	0.10	.298	0.21	0.07	0.06	.249
	INR	0.02	0.03	0.16	.843	0.07	0.04	0.10	.696
N2 No-Go amplitude	Age (Pre)	-0.13	-0.97	0.68	.154	0.36	0.63	0.41	.122
	Gender	-0.02	-0.11	0.54	.842	0.17	0.24	0.32	.455
	Mat Edu	-0.18	-0.23	0.14	.090	0.35	0.11	0.08	.182
	INR	-0.05	-0.09	0.22	.663	-0.29	-0.14	0.13	.276
ΔN2 amplitude	Age (Pre)	-0.19	-1.21	0.58	.037	0.43	1.08	0.38	.004*
	Gender	-0.05	-0.24	0.47	.608	0.09	0.17	0.29	.573
	Mat Edu	-0.11	-0.12	0.12	.307	0.05	0.02	0.07	.768
	INR	-0.08	-0.13	0.19	.471	-0.24	-0.16	0.12	.179
P3b Go amplitude[a,b]	Age (Pre)	0.03	0.45	1.04	.667				
	Gender	-0.06	-0.68	0.81	.401				
	Mat Edu	0.24	0.60	0.21	.004*				
	INR	-0.12	-0.45	0.33	.166				
P3b No-Go amplitude[a,b]	Age (Pre)	0.02	0.42	1.41	.767				
	Gender	-0.06	-0.97	1.09	.375				
	Mat Edu	0.24	0.82	0.28	.004*				
	INR	-0.07	-0.38	0.44	.389				

Note. Pre: preschool; Mat Edu: years of maternal education; INR: income-to-needs ratio; To correct for multiple comparisons per ERP component, Bonferroni correction was applied. [a]Slope variance fixed to [0]. [b]Slope covariates were not included in the conditional model. * $p <$ corrected alpha level (.017 for N2 models; .025 for P3b models).

Table 8

Paired Samples T-Tests Results for Unconditional Models with Poor Fit

Pair	n	Mean Difference	SE Difference	*t*	df	Two-sided *p*	Cohen's *d*
ΔP3b amplitude Pre - ΔP3b amplitude K	171	-1.51	0.58	-2.59	170	.011*	-0.20
ΔP3b amplitude K - ΔP3b amplitude 1^{st}	173	0.92	0.56	1.66	172	.099	0.13
ΔP3b amplitude Pre - ΔP3b amplitude 1^{st}	167	-0.33	0.67	-0.49	166	.626	-0.04

Note. Δ: No-Go minus Go difference wave; Pre: preschool; K: kindergarten; 1^{st}: first grade; To correct for multiple comparisons, Bonferroni correction was applied. Specifically, we used an alpha level of 0.017 for each measure (0.05 / 3 comparisons). * $p < .017$.

