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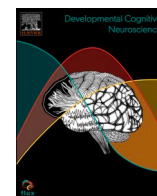
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Characterizing neural indices of cognitive control in young children: A school-based ERP study with naturalistic stimuli

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ABSTRACT

A large body of work has advanced our understanding of the neurodevelopment of cognitive control in early childhood. Such work frequently used simplistic visual stimuli, making them well-suited for event-related potentials (ERP) research. However, more naturalistic stimuli may better mirror visually rich environments where cognitive control is engaged. Here, we measured ERPs from 171 kindergartners at public schools with diverse socioeconomic characteristics during a Go/No-Go task using photographs of animals in natural scenes. Instead of the commonly reported N2 in Go/No-Go tasks with simplistic stimuli, the earlier-occurring ERP morphology was dominated by a P2. The later-occurring ERP morphology was consistent with the P3b reported in Go/No-Go tasks with simplistic stimuli. Both the P2 and P3b displayed more positive mean amplitudes for No-Go compared to Go trials. Additionally, P2 amplitudes decreased with age for No-Go stimuli whereas P3b amplitudes decreased for both Go and No-Go stimuli, indicating different developmental changes across earlier- and later-occurring neural processes. Only larger P3b mean amplitudes were associated with better task performance, suggesting that variability in later-occurring neural processes may be more closely related to individual differences in behavioral performance. These findings suggest that earlier-occurring neural indices of cognitive control may not generalize across paradigms varying in stimulus complexity, while later-occurring indices may. Furthermore, results indicate that earlier- and later-occurring ERPs exhibit distinct age-related differences and associations with behavioral performance. Furthermore, our study highlights the feasibility of conducting school-based developmental cognitive neuroscience research, facilitating the inclusion of children from diverse socioeconomic backgrounds.

1. Introduction

Cognitive control, the ability to control attention and actions in service of goals amid distractions and irrelevant behavioral choices (Badre, 2025; Cohen, 2017; Gratton et al., 2018), develops rapidly during the early school years (Chevalier and Blaye, 2022; Munakata et al., 2012). Cognitive control during the early school years is linked to academic outcomes both concurrently (Coldren, 2013) and prospectively (Welsh et al., 2010). Furthermore, poorer cognitive control during early school years has been observed in clinical disorders such as anxiety and attention-deficit/hyperactivity disorder (ADHD; Breaux et al., 2016; Godoy et al., 2021; Jarrett et al., 2016; Kertz et al., 2016). Given that early cognitive control skills are important for academic outcomes and

implicated in various clinical disorders, it is important to delineate neural processes that support cognitive control during early school years.

Event-related potentials (ERPs) have been widely used to characterize the development of brain functions supporting cognitive control in children (Buss et al., 2011; Elke and Wiebe, 2017; Troller-Renfree et al., 2020). One of the most commonly used ERP paradigms for studying cognitive control in childhood is the Go/No-Go task (Abdul Rahman et al., 2017; Isbell et al., 2019; St. John et al., 2019). In such Go/No-Go tasks, participants are presented with a visual oddball paradigm in which they must quickly respond to frequent standard (Go) stimuli and withhold their response for the infrequent target (No-Go) stimuli. Successful performance on these tasks relies on multiple aspects

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of cognitive control, such as maintaining task rules in working memory (e.g., when to press the button and when to inhibit the button press), evaluating conflicting task stimuli to choose a response, inhibiting prepotent automatic responses, and detecting errors and adjusting behavior accordingly (Gratton et al., 2018). The stimuli in these ERP tasks are intentionally simple and easy to differentiate (e.g., basic shapes, line drawings with few details) and are presented against monochromatic backgrounds (typically white or gray). Such tightly controlled visual input minimizes perceptual confounds, which is especially important given the sensitivity of ERPs to stimulus properties (Kappenman and Luck, 2011; Luck, 2014). This high level of experimental control has been foundational for building our current understanding of the neurodevelopment of cognitive control across childhood.

