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Component-specific developmental trajectories of ERP indices of cognitive control in early childhood

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ABSTRACT

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.

1. Introduction

Cognitive control (executive functioning) skills support goal-directed behaviors, especially in the face of distractions or irrelevant but more automatic or enticing behavior choices (Cohen, 2017; Gratton et al., 2018). Early cognitive control skills are linked to academic success (Mann et al., 2017; Ribner et al., 2023; Schmitt et al., 2017) while cognitive control difficulties are implicated in various neurodevelopmental disorders (Yang et al., 2022; Zelazo, 2020). A growing body of research has investigated the neurodevelopment of cognitive control in early childhood (Fiske and Holmboe, 2019), with many studies using the event-related potential (ERP) technique (Downes et al., 2017). However, our understanding of intra-individual change in ERP indices of cognitive control in early childhood remains limited.

In the current study, we used a longitudinal design to delineate the developmental trajectories of two widely studied neural indices of cognitive control, ERP components N2 and P3b, across early childhood – specifically, the transition from preschool to first grade. This developmental period is characterized by robust behavioral improvements in cognitive control (Munakata et al., 2012; Willoughby et al., 2012) as well as substantial brain development (Fiske and Holmboe, 2019; Houston et al., 2013). Furthermore, this period encompasses the transition to formal schooling which has significant and unique effects on children's developmental outcomes (Morrison et al., 2019). Thus, examining the neurodevelopment of cognitive control across this period is of great importance.

1.1. N2 and P3b as neural indices of cognitive control

The N2, a negative deflection in the ERP waveform, is commonly observed during tasks with competing responses, with more negative amplitudes generally seen for infrequent trials requiring controlled actions versus frequent trials eliciting automatic responses (Folstein and Van Petten, 2007; Hoyniak, 2017). Researchers have contended that this amplitude difference reflects the inhibition of a planned motor response (e.g., Bokura et al., 2001) and the monitoring of conflict between competing response representations (e.g., Nieuwenhuis et al., 2003). The anterior cingulate, ventral prefrontal, and orbitofrontal cortices

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have been identified as N2 generators both in adults and children (Bokura et al., 2001; Lahat et al., 2010). In children, N2 occurs around 250–500 ms over frontocentral electrodes (Hoyniak, 2017; Lo, 2018).

The P3b[1] is a positive deflection and commonly observed during tasks requiring the discrimination between frequent and infrequent stimuli, with more positive amplitudes typically observed for rare stimuli (Polich, 2011). It has been argued that the P3b amplitude difference between rare and frequent stimuli reflects context updating and information processing associated with attentional and memory mechanisms (for a review, see Polich, 2011). In both adults and children, proposed neural generators of the P3b include the inferior temporal and posterior parietal cortices (Bledowski et al., 2004; Polich, 2011). In children, P3b occurs around 300–700 ms over centroparietal electrodes (Riggins and Scott, 2020; St. John et al., 2019). Given N2 and P3b differ in the cognitive processes they are considered to reflect, and in their neural generators, scalp distribution, and timing, they may display distinct developmental trajectories in childhood.

1.2. Distinguishing between observed waveforms and difference waves

Several researchers have successfully adapted the visual Go/No-Go task to elicit N2 and P3b in children (e.g., Lahat et al., 2010; Ruberry et al., 2017). ERPs elicited during this task 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 brain activity from multiple neural generators (Luck, 2014). In contrast, difference waves eliminate concurrent neural processes across conditions, isolating experimental effects on ERP components (Luck, 2014). Thus, Go and No-Go observed waveforms more closely reflect underlying neurophysiology, while the No-Go minus Go difference wave provides a closer index of brain functions involved in cognitive control. Therefore, observed waveforms and difference waves may capture unique aspects of neurodevelopment.

In addition to differing in the neural activity they reflect, observed waveforms and difference waves also vary in their measurement properties. Specifically, difference waves are always noisier than observed waveforms, reducing ERP data quality (Luck, 2014). Altogether, given these differences, it is important to distinguish between observed waveforms and difference waves to improve our understanding of the neurodevelopment of cognitive control.

1.3. Development of N2 and P3b

Cross-sectional work has reported that N2 No-Go amplitude linearly decreases in magnitude (becomes less negative) while N2 Go amplitude shows no change across childhood (Hoyniak, 2017; Lo, 2018). Correlational studies have found no relation between children's age and P3b Go and No-Go amplitudes (St. John et al., 2019; Willner et al., 2015). Regarding the No-Go minus Go difference wave, cross-sectional studies have reported increases and decreases in ΔN2 amplitude across middle and late childhood (Cragg et al., 2009; Jonkman, 2006). It is unclear how ΔP3b amplitude changes with age as P3b has primarily been examined using observed waveforms (St. John et al., 2019; Willner et al., 2015). Overall, these seemingly inconsistent findings may stem from variations across studies in ages of interest and task characteristics, which are limitations that can be addressed with longitudinal designs that use the same task across assessments.

1.4. Individual differences in cognitive control development

While age-related differences in ERP indices of cognitive control have been somewhat inconsistent, older children have consistently been found to exhibit better behavioral performance on cognitive control tasks (Willoughby et al., 2012). In contrast, gender differences in cognitive control have not been consistent. Some studies found that girls outperformed boys (Clark et al., 2013), while others 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 children's cognitive control, with parental stress and environmental enrichment as candidate mediators of this association (Ursache and Noble, 2016). Specifically, lower SES has been linked to poorer behavioral performance and altered neural functioning during cognitive control tasks (Merz et al., 2019; Ursache and Noble, 2016). However, 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 (Ruberry et al., 2017). Overall, it is unclear how these child- and family-level characteristics contribute to the longitudinal trajectories of N2 and P3b in early childhood.