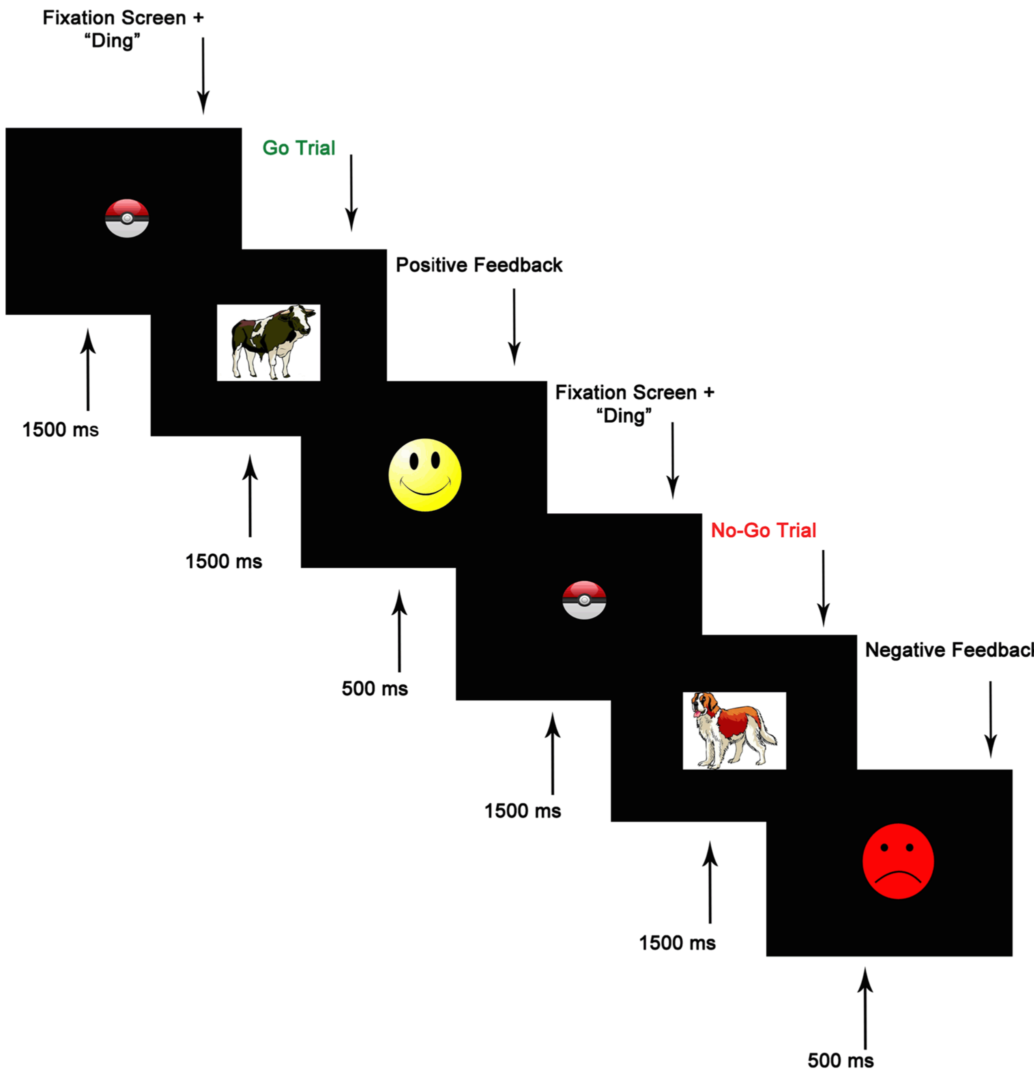


Figure 1. Schematic of Go/No-Go task structure. Reprinted from Lahat et al. (2010), retrieved from doi: 10.3389/neuro.09.072.2009, © 2010 Lahat, Todd, Mahy, Lau, and Zelazo.