However, the very features that make these tasks methodologically rigorous also make them unlike the visually rich environments in which children typically engage cognitive control. In everyday contexts, children must detect, evaluate, and respond to information embedded in complex visual scenes. Using more naturalistic stimuli, such as real-life photographs, can allow researchers to examine neural responses under conditions that more closely approximate real-world demands (Gert et al., 2022; Sonkusare et al., 2019). A growing body of ERP research has used naturalistic stimuli in Go/No-Go tasks to investigate neural mechanisms of error monitoring in children (Grabell et al., 2017; Grammer et al., 2014; Kim et al., 2020; Liu et al., 2024). In contrast, relatively little work with children has examined neural responses associated with the detection and evaluation of task-relevant information and the selection of appropriate responses during Go/No-Go tasks using complex, more naturalistic visual input. The few studies that have examined these neural responses have not consistently focused on the same ERP components and have reported mixed findings, particularly with respect to earlier-occurring ERP components (e.g., N2 or P2) associated with cognitive control (Grabell et al., 2017; St. John et al., 2019; Xu et al., 2025). It remains unclear whether neural responses commonly observed in cognitive control tasks with simple visual stimuli generalize to tasks with more naturalistic visual stimuli. Such work is important for advancing our understanding of how cognitive control is engaged under conditions that more closely resemble children's everyday visual experiences. Accordingly, the goal of the present study was to characterize the neural indices of cognitive control in young children during a Go/No-Go task comprising complex, more naturalistic stimuli.

1.1. Stimulus-related ERP indices of cognitive control

1.1.1. N2

One earlier-occurring ERP component frequently observed in children during Go/No-Go tasks is the N2, a negative-going deflection in the ERP waveform that is typically measured between 250 and 500 ms post-stimulus onset over frontocentral channels (Abdul Rahman et al., 2017; Isbell et al., 2019; Lahat et al., 2010). The N2 is typically larger (more negative in amplitude) for infrequent trials, which require participants to inhibit the prepotent response (i.e., No-Go trials), than for frequent trials, in which participants respond more automatically (i.e., Go trials; Hoyniak, 2017; Lo, 2018). The N2 has been suggested to index neural processes involved in the detection of conflicting response representations (Chmielewski and Beste, 2017; Groom and Cragg, 2015; Nieuwenhuis et al., 2003; Randall and Smith, 2011) and response inhibition (Barry and De Blasio, 2015; Lavric et al., 2004).

Studies using relatively simple visual stimuli presented on monochromatic backgrounds, such as shapes and colored drawings with white or gray backgrounds, have consistently reported larger (more negative) N2 amplitudes for No-Go than for Go conditions in children (Abdul Rahman et al., 2017; Isbell et al., 2019). In contrast, findings from studies using complex, more naturalistic visual stimuli have been less consistent. For example, in a study of 3- to 5-year-old children with and without high levels of disruptive behavior, an N2 component was

observed, but there were no amplitude differences between Go and No-Go trials (Grabell et al., 2017). Similarly, in a study of 4- to 10-year-old children, no differences in N2 amplitude were observed between Go and No-Go trials (Lewin et al., 2023). In contrast, in a large sample of 4- to 11-year-old children, N2 mean amplitudes were larger (more negative) for Go compared to No-Go trials (Xu et al., 2025), a pattern opposite to that typically observed in Go/No-Go tasks with simpler visual stimuli (Abdul Rahman et al., 2017; Isbell et al., 2019). Together, these findings suggest that the larger N2 amplitudes observed for the No-Go compared to Go conditions in tasks with simpler visual stimuli may not generalize consistently to tasks using complex, naturalistic visual input.

1.1.2. P2

Although not as commonly reported as the N2, another earlier-occurring ERP component observed in Go/No-Go tasks is the P2 (Liu et al., 2020; Moretta and Buodo, 2021). The frontocentral P2 is a positive-going deflection in the ERP waveform observed around 150–300 ms post-stimulus onset in children and was found to be larger (more positive) in amplitude for No-Go than for Go trials in a study using animal cartoons (Liao et al., 2017). The P2 is believed to index early stimulus evaluation or categorization processes (Gajewski et al., 2008; Moretta and Buodo, 2021; Nijs et al., 2010; Potts, 2004), and has therefore been referred to by some researchers as the frontal selection positivity (Potts, 2004; Rojas-Benjumea et al., 2015).

Reports of the P2 in children in Go/No-Go studies using naturalistic stimuli have been mixed. In some studies, the P2 component was not reported (Grabell et al., 2017; Xu et al., 2025). In a study with 7-year-old children, a P2 component was visually observed in the ERP waveforms, but amplitude differences between No-Go and Go conditions were not assessed (Lamm et al., 2014). Notably, in a pilot study with children aged 4–10 years, a larger (more positive) P2 for No-Go trials than for Go trials was reported (Lewin et al., 2023). Such variability in analytic approaches and findings across studies warrants further research to investigate whether the P2 is reliably elicited during Go/No-Go tasks using complex, more naturalistic stimuli and is modulated by different demands on cognitive control in children.