1.5. Current study

We examined developmental changes in two neural indices of cognitive control, N2 and P3b, across early childhood. ERPs were recorded during a visual Go/No-Go task (Lahat et al., 2010) from a large and socioeconomically and racially/ethnically diverse sample of children. N2 and P3b mean amplitudes were extracted from observed waveforms (Go and No-Go) *and* the difference wave (No-Go minus Go) at three time-points: preschool, kindergarten, first grade.

First, we used latent growth curve modeling to characterize the longitudinal changes in N2 and P3b amplitudes. Given N2 and P3b differ in the cognitive processes they index, and in their neural generators, scalp distribution, and timing, we expected these components to show unique developmental trajectories. Considering the pronounced brain maturation occurring in childhood (Fiske and Holmboe, 2019; Houston et al., 2013), we expected that amplitudes extracted from both observed waveforms and difference waves would display developmental changes. Additionally, we predicted that amplitudes extracted from observed waveforms and difference waves would show distinct developmental trajectories given the disparities in the neural activity they reflect (Luck, 2014).

Second, we examined whether sociodemographic factors previously linked to cognitive control relate to initial levels and developmental trajectories of N2 and P3b amplitudes. Previous inconsistent findings regarding links between age, gender, SES, and N2 and P3b amplitudes precluded us from having a priori hypotheses regarding relations between these sociodemographic factors and longitudinal characteristics of N2 and P3b amplitudes.

2. Method

2.1. Participants

Participants were part of a longitudinal study examining school readiness and early academic success in early childhood. The original 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. Data was collected in preschool, kindergarten, and first grade. Assessments were conducted throughout the school year and summer months as laboratory visits were scheduled based on family availability. At the preschool laboratory visit, none of the participants had started kindergarten. The kindergarten visit took place approximately one year after the preschool visit and was proceeded approximately one 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

[1] The P3b should be distinguished from the related P3a, novelty P300, and no-go P300 subcomponents (Polich, 2011).

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. Pre: preschool; Maternal education: years of education; Δ: No-Go minus Go difference wave; μV: microvolts.

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 gender, $\chi^2(1) = 0.49$, $p = .649$, age at initial assessment, maternal education, or income-to-needs ratio (see Supplementary Table 1 for t-test results).

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). The socio-demographic information of participants is summarized in Table 1. Children who participated in all three visits (84%) did not differ from children who participated in only one or two visits in terms of gender, $\chi^2(1) = 1.18$, $p = .308$, age at initial assessment, maternal education, or income-to-needs ratio (see Supplementary Table 1 for t-test results). The covariance coverage is reported in Supplementary Table 2.

2.2. Procedure

Informed written consent was obtained from parents and verbal assent was obtained from the child before data collection. Each laboratory visit took approximately 2 hours and consisted of cognitive and emotional development tasks. 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.

2.3. Measures

2.3.1. Demographics

Parents reported on children's age, gender, race and ethnicity, and family SES at the preschool time point. Income-to-needs ratio and maternal education were used as measures of family SES (see Supplementary Figures 1 and 2 for frequency distributions of each measure, respectively). Income-to-needs ratio was computed by dividing the annual family income by the appropriate federal poverty threshold based on 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. Maternal education level was re-coded to correspond to approximate years of education (see Supplementary Table 3 for the coding scheme).

2.3.2. Cognitive control

A computerized Go/No-Go task was used to assess children's cognitive control (Lahat et al., 2010; see Fig. 1 for a schematic of task structure). The task was presented using E-Prime version 2.0 (PST, Pittsburgh, PA, USA). In each trial, a fixation point accompanied by a "ding" sound appeared in the middle of the screen and was shown for 1500 ms. This was followed by an animal stimulus displayed for 1500 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 1500 ms. Before the task, children completed 10 practice trials (6 Go). The practice block was repeated until children achieved at least 90% accuracy. 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.

2.4. 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). To increase child comfort, the sensor nets were customized for the study by removing four face electrodes. EEG data were sampled at 250 Hz and referenced online to a single vertex electrode (Cz). Electrode impedances were kept at or below 80 kΩ. Electrodes approximating the international 10–20 locations were renamed and clusters were defined around these electrodes (Vanderwert et al., 2016; see Supplementary Figure 3 for the electrode configuration).

EEG preprocessing and ERP analyses were conducted in MATLAB using customized EEGLAB (Delorme and Makeig, 2004) and ERPLAB (Lopez-Calderon and 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 preprocessing steps, including re-referencing, filtering, eye movement correction, artifact rejection, iterative data quality checks, and parameter customization are described in detail in the Supplementary Materials. The EEG scripts used in the current study can be found on OSF: https://osf.io/ngmf8/.

The EEG data exclusion criteria included the following: (1) equipment error; (2) absence of discernible visual evoked potentials; (3) less than 10 correct trials per probe type (Go and No-Go); (4) poor data quality detected via visual inspection of the final clusters of analysis (e.g., excessive drift). In addition, data quality was assessed for the final clusters of interest with the standardized measurement error for the observed waveforms (Luck et al., 2021). The number of children excluded based on each criterion is shown in Supplementary Table 4. Even with these relatively stringent exclusion criteria, our EEG data retention rates were 85% for preschool, 86% for kindergarten, and 88% for first grade. Without compromising data quality, our preprocessing pipeline enabled us to recover the EEG data from 24% of the preschool, 17% of the kindergarten, and 18% of the first grade participants who were excluded from a previous publication due to EEG artifacts (Isbell et al., 2018).