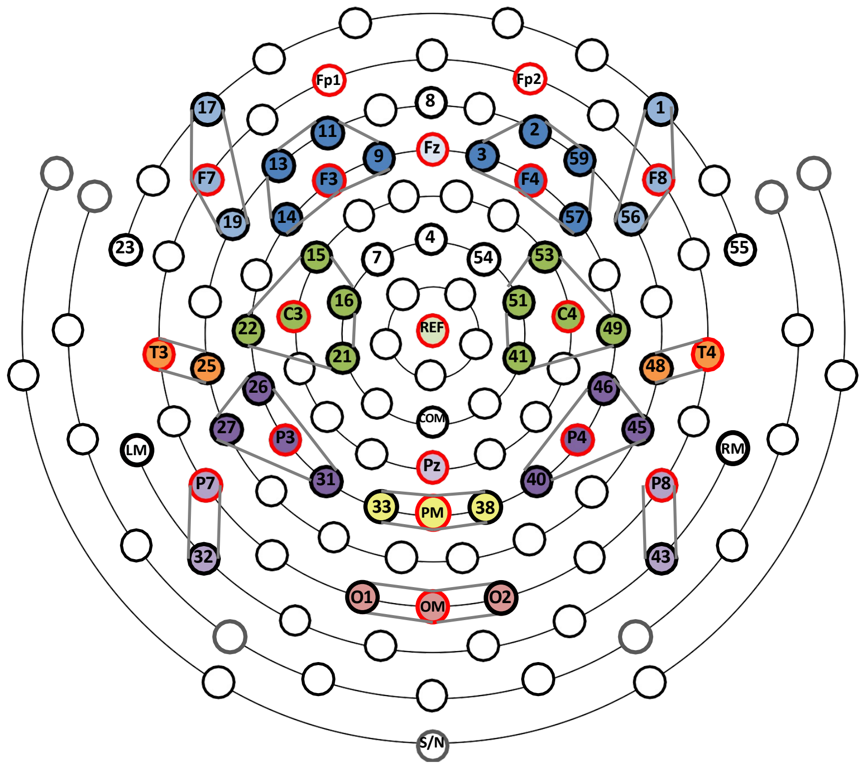
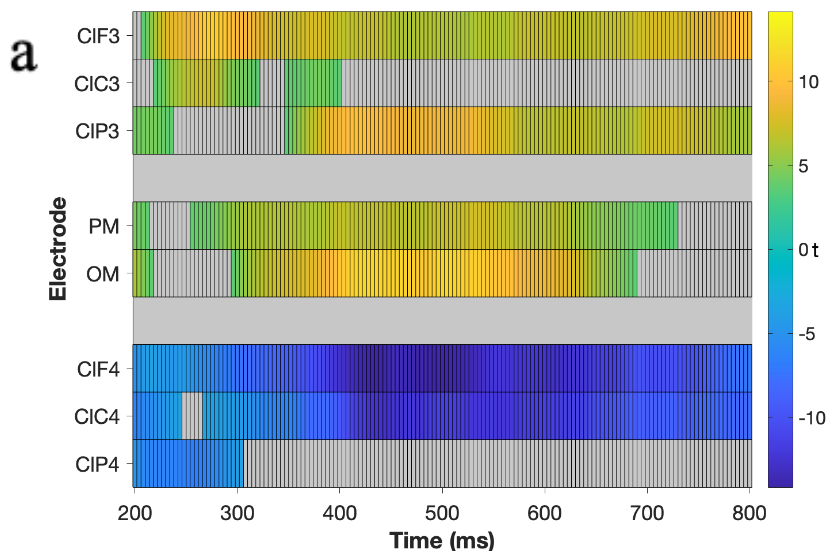
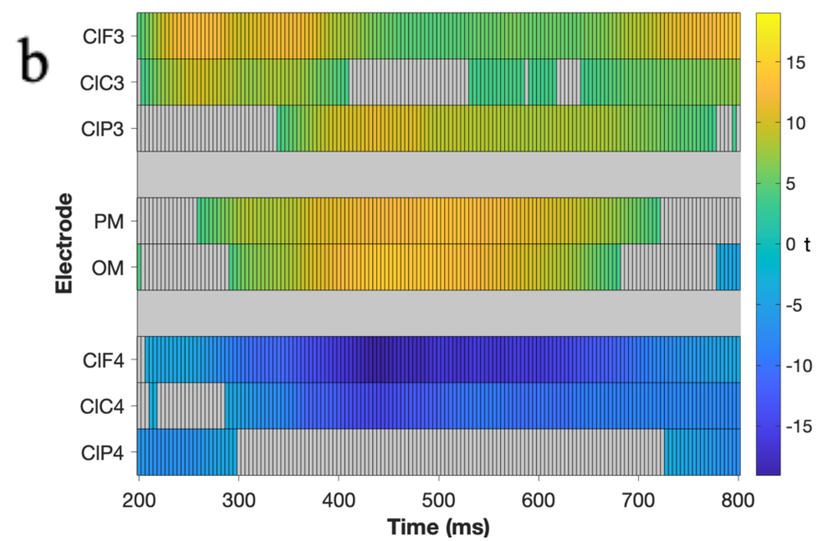


Figure 2. 64-channel net with electrodes renamed to approximate 10-20 locations, following the configuration reported by Vanderwert et al. (2016). Frontal, central, and posterior clusters for each hemisphere were created as well as two posterior midline clusters (PM and OM). Channels of interest are colored.