1.1.3. P3b

The most commonly observed later-occurring ERP component during Go/No-Go tasks is the P3b, a positive-going deflection in the ERP waveform typically measured between 300 and 700 ms post-stimulus onset over posterior channels in children (Polich, 2011; Riggins and Scott, 2020). In Go/No-Go tasks, the P3b is typically larger (more positive) in response to No-Go compared to Go stimuli (Abdul Rahman et al., 2017; Liao et al., 2017; Peters et al., 2023). The P3b has been hypothesized to index context-updating mechanisms, particularly the updating of stimulus-response mappings during cognitive control tasks involving stimuli that require different responses (Polich, 2011; Verleger, 2020).

Unlike the earlier-occurring N2 and P2 components, findings regarding the P3b in Go/No-Go tasks using complex, naturalistic stimuli have been notably consistent (Lewin et al., 2023; St. John et al., 2019; Xu et al., 2025). Similar to the findings from Go/No-Go studies using simpler stimuli like shapes and colored drawings of animals presented on monochromatic backgrounds (Abdul Rahman et al., 2017; Liao et al., 2017; Peters et al., 2023), larger (more positive) P3b amplitudes for No-Go compared to Go trials have been observed in studies using complex, naturalistic visual stimuli (Lewin et al., 2023; St. John et al., 2019; Xu et al., 2025). Overall, these studies suggest that the P3b findings in Go/No-Go studies with children may generalize across paradigms with both simpler and complex, more naturalistic stimuli.

1.2. Present study

The primary aim of this study was to characterize the morphology,

timing, and amplitude of ERPs indexing neural mechanisms of cognitive control during the monitoring, detection, and evaluation of complex, more naturalistic visual stimuli (i.e., real-life photographs) in early school years. We specifically focused on the first formal year of schooling, corresponding to kindergarten (~ages 5–6 years) in the United States, because cognitive control processes undergo substantial development during the transition to formal schooling (Brod et al., 2017; Davidson et al., 2023; Morrison et al., 2019). Importantly, delineating neural indices of cognitive control during this important developmental period using complex, more naturalistic visual stimuli can serve as a foundation for future research. Such work can advance our understanding of how brain functions that support cognitive control develop in both typical and neurodivergent children during early school years as they evaluate and respond to stimuli that more closely resemble their everyday visual environments.

We also had a secondary, exploratory aim to examine whether ERP indices that reflect earlier (N2 and P2) and later (P3b) neural indices of cognitive control show distinct associations with child characteristics (age and sex) and behavioral task performance. This aim was motivated by prior work suggesting that earlier- and later-occurring neural responses may reflect partially distinct cognitive control processes, including stimulus evaluation and conflict monitoring, and updating of working memory and stimulus-response mappings, respectively (Gratton et al., 2018; Polich, 2011; Potts, 2004). Moreover, earlier- and later-occurring neural responses associated with cognitive control may show distinct developmental trajectories and may be differentially sensitive to children's environments (Peters et al., 2023; St. John et al., 2019). Therefore, we hypothesized that earlier- and later-occurring neural indices of cognitive control may have different associations with child characteristics and behavioral task performance.

EEG data were collected at public elementary schools from 171 kindergarten students using a Go/No-Go task containing real-life photographs of animals in naturalistic scenes—the “Zoo Game” (Grammer et al., 2014; He et al., 2010; Lamm et al., 2014; Xu et al., 2025). This task has successfully been used in both behavioral and ERP studies to examine various aspects of cognitive control in typically developing and neurodivergent children (Kim et al., 2017; Kim et al., 2020; Liu et al., 2024; Morales et al., 2020; Troller-Renfree et al., 2019; Xu et al., 2025). However, there has been limited previous neurodevelopmental research examining how young children's brains respond when they are tasked with detecting and evaluating conflicting complex, naturalistic stimuli, and existing findings have been mixed (Grabell et al., 2017; Lewin et al., 2023; St. John et al., 2019; Xu et al., 2025). Therefore, we adopted a data-driven approach, informed by existing literature, to characterize the temporal dynamics of the ERPs elicited by the task used in the current study. Specifically, we used temporal principal component analysis (PCA), which characterizes covariance patterns in the data attributable to latent ERP component factors and identifies their corresponding latencies (Dien, 2012; Dien and Frishkoff, 2005). As this technique separates patterns of variance from noisy signals, it is particularly advantageous for characterizing the temporal dynamics of ERP components in young children, whose data typically have lower signal-to-noise ratios than those of older children and adults (Dien, 2012; Scharf et al., 2022).