The ERP analyses focused on the mean amplitude of N2 and P3b. Only correct trials were included in the analyses. To examine whether our a priori time windows, 250–450 ms for N2 and 300–600 ms for P3b

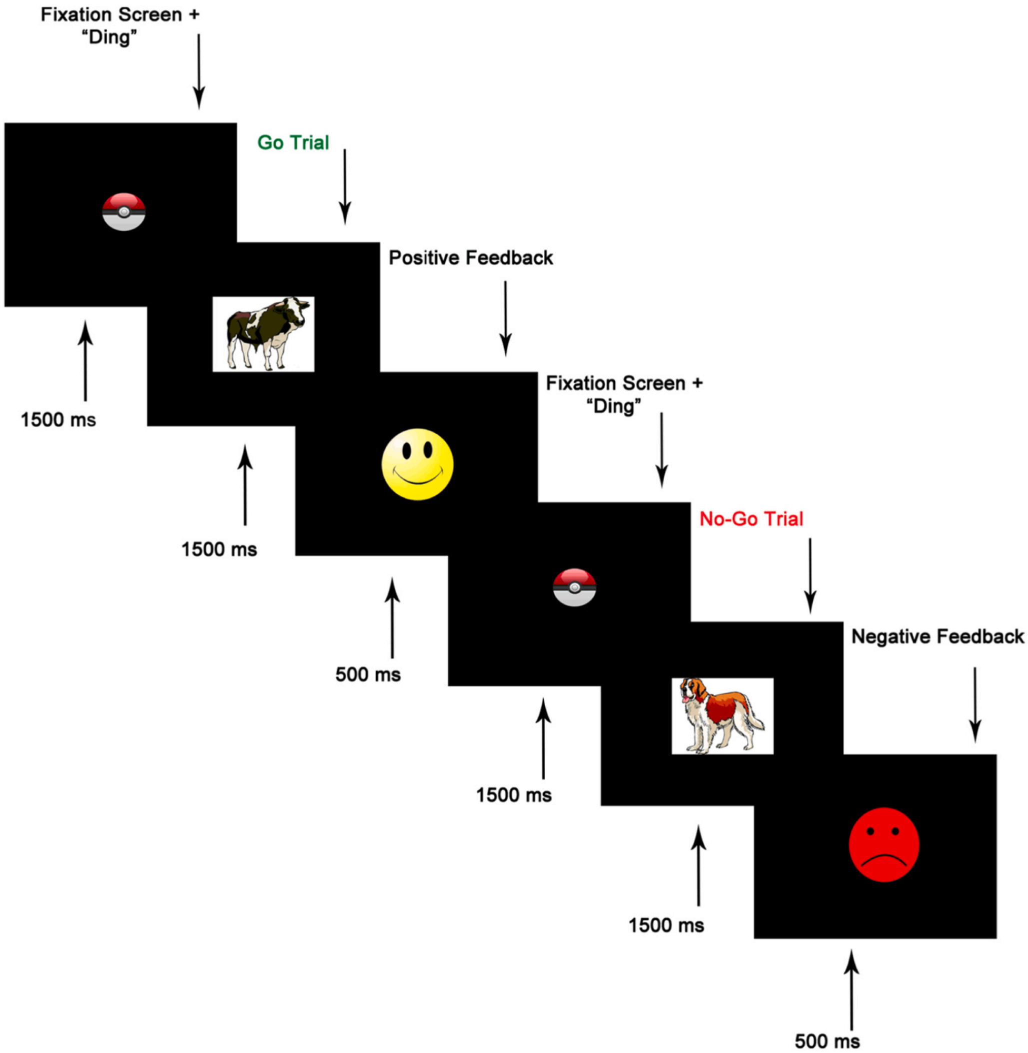

Fig. 1. Schematic of Go/No-Go task structure.
Reprinted from Lahat et al. (2010), retrieved from doi: 10.3389/neuro.09.072.2009, © 2010 Lahat, Todd, Mahy, Lau, and Zelazo.

(Abdul Rahman et al., 2017; Lahat et al., 2010; St. John et al., 2019), captured the experimental effects in the current dataset and to determine the scalp distribution of these effects, we conducted permutation-based mass univariate analyses using the difference waves (Groppe et al., 2011; see Supplementary Figure 4 for raster diagrams). To reduce the number of factors used in the statistical analyses, we used channel clusters instead of single channels (Luck and Gaspelin, 2017). Pre-analysis data quality checks, the formation of channel clusters, and the details of the mass univariate analyses are described in the Supplementary Materials.

The mass univariate analyses supported the use of the time windows selected for N2 and P3b a priori. These analyses also revealed that the experimental effect (larger No-Go versus Go trials) was observed over a frontocentral cluster of channels on the right hemisphere for N2 and over a midline posterior cluster for P3b across data collection time points. The channel clusters included in the statistical analyses are shown in Fig. 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. Grand-average ERPs elicited by the No-Go versus Go conditions across time points and the left hemisphere, right hemisphere, and midline electrodes are shown in Supplementary Figures 5–10.

2.5. Analytic strategy

To examine the average trajectories of N2 Go, N2 No-Go, ΔN2, P3b Go, P3b No-Go, and ΔP3b amplitudes across preschool, kindergarten, and first grade, we conducted an unconditional latent growth curve model for each outcome separately.[2] 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.[3] Poor fit between an unconditional model and the observed

[2] This study focused on the developmental trajectories of neural indices of cognitive control; however, behavioral data was also collected. Descriptive statistics and latent growth curve model estimates for behavioral performance (d') are provided in Supplementary Tables 5 and 6, respectively.

[3] 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 Supplementary Table 7 for bivariate correlations), we used a stringent multiple comparison correction method.