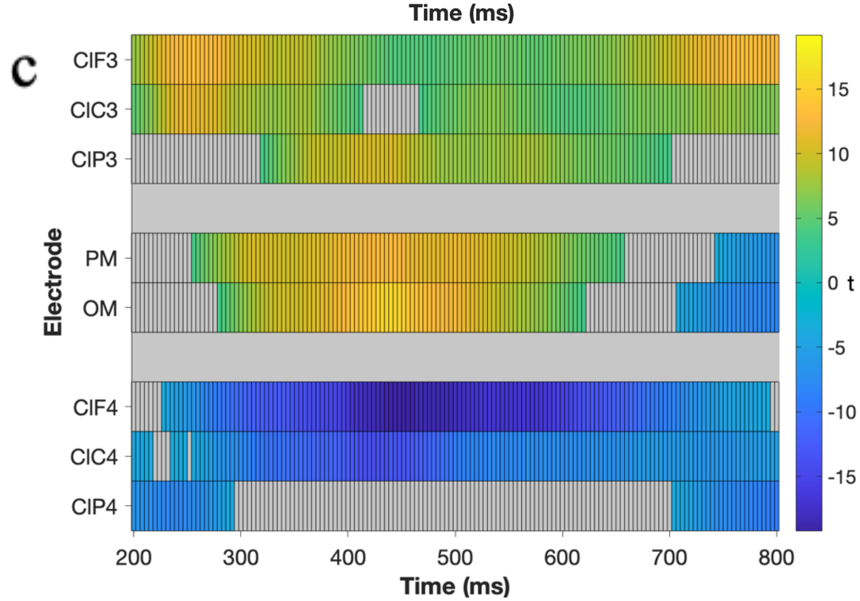


Figure 3. Raster diagrams showing results for the preschool (a), kindergarten (b), and first grade (c) permutation tests. Each box represents the result of a t-test. A temperature scale is used to represent the graded degree of significance at each time point and electrode cluster. If the box is colored, the difference wave is significantly different from zero at that time point and electrode cluster (even after effectively correcting for multiple comparisons). Electrodes on the left and right sides of the head are grouped on the figure's top and bottom, respectively. Midline electrodes are shown in the middle. Within those three groupings, y-axis top-to-bottom corresponds to scalp anterior-to-posterior. Across time points, the N2 effect (more negative No-Go amplitude compared to Go) is observed over the right frontocentral hemisphere only. The P3b effect (more positive No-Go amplitude compared to Go) is observed over midline and left posterior electrodes.

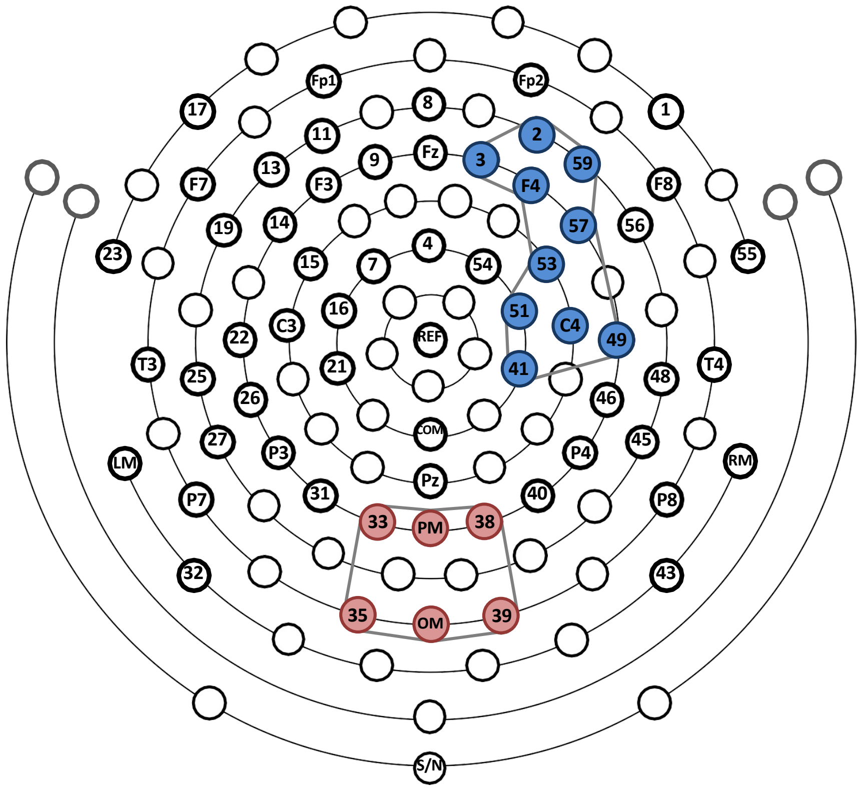


Figure 4. Final channel clusters of analysis, following the configuration reported by Vanderwert et al. (2016). Blue-colored channels make up the right frontocentral cluster used in the final analyses of the N2 component. Red-colored channels make up the midline posterior cluster used in the final analyses of the P3b component.