To address our primary aim of delineating the neural responses associated with cognitive control in children, we examined both the earlier- and later-occurring ERP components. Regarding earlier-occurring ERP components, mixed findings from studies using more naturalistic stimuli with children made it difficult to predict whether we would observe an N2 or P2 component (Grabell et al., 2017; Lewin et al., 2023; Xu et al., 2025). Based on the previous research with more commonly used simpler visual stimuli (Abdul Rahman et al., 2017; Isbell et al., 2019), it is plausible that we would observe an N2 component, with larger (more negative) amplitudes for stimuli that place higher demands on cognitive control (i.e., No-Go compared to Go stimuli). However, given that visually complex stimuli may instead elicit the P2

component associated with stimulus evaluation and categorization (Liu et al., 2020; Moretta and Buodo, 2021), it is also possible that we would observe a P2 component with larger (more positive) amplitudes for No-Go versus Go stimuli. Regarding the later-occurring neural index of cognitive control (P3b), in line with the converging evidence from developmental studies with both simpler and complex, more naturalistic stimuli (Abdul Rahman et al., 2017; Peters et al., 2023; St. John et al., 2019; Xu et al., 2025), we hypothesized that P3b amplitudes would be larger (more positive) for No-Go compared to Go stimuli.

To address our exploratory aim, we examined associations between ERP amplitudes and commonly studied child characteristics (age and sex) and behavioral task performance. Although all children in our study were enrolled in kindergarten, the age range in our sample spanned almost two years. Given the notable age-related improvements in the accuracy, speed, and efficient coordination of cognitive control in early childhood (Chevalier and Blaye, 2022; Macdonald et al., 2014; Munakata et al., 2012), we expected age-related differences in ERP amplitudes. Based on findings from longitudinal work, suggesting that the developmental trajectories of neural indices of cognitive control may be component-specific from preschool through first grade (Peters et al., 2023), we explored component-specific associations with age. However, because previous work has reported both increases and decreases in neural responses associated with cognitive control across childhood (Crone and Steinbeis, 2017; Peters et al., 2023), we did not formulate directional hypotheses regarding the nature of these age-related associations. In line with findings from prior studies with young children using Go/No-Go tasks (Lahat et al., 2010; Peters et al., 2023; St. John et al., 2019), we did not expect sex-related differences in ERP amplitudes. Lastly, we examined the associations between ERP amplitudes and behavioral task performance. Our goal was to determine whether earlier- and later-occurring neural responses were differentially related to variability in successful task performance across children. Given the mixed findings regarding associations (or lack thereof) between N2, P2, and P3b ERP amplitudes and behavioral performance in Go/No-Go tasks in early childhood (Barry and De Blasio, 2015; Isbell et al., 2019; Peters et al., 2023; St. John et al., 2019), our analyses were exploratory.

2. Method

2.1. Participants

Participants were recruited as part of a larger longitudinal school-based study on the effects of schooling on children's executive functions, conducted across 7 public elementary schools located in the Midwestern United States. The initial sample included 238 kindergarten students, who were assessed throughout the school year. Analytic sample exclusion criteria were EEG equipment error ($n = 28$), completion of less than half of the task ($n = 20$), low ERP trial counts (i.e., less than 10 artifact-free correct Go or No-Go trials; $n = 11$), low accuracy (i.e., less than 50% accuracy for Go trials; $n = 6$), or the child repeating kindergarten ($n = 2$). The final analytic sample consisted of 171 children (female = 51.46%, mean age (SD) = 5.75 (0.41) years; range: 4.96–6.94 years). Demographic information was not collected as part of the original study design; however, school-level free or reduced-price lunch (FRPL) data are reported in [Supplementary Figure 1](#) to provide context on the socioeconomic characteristics of the schools from which participants were recruited. Sixty percent of children in the current sample attended a school where at least half of the students qualified for FRPL (range: 2–83%; see [Supplementary Figure 1](#) for FRPL distribution). Written consent was acquired from school principals, classroom teachers, and families, and verbal assent was obtained from all children prior to testing. The study was approved by the University of Michigan Institutional Review Board (study ID: HUM00085500).