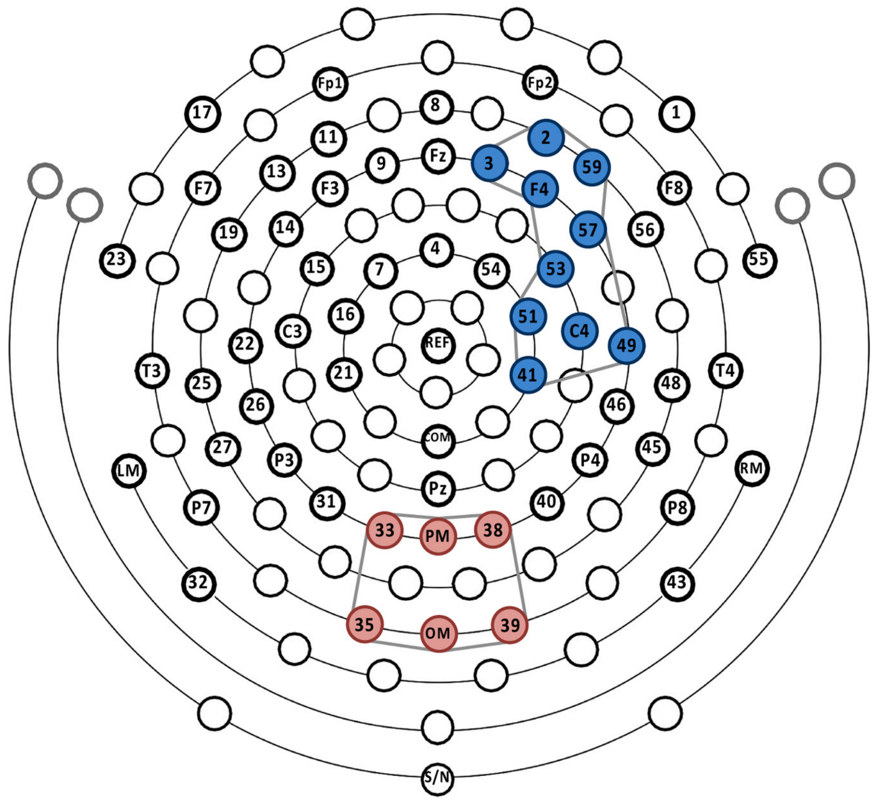

Fig. 2. 64-channel net with 10–20 channels following the configuration reported by Vanderwert et al. (2016). Blue-colored channels make up the right frontocentral cluster used in the final analyses of the N2 component. Red-colored channels make up the midline posterior cluster used in the final analyses of the P3b component.

data was addressed by conducting post-hoc pairwise comparisons between time points, 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. Bonferroni correction was applied per ERP component to control for the family-wise error rate.[4]

Missing data were handled using full information maximum likelihood (FIML) estimation to reduce potential bias in the parameter estimates (Enders and Bandalos, 2001). Model fit was evaluated using χ^2, CFI ($\geq$.90), and RMSEA ($\leq$.06; Hu and Bentler, 1999). Data were analyzed 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).

3. Results

3.1. Preliminary analyses

Descriptive statistics and bivariate correlations are reported in Table 1 and Supplementary Table 7, respectively. 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 and Fidell, 2007). The following outliers were identified: 2 children for kindergarten N2, 3 children for preschool P3b, and 2 children for first grade P3b.[5] All analyses were conducted with children's original scores as well as 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 trials over the right frontocentral cluster and the midline posterior cluster are shown in Figs. 3 and 4, respectively. Descriptive statistics for the number of ERP trials included in the analyses, analytic standardized measurement error, N2 mean amplitudes for left and right hemisphere clusters, and P3b mean amplitudes for left, right, and midline clusters for Go and No-Go conditions are reported in Supplementary Tables 8 and 9.

3.2. Developmental trajectories of N2 amplitude

The unconditional models examining the trajectories of N2 Go, N2 No-Go, and ΔN2 amplitudes demonstrated good model fit (see Table 2 for fit indices). 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 3 for model estimates). The individual and predicted growth curve trajectories are shown in Supplementary Figure 11. The initial average N2 Go amplitude during

[4] Prior to applying this correction method, younger age in 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.

[5] 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.