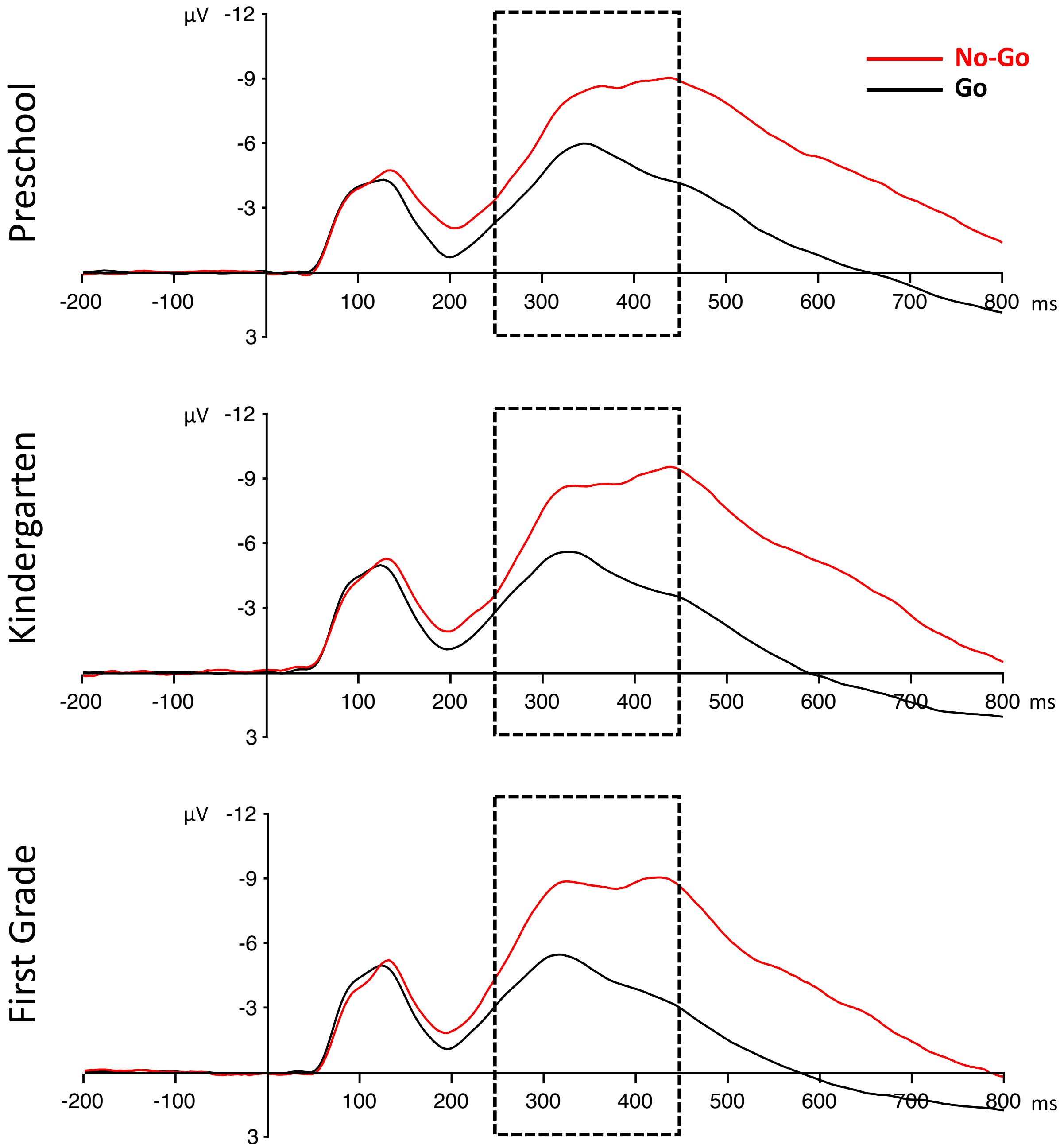


Figure 5. Right hemisphere grand average ERP plots for Go (black waveform) and No-Go (red waveform) conditions over the frontocentral channel cluster. By convention, negative is plotted upward. The measurement window is shown with a dotted rectangle (250-450 ms post stimulus onset). Preschool: n = 209; Kindergarten: n = 200; First grade: n = 204.