2.2. Procedure

EEG data collection took place in a quiet room designated by school staff for research use (e.g., empty classrooms, conference rooms, libraries) at times agreed upon with teachers during the school day, and on a day separate from other study assessments to minimize participant fatigue. EEG equipment was positioned on a table behind children, who were seated at a separate table. Children completed the EEG task using a game controller while visual stimuli were presented on a monitor. Upon completion of the task, children selected a small toy prize.

2.3. Go/No-Go task

Children completed the “Zoo Game” (Grammer et al., 2014; He et al., 2010; Morales et al., 2020; Troller-Renfree et al., 2019; Xu et al., 2025), a child-friendly Go/No-Go task containing real-life photographs of animals appearing in natural backgrounds (see Fig. 1 for task illustration). In this game, children were instructed that animals at the zoo escaped from their cages, and they must help the zookeeper find and return the animals. They were also told that 3 orangutans were helping, and they should not be returned to their cages. Thus, children were instructed to press a button as quickly as possible whenever they saw an animal (i.e., Go trials) except when they saw an orangutan, in which case they should withhold their response (i.e., No-Go trials). Children first completed 12 practice trials (9 Go trials, 3 No-Go trials). The practice block was followed by test trials comprising 8 blocks of 40 stimuli (30 Go, 10 No-Go), for a total of 320 trials (75% Go trials). The Go stimuli consisted of 240 novel animal photos (no repeats). The No-Go stimuli consisted of 3 orangutan images presented in random order. Each trial began with the presentation of a fixation cross for a randomized duration between 200 and 300 ms. After the fixation screen, an image of an animal was presented for 750 ms, followed by a 500 ms blank screen. Responses were allowed during the stimulus presentation and the subsequent blank-screen period. Subsequent trials began after the blank screen period. Children were encouraged to respond as quickly and as accurately as possible. Responses were made using a handheld Logitech Dual Action gamepad. Between blocks, children received feedback such as “Try to catch them even faster next time!” or “Watch out for the orangutan friends!” based on their performance on the prior block. Children were allowed short breaks throughout the game.

2.4. Behavioral performance

A discriminability index (d') was calculated ($Z(\text{correct}/\text{hit}) - Z(\text{incorrect}/\text{false alarm})$) to measure behavioral performance (Stanislaw and Todorov, 1999). This measure considers both the hit rate and the false alarm rate, distinguishing signal from noise independent of response bias. d' values are commonly used as a measure of behavioral task performance (Ellis et al., 2021), with larger values indicating better detection of targets in the presence of non-targets.

2.5. EEG recording

EEG data were collected with a Biosemi Active 2 (Biosemi, Amsterdam, Netherlands) system with 32 Ag/AgCl electrodes embedded in an elastic cap (see Fig. 2 for electrode configuration). Two electrodes were placed over the mastoid bones behind the left and right ears. Two electrodes were placed lateral to the external canthus of each eye, and two electrodes were placed below each eye, along the inferior orbital ridge, to record electrooculogram (EOG). A common mode sense electrode was used during EEG recording, which was recorded at 512 Hz. Since the Active 2 system does not require impedance measures or gain adjustments, electrode offsets (the voltage between the common mode sense and each active electrode) were monitored and kept below ± 20 mV, which is lower than the company-recommended ± 50 mV (Biosemi, 2023). Offline, the data were down sampled to 256 Hz to speed up data processing.

2.6. EEG processing

All analyses were conducted in MATLAB via customized EEGLAB (Delorme and Makeig, 2004) and ERPLAB scripts (Lopez-Calderon and Luck, 2014), as well as scripts adapted from the ERP CORE (Kappenman et al., 2021) and ICLABEL (Pion-Tonachini et al., 2019). First, EEG data were re-referenced offline to the average of the left and