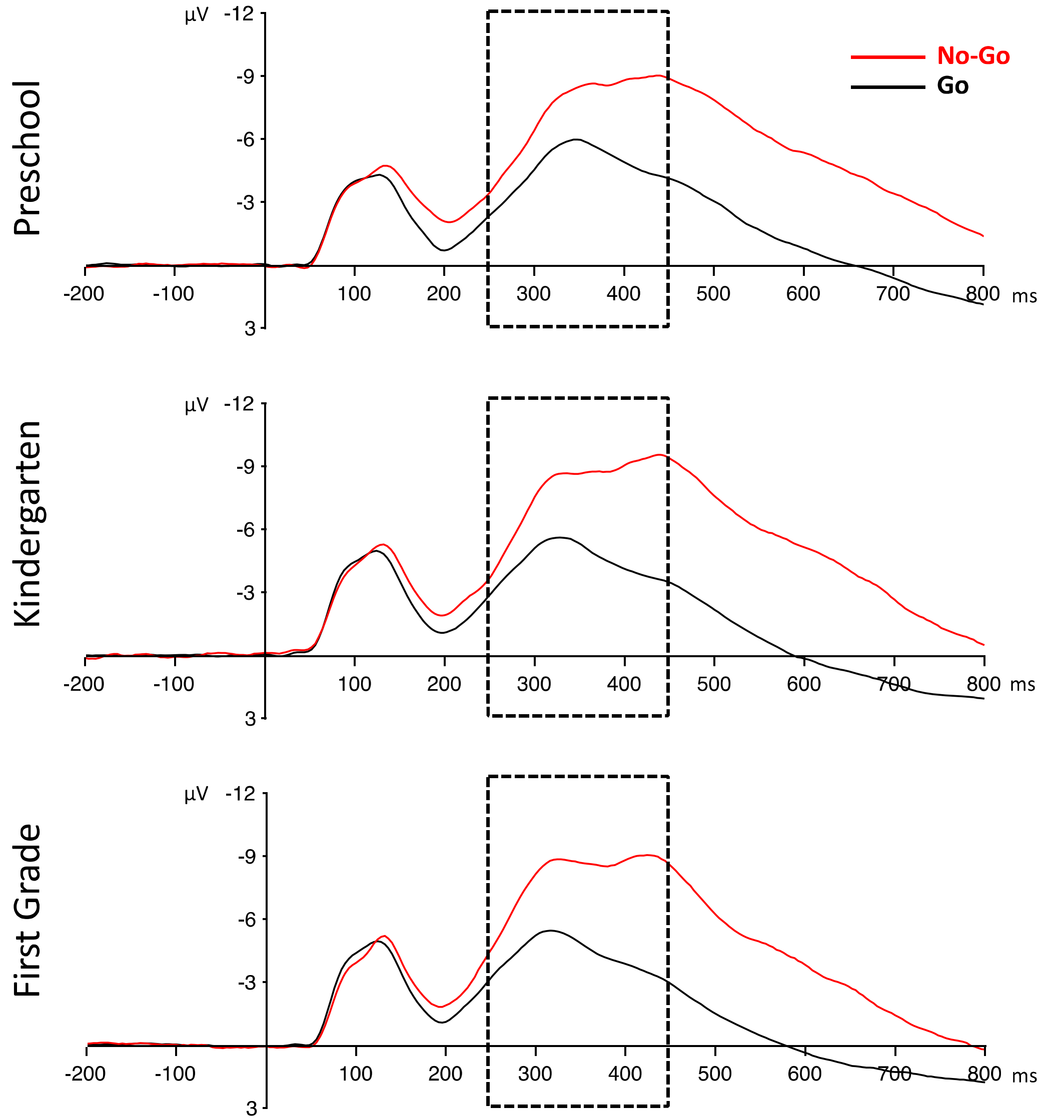

Fig. 3. Right hemisphere grand average ERP plots for Go (black waveform) and No-Go (red waveform) conditions over the frontocentral channel cluster. By convention, negative is plotted upward. The N2 measurement window is shown with a dotted rectangle (250–450 ms post stimulus onset). Preschool: n = 209; Kindergarten: n = 200; First grade: n = 204.

preschool was − 4.61 μV which did not change across time. The initial average N2 No-Go amplitude was − 7.42 μV and did not change across time. Finally, the initial average 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, but not in the rate of linear change.

The slope variances were not significant. However, we included covariates to predict both the intercept and slope as covariates can predict slopes with non-significant variances (e.g., Morales et al., 2022). The conditional models for all three N2 amplitude measures demonstrated good model fit (see Table 2 for fit indices). Age at the initial assessment, gender, maternal education, and income-to-needs ratio did not predict the intercept or slope 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 4 for model estimates).

3.3. Developmental trajectories of P3b amplitude

The unconditional models examining the trajectories of P3b Go and No-Go amplitudes yielded negatively estimated slope variances, resulting in non-positive definite covariance matrices. To address this issue, as recommended by Chen and colleagues (2001), for each model, we conducted a Wald test for the null hypothesis that the slope variance is zero (versus smaller than zero). The non-significant 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 model fit (see Table 2 for fit indices). P3b Go and No-Go amplitudes linearly decreased (became less positive) across time (see Table 3 for model estimates). The individual and predicted growth curve trajectories are shown in Supplementary Figure 12. The initial average P3b Go amplitude during preschool was 16.38 μV, which declined 1.53 μV on average across each time point. The initial average P3b No-Go amplitude was 21.67 μV, which declined 1.27 μV on average across each time point. The intercepts of both outcomes showed significant variability.