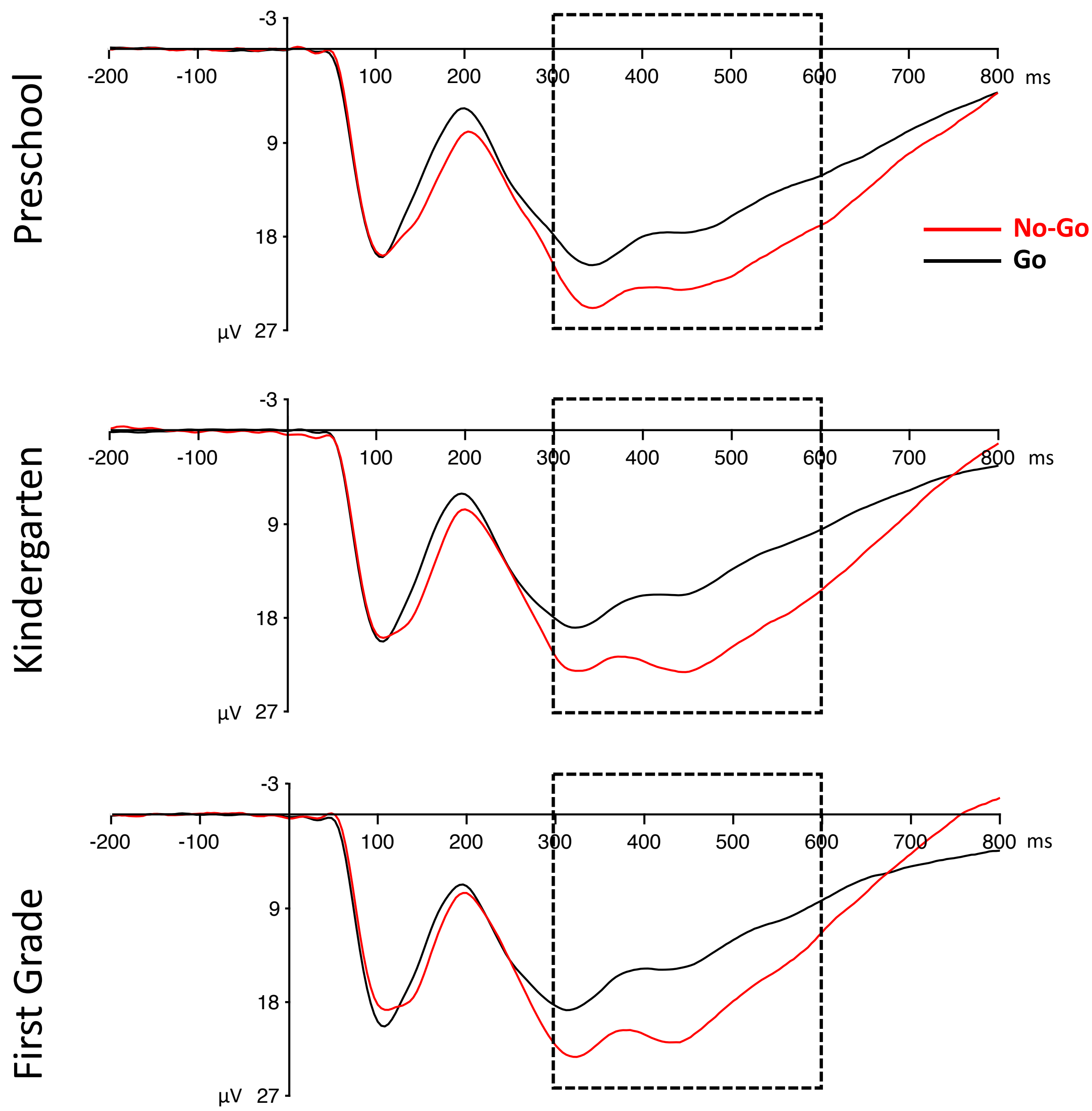


Figure 6. Midline grand average ERP plots for Go (black waveform) and No-Go (red waveform) conditions over the posterior channel cluster. By convention, negative is plotted upward. The measurement window is shown with a dotted rectangle (300-600 ms post stimulus onset). Preschool: n = 212; Kindergarten: n = 201; First grade: n = 209.