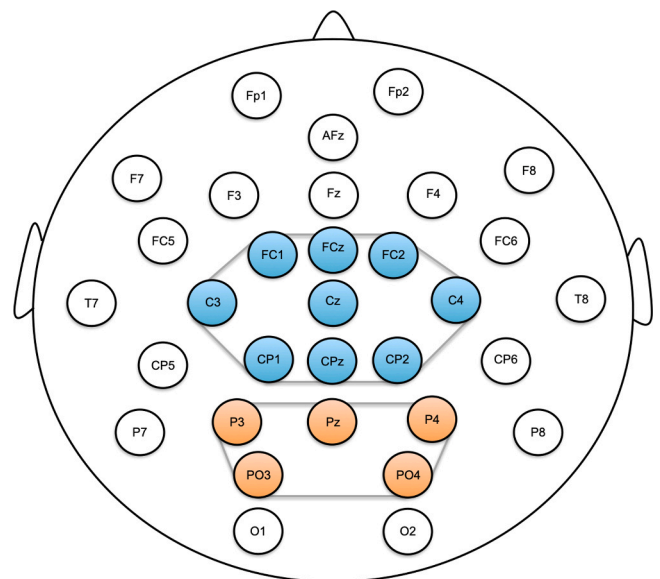


Fig. 2. Electrode configuration. The P2 cluster that was used for analyses is indicated by the blue-colored channels. The P3b cluster that was used for analyses is indicated by the orange-colored channels.

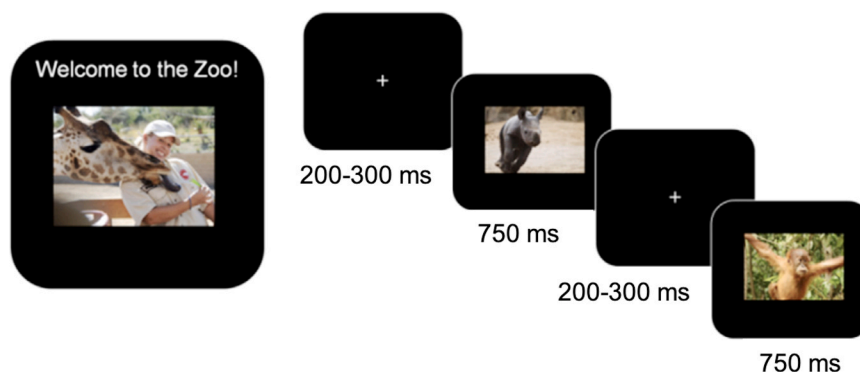


Fig. 1. Illustration of the Zoo Game.

right mastoid electrodes. Bipolar HEOG was created by subtracting the right HEOG from the left HEOG. Bipolar left VEOG was created by subtracting Fp1 from left VEOG; bipolar right VEOG was created by subtracting Fp2 from right VEOG. DC offset was removed, and a band-pass filter of 0.1–40 Hz was applied. To remove ocular artifacts, first, an independent component analysis (ICA) was conducted. In preparation for ICA, portions of the EEG recording that had no event codes (e.g., instructions, breaks) were removed, defined as lasting more than 2000 ms with a 2000 ms buffer before and after event codes. Furthermore, electrodes that would lead to excessive data loss were identified prior to ICA as follows: the ERPLAB moving window peak-to-peak algorithm (300 ms window, moving in 50 ms increments, $\pm 300 \mu\text{V}$ threshold) was applied to all scalp channels, excluding Fp1 and Fp2. The percent data loss per scalp channel was reviewed, and any channel that would have caused excessive data loss compared to other channels for each participant was excluded from pre-ICA cleaning. In addition, we excluded Fp1 and Fp2 from pre-ICA cleaning because large deflections in these frontal channels often reflect eye artifacts. T7 and T8 were also excluded because these channels exhibited high-frequency noise across the study sample, most likely due to muscle tension. Then, extreme artifacts were identified and removed using a moving window peak-to-peak algorithm (500 ms window, moving at 50 ms increments, $\pm 300 \mu\text{V}$ threshold) applied to the remaining scalp channels, which was followed by ICA, and the application of ICLabel (Pion-Tonachini et al., 2019) to detect ICA components most likely to represent ocular artifacts. ICA components labeled with 70% or higher probability as “Eye” and 5% or less probability as “Brain” were removed from the data. These thresholds were previously recommended for use with EEG data from 5- to 8-year-old children (Richardson et al., 2022).