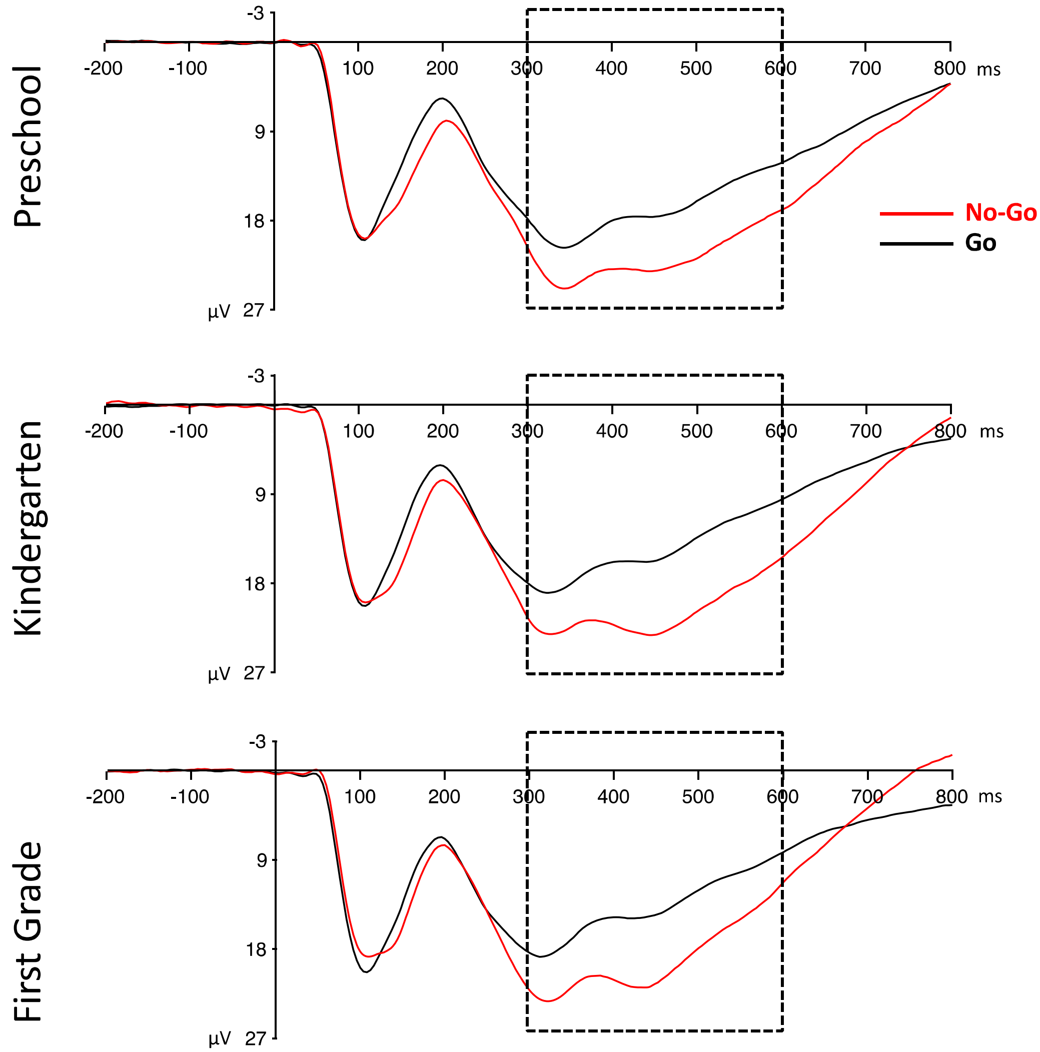

Fig. 4. Midline grand average ERP plots for Go (black waveform) and No-Go (red waveform) conditions over the posterior channel cluster. By convention, negative is plotted upward. The P3b measurement window is shown with a dotted rectangle (300–600 ms post stimulus onset). Preschool: n = 212; Kindergarten: n = 201; First grade: n = 209.

Table 2
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. * $p < .050$.

The unconditional model examining the trajectory of ΔP3b amplitude demonstrated poor model fit (see Table 2 for fit indices), which may be due to the nonlinear developmental trend of ΔP3b mean amplitude (see Table 1 for descriptive statistics). Given that we had data from only three time points, we could not test for nonlinear growth models. The individual trajectories of ΔP3b amplitude for each participant are shown in Supplementary Figure 12. Results from post-hoc pairwise comparisons demonstrated a significant difference in ΔP3b amplitude only between preschool and kindergarten such that larger (more positive) ΔP3b amplitudes were observed in kindergarten ($p = .011$; see Supplementary Table 10 for pairwise comparison results).

Following the approach used in Verstaen et al. (2020), in instances where we set slope variances to zero, we did not include slope covariates. We only examined whether the sociodemographic factors

Table 3
Estimates for Unconditional Latent Growth Curve Models.

Outcome	Parameter	β	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 per ERP component to correct for multiple comparisons ($\alpha = 0.05$ / 3 tests). [a]Slope variance fixed to [0]. * $p < .017$.

Table 4
Estimates for Conditional Latent Growth Curve Models.

Outcome		Intercept				Slope			
	Predictor	β	b	SE	p	β	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. Δ: No-Go minus Go difference wave; Pre: preschool; Gender: 0 = male, 1 = female; Mat Edu: years of maternal education; INR: income-to-needs ratio; Bonferroni correction was applied per ERP component to correct for multiple comparisons. [a]Slope variance fixed to [0]. [b]Slope covariates were not included in the conditional model. * $p <$ Bonferroni-corrected α (.017 for N2 models;.025 for P3b models).

predicted the intercepts of P3b Go and No-Go amplitudes. The conditional models demonstrated good model fit (see Table 2 for fit indices). Maternal education predicted the intercept of P3b Go (b = 0.60, p = .004) and No-Go amplitudes (b = 0.82, p = .004). On average, higher maternal education predicted larger (more positive) P3b Go and No-Go amplitudes during preschool. Initial age, gender, and income-to-needs ratio did not predict the intercepts of P3b Go or No-Go amplitudes (all ps > .166; see Table 4 for model estimates). Given the poor fit of the unconditional model for ΔP3b amplitude, we did not add the covariates of interest.

4. Discussion

This study examined the longitudinal characteristics of two commonly studied neural indices of cognitive control, ERP components N2 and P3b, from preschool through first grade in a large and socioeconomically and racially/ethnically diverse sample of children. We found that for observed waveforms and difference waves, developmental trajectories were component specific. In particular, across the observed waveforms, although N2 Go and No-Go mean amplitudes did not show developmental changes, P3b Go and No-Go mean amplitudes demonstrated linear decreases (became less positive) from preschool to first grade. Further, ΔN2 mean amplitude linearly increased in magnitude (became more negative) over time, whereas ΔP3b mean amplitude was larger (more positive) in kindergarten compared to preschool. Similarly, the links between children's sociodemographic characteristics and ERP mean amplitudes partly depended on whether observed waveforms or the difference wave was used and the ERP component of interest. Specifically, younger children demonstrated a sharper rate of change in ΔN2 mean amplitude over time. Additionally, higher maternal education related to larger (more positive) P3b Go and No-Go mean amplitudes in preschool. 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.

4.1. Observed waveforms

Contrary to our expectations, we did not find discernable changes in N2 Go and No-Go amplitudes from preschool to first grade. Previous meta-analyses reported that N2 No-Go amplitude linearly decreases in magnitude (becomes less negative) over time (Hoyniak, 2017; Lo, 2018). However, the included studies varied in task characteristics and examined age-related changes in N2 amplitudes from a wider age range (2–12 years in Hoyniak, 2017; 3–17 years in 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.