After the removal of ocular ICA components, epochs were extracted, defined as -150 to $+750$ ms relative to stimulus onset, with baseline correction performed from -150 – 0 ms post-stimulus onset. The end of the epoch corresponded with the end of the stimulus presentation to avoid changes in the visual-perceptual experience (i.e., the transition to the blank screen), which can influence ERPs (Luck, 2014). Before the removal of the residual artifacts, to avoid unnecessary data loss due to “bad” channels, a simple voltage threshold ($\pm 200 \mu\text{V}$) algorithm was applied to scalp channels, excluding Fp1, Fp2, F7, F8, T7, T8, P7, and P8, which were not of analytic interest. For outlier detection at this step and at all other steps throughout data preparation and analysis, univariate outliers were defined as scores more than 3.29 *SD* from the mean (Tabachnick and Fidell, 2007). In large samples, nearly all observations are expected to fall within ± 3.29 *SD* from the mean (Tabachnick and Fidell, 2007). Therefore, cases with absolute *z*-scores exceeding 3.29 are considered likely outliers, as such extreme values are expected to occur in fewer than 0.1% of observations drawn from the population (Tabachnick and Fidell, 2007). Thus, for each participant, scalp channels that caused 10% or more data loss and had a data loss rate at or above 3.29 *SD* relative to the other channels of each participant were excluded from post-ICA artifact rejection.

Next, ICA-corrected bipolar channels were created for the removal of residual ocular artifacts. To reject trials with residual eye movements, a moving window peak-to-peak algorithm (200 ms window, moving at 50 ms increments, $\pm 150 \mu\text{V}$ threshold) was applied to the ICA-corrected bipolar channels. To reject residual extreme artifacts, a simple voltage threshold of $\pm 200 \mu\text{V}$ was applied to scalp channels of analytic interest. To identify and reject trials containing blinks that occurred close to the stimulus presentation, a moving window peak-to-peak algorithm (-25 – 225 ms pre- and post-stimulus onset, moving at 10 ms increments, $\pm 150 \mu\text{V}$ threshold) was applied to the uncorrected bipolar right VEOG channel. Similarly, to identify and reject trials containing eye saccades that occurred close to stimulus presentation, a step-like algorithm (-50 – 250 ms pre- and post-stimulus onset, moving at 10 ms increments, $\pm 32 \mu\text{V}$ threshold) was applied to the uncorrected bipolar HEOG channel. The parameters for the post-ICA artifact rejection algorithms were iteratively tested and visually inspected to ensure they were

appropriate for the current sample, and were selected based on their performance with the current data as well as their consistency with parameters used in prior developmental ERP research (Isbell and Grammer, 2022; Peters et al., 2023). After all post-ICA artifact rejection steps, an average of 28.5% of Go trials and 27.3% of No-Go trials were rejected across participants (see Table 2 for descriptive statistics of usable trial numbers per condition).

To detect data quality outliers across scalp channels of analytic interest among participants, analytic standardized measurement error (aSME; Luck et al., 2021) was extracted for the correct trials. Four participants had 4 or more channels with extreme aSME values. However, these participants had low total trial counts, which can bias aSME values. To confirm whether the data for these participants contained extreme noise, the grand average ERP plots were further visually inspected. The data for these participants were deemed adequate; thus, all analyses were conducted with these aSME outliers to capture the true range of scores.

2.7. Statistical analyses

Given the limited prior ERP research using cognitive control tasks with more naturalistic stimuli in early childhood, we used temporal PCA conducted with the ERP PCA Toolkit (Dien, 2010; Dien, 2012) and custom R scripts to empirically determine the time windows for mean amplitude extraction. Only correct trials were included in the temporal PCA analyses. Consistent with recommendations to maximize scalp coverage in ERP PCA analyses (Dien, 2012), we retained all scalp channels in temporal PCA analyses to capture the broad scalp topography of ERP components observed in young children, except Fp1, Fp2, F7, F8, T7, T8, P7, and P8, because these channels were especially prone to noise in our sample. Temporal PCA was applied to the remaining 24 scalp channels. To account for potential latency differences across conditions, similar to previous studies with young children (Dercksen et al., 2022; Mistry-Patel et al., 2024), temporal PCA was computed on individual averages for each trial type (Go and No-Go). The number of factors to retain was determined using Parallel Analysis, which compares the observed factor structure to that obtained from random data (Dien, 2012; Horn, 1965).