Consistent with our prediction, P3b amplitudes extracted from observed waveforms displayed developmental changes over time. Specifically, P3b Go and No-Go amplitudes demonstrated linear decreases in magnitude (became less positive) from preschool to first grade. While previous correlational studies have reported no relation between age and P3b Go and No-Go amplitudes (St. John et al., 2019; Willner et al., 2015), our longitudinal design allowed us to examine intra-individual change over time. This decline in amplitude may reflect maturational changes in neural generators of P3b observed waveforms, especially in factors that may affect the magnitude of observed ERP waveforms, including changes in synaptic density, myelination, and cerebral blood flow (Coch and Gullick, 2011).

These findings suggest that the underlying neurophysiology reflected by observed waveforms shows unique developmental changes depending on the ERP component of interest. 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). Structural and functional neuroimaging studies have reported different maturational changes in these regions across childhood (Fiske and Holmboe, 2019; Houston et al., 2013). Thus, developmental differences in the neural generators of N2 and P3b may give rise to the disparate longitudinal trajectories of N2 and P3b observed waveforms. Altogether, our findings suggest that the developmental trajectories of observed waveforms are component specific.

4.2. Difference waves

We found that ΔN2 and ΔP3b amplitudes displayed distinct developmental trajectories, compared to amplitudes extracted from observed waveforms. Unlike N2 Go and No-Go amplitudes, which showed no discernable change, ΔN2 amplitude linearly increased in magnitude (became more negative) over time. Our findings imply that while the neural generators of N2 observed waveforms may not go through maturational changes that are manifest at the scalp level from preschool through first grade, brain functions supporting cognitive control and indexed by ΔN2 go through robust changes during this developmental period. Indeed, notable structural changes occur within a broad network of prefrontal to posterior cortices supporting cognitive control (Goddings et al., 2021; Houston et al., 2013). Additionally, there are developmental changes in the activation patterns and functional connectivity of the frontoparietal network involved in cognitive control (Buss et al., 2014; Fiske and Holmboe, 2019). Therefore, change in ΔN2 amplitude over time 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 and Holmboe, 2019; Willoughby et al., 2012).

In contrast to our findings that P3b Go and No-Go amplitudes linearly decreased in magnitude (became less positive) over time, our exploratory analyses suggested that ΔP3b amplitude was larger (more positive) in kindergarten compared to preschool. 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., 2021). Thus, the transition to kindergarten may have contributed to the development of neural processes subserving cognitive control and indexed by ΔP3b. However, given that our exploratory analyses did not reveal any differences in ΔP3b amplitudes between preschool and first grade nor between kindergarten and first grade, we will refrain from overinterpretation. Given that longitudinal behavioral studies have provided some evidence for nonlinear growth rates in cognitive control across early childhood (Reilly et al., 2022; Willoughby et al., 2012), it is possible that the rate of change in neural indices of cognitive control also follow a nonlinear trend.

Our finding that observed waveforms and difference waves displayed unique developmental trajectories across early childhood suggests that they may capture distinct aspects of neurodevelopment. These results emphasize the need for future ERP work and multimodal neuroimaging studies that can unravel the overlapping and distinct neural underpinnings and functional significances of observed waveforms and difference waves. This has implications for understanding whether ERP scores extracted from observed waveforms and difference waves have unique associations with other constructs of interest, such as academic achievement and clinical symptomatology. Altogether, our study highlights the importance of distinguishing between observed waveforms and difference waves in developmental ERP studies.

Additionally, we found that ΔN2 and ΔP3b amplitudes showed unique developmental trajectories, which may stem from divergencies in the cognitive processes these components reflect and in their timing and neural generators (Lahat et al., 2010; Luck, 2014; Polich, 2011). Indeed, studies examining ERP indices of cognitive control, as well as perception, language, emotion, and social cognition have reported different developmental changes as a function of the component of interest (Coch and Gullick, 2011; Downes et al., 2017; Taylor and

Baldeweg, 2002). These disparate developmental changes may stem from differences in the complexity of the cognitive processes ERP components reflect and the development of brain structures and functions that give rise to the components (Coch and Gullick, 2011). Together, our findings suggest that similar to observed waveforms acquired during a cognitive control task, the development of ERP indices of cognitive control are also component specific.

An important strength of the current study is that the same Go/No-Go task was used across time points, preventing task changes from influencing N2 and P3b amplitudes. Considering that ERP data collected from young children tends to have higher noise levels (Brooker et al., 2020), reducing additional sources of variability is particularly important to provide a more accurate depiction of developmental change in ERP amplitudes across childhood. However, it is important to acknowledge that our findings may be limited in their generalizability to other tasks. 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 and Scott, 2020). Additionally, child-friendly ERP tasks vary in the use of trial-to-trial feedback (e.g., Grammer et al., 2014; Lahat et al., 2010; Wiebe et al., 2012) which may contribute to disparities in the amount of effort and attention children allocate to a task – factors that can modulate the amplitudes of stimulus-locked ERP components (Luck, 2014; Polich, 2011). Importantly, ERP components exhibiting the same polarity and timing as components elicited during similar experiments may not necessarily reflect the same underlying neural processes (Luck, 2014). Altogether, future work is needed to enhance our understanding of the developmental trajectories of ERP components elicited across a wide range of experimental paradigms with varying task characteristics.

4.3. Sociodemographic factors

Our second goal was to examine to what extent children's sociodemographic characteristics contributed to N2 and P3b amplitudes in early childhood. We found that age at the initial assessment did not relate to preschool values or the rate of change in N2 Go and No-Go amplitudes. Although age did not relate to ΔN2 amplitude at preschool, ΔN2 amplitude became more negative at a faster rate over time for younger children. Increased neural plasticity observed in younger compared to older children (Tooley et al., 2021) may have contributed to the greater rate of change in brain functions supporting cognitive control and indexed by ΔN2 as children transitioned from preschool to formal schooling. Similarly, behavioral studies have reported greater rates of improvement in cognitive control in younger compared to older children (Lensing and Elsner, 2018). Gender did not relate to the longitudinal characteristics of N2 amplitudes which is consistent with previous studies that found no gender differences in the amplitudes of N2 observed waveforms or ΔN2 (Lahat et al., 2010).

Income-to-needs ratio and maternal education did not relate to preschool values or the rate of change in N2 amplitudes extracted from observed waveforms or the difference wave. Although some studies found no links between family income and N2 amplitudes in 4.5–5.5-year-olds (e.g., Ruberry et al., 2017), other studies have reported that higher SES, based on parental education and family income, related to larger N2 amplitudes in 7–12-year-olds (Kishiyama et al., 2009). To speculate, SES-related disparities in access to higher-quality schools, after-school programs, extracurricular activities, and additional learning opportunities may play a larger role later in development as children spend more time in such settings. Thus, the contributions of SES on N2 development may become more apparent later than the period examined in the current study. Our null findings may also be due to the limited variability in our sample in the rate of change in N2 amplitudes. Future work should examine variability in ERP component trajectories during other developmental periods and across wider time spans and investigate what factors may contribute to individual differences in these trajectories.

We found that age and gender did not relate to P3b amplitudes extracted from observed waveforms in preschool, which aligns with previous research (St. John et al., 2019; Willner et al., 2015). Income-to-needs ratio also did not relate to P3b amplitudes extracted from observed waveforms in preschool, consistent with the findings of Ruberry et al. (2017). However, in a study with high parental education levels, parent income was negatively related to P3b amplitudes extracted from observed waveforms in children (St. John et al., 2019). In contrast, in our study with diverse maternal education levels, higher maternal education, but not income-to-needs ratio, related to larger (more positive) P3b Go and No-Go amplitudes during preschool. Relative to other SES indicators, educational attainment may more strongly relate to the quality of caregiver behaviors and environmental stimulation provided in and out of the home (Davis-Kean et al., 2021), which may contribute to differences in cognitive control skills and structural and functional development of the frontoparietal network (Rosen et al., 2018; Zeytinoglu et al., 2017). Similar to the potentially stronger association to cognitive control, compared to family income, maternal education may also more strongly contribute to underlying neurophysiology reflected by P3b observed waveforms.

Because of the model constraints placed on slope variance estimates, we were unable to examine relations between sociodemographic factors and the rate of change in P3b Go and No-Go amplitudes. Additionally, our results suggested that ΔP3b amplitude may display a nonlinear trajectory of change which precluded us from examining the links between sociodemographic factors and linear change in ΔP3b. Future work is needed to examine how sociodemographic characteristics contribute to developmental changes in the amplitudes of P3b observed waveforms and difference waves. Nevertheless, our findings suggest that the contributions of child- and family-level sociodemographic factors on ERP indices of cognition may depend on whether observed waveforms or difference waves are used and the ERP component of interest.

Formal schooling may also have important contributions to the neurodevelopment of cognitive control. Indeed, the transition to formal schooling has been found to shape brain mechanisms underlying cognitive control and contribute to growth in cognitive control skills (Brod et al., 2017; Kim et al., 2021; Morrison et al., 2019). Additionally, more robust changes in cognitive control may be observed during the school year compared to the summer months (Finch, 2019). Although we examined developmental changes in N2 and P3b amplitudes across the critical transition to formal schooling and early years of elementary school, the design of our study precluded us from systematically addressing questions about schooling effects directly. Specifically, we did not have a school cut-off design (for a review, see Morrison et al., 2019) and the timing of assessments was variable across the three data collection points (i.e., instead of collecting data from all children during a particular semester each year, we collected data throughout the school year and summer months). While this approach was necessary to accommodate family availability, it also prevented us from systematically examining the contributions of schooling experiences to the development of N2 and P3b amplitudes. Taken together, future research is needed to improve our understanding of how schooling experiences contribute to the neurodevelopment of cognitive control in early childhood.

5. Conclusion

We examined longitudinal changes in ERPs recorded during a cognitive control task in early childhood in a relatively large sample of children from diverse socioeconomic and racial/ethnic backgrounds. Although previous cross-sectional studies have contributed to our understanding of age-related changes in ERP indices of underlying neurophysiology and cognitive control, an important strength of our current longitudinal study was the examination of intra-individual change, providing a more compelling depiction of developmental change across time. In summary, our results suggested that observed waveforms and difference waves collected during cognitive control tasks may tap into unique aspects of neurodevelopment and therefore may not be interchangeable, and that the longitudinal trajectories of specific ERP indices of cognitive control are not uniform in early childhood.

Our findings emphasize that in future developmental ERP studies, researchers need to take into consideration that different ERP indices of cognitive control display distinct longitudinal characteristics, and that observed waveforms and difference waves are not interchangeable in studying these longitudinal characteristics. Considering that our study is among the first longitudinal ERP studies with young children, the results reported here can inform these future developmental ERP studies in conducting a priori power analyses. Such power analyses will likely underscore the need for ERP studies with relatively large sample sizes and more importantly, population neuroscience work, which will allow us to better understand typical and atypical brain development and increase the generalizability of neuroimaging results (Falk et al., 2013). Overall, our findings highlight the importance of longitudinal ERP studies to better understand the nuances of the neurodevelopment of cognitive control in early childhood.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

The data used in the analyses and EEGLAB/ERPLAB scripts and R code used in this study are publicly available on OSF: https://osf.io/ngmf8/.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.dcn.2023.101319.

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