After factor retention, instead of using the ERP PCA Toolkit’s default peak-based scores (Dien, 2012), which rely on the single time point of maximal loading, we defined time windows for each factor from the factor loadings (Scaled Factor Pattern; Dien, 2012) via customized R scripts. To limit baseline and edge artifacts, this method was applied to 150–740 ms post-stimulus onset. For each factor, we took the absolute loading over time and defined the window as the interquartile range of the loading, focusing on the middle 50% of the loading within 150–740 ms. This approach enabled us to specify data-driven time windows without relying on peak-based methods, which are less robust to noise (Isbell and Grammer, 2022; Zhang and Luck, 2023).

To isolate the effects of the experimental conditions on the ERP mean amplitudes, we determined overlapping time windows between Go and No-Go conditions by matching each Go factor to the No-Go factor with the most similar time course within 150–740 ms. Similarity was quantified as the absolute Pearson correlation between their standardized (*z*-scored) temporal loadings (derived from the Scaled Factor Pattern output in the PCA Toolkit). Matches were formed stepwise by selecting the most similar pair, removing it, and repeating the procedure until no matching pairs remained. For each matched pair, the final window was the overlap of the Go and No-Go 25th–75th percentile time windows of the time-cumulative absolute loading. Only the pairs with overlap were further examined to determine whether they aligned with the P2, N2, or P3b ERP components in latency, morphology, and scalp distribution, based on previous literature and inspection of the grand-average ERP waveforms and scalp topographies. The limited number of scalp channels we had precluded us from conducting robust spatial PCA analyses. Therefore, once the time windows were finalized, the scalp topographies

were further examined to determine channels of interest for analyses. Given that multi-channel clusters are less prone to noise than single channels (Zhang and Kappenman, 2024), channel clusters were used for all analyses.

ERP measures included mean amplitudes for Go and No-Go observed waveforms. After extracting the ERP time-window mean amplitudes, we first examined the data for potential univariate outliers. Scores more than 3.29 *SD* from the mean were considered outliers (Tabachnick and Fidell, 2007). Next, to determine whether the expected experimental effects (i.e., larger No-Go than Go amplitudes) were observed, we ran separate paired *t*-tests comparing the mean amplitudes of Go and No-Go for each ERP component of interest. In addition, we conducted zero-order correlation analyses to assess the links between child age, sex, behavioral task performance (indexed by *d'*), and ERP scores.

To examine the relation between ERP amplitudes and behavioral performance above and beyond child age and sex, we estimated 2 regression models per component, including age and sex as covariates. Given that ERPs elicited by different trial types often share substantial variance, entering both predictors into the same model can inflate multicollinearity and reduce the interpretability of the regression coefficients. Thus, each model tested condition-specific effects by examining Go-related and No-Go-related neural activity separately. The Bonferroni correction procedure was used to control for multiple comparisons per component of interest, and statistically significant *p*-values were evaluated at a threshold of $p < 0.025$ to control for 2 regression tests per component.

3. Results

3.1. PCA results

The PCA Parallel Analysis (Dien, 2012; Horn, 1965) revealed 4 factors for the Go and 6 factors for the No-Go conditions to be initially retained (see Supplementary Table 1 for temporal PCA results). Across the experimental conditions, 4 time windows were identified as overlapping (see Supplementary Table 2 for the temporal PCA overlapping time windows). Upon further examination, two of these time windows matched the expected latency, morphology, and scalp distribution of the P2 and P3b ERP components and, thus, were selected for further analyses (see Supplementary Figure 2 for grand average ERP plots for each scalp channel). As described below, channel clusters were selected based on the observed scalp topography of each ERP component in the current sample and their alignment with scalp distributions reported in prior developmental research. Lateral channels (F7, F8, T7, T8, P7, and P8) were excluded from all clusters due to their high susceptibility to noise. The other 2 time windows did not match any characteristics of ERPs typically observed in cognitive control tasks with children and were excluded from any further analyses. No PCA factors corresponded with characteristics of the N2; thus, no channel clusters were selected and no analyses were conducted for the N2.

During the first time window we selected based on the temporal PCA results (229–397 ms), we observed an early and broadly distributed positive-going deflection in the ERP waveform, matching the characteristics of a P2 ERP component in cognitive control tasks during childhood (Lewin et al., 2023; Liao et al., 2017; see Fig. 3 for the grand average plot, mean amplitude plot, and scalp topography for P2). Based on visual inspection of the grand average ERP waveforms and scalp topography, the following channels were included in the cluster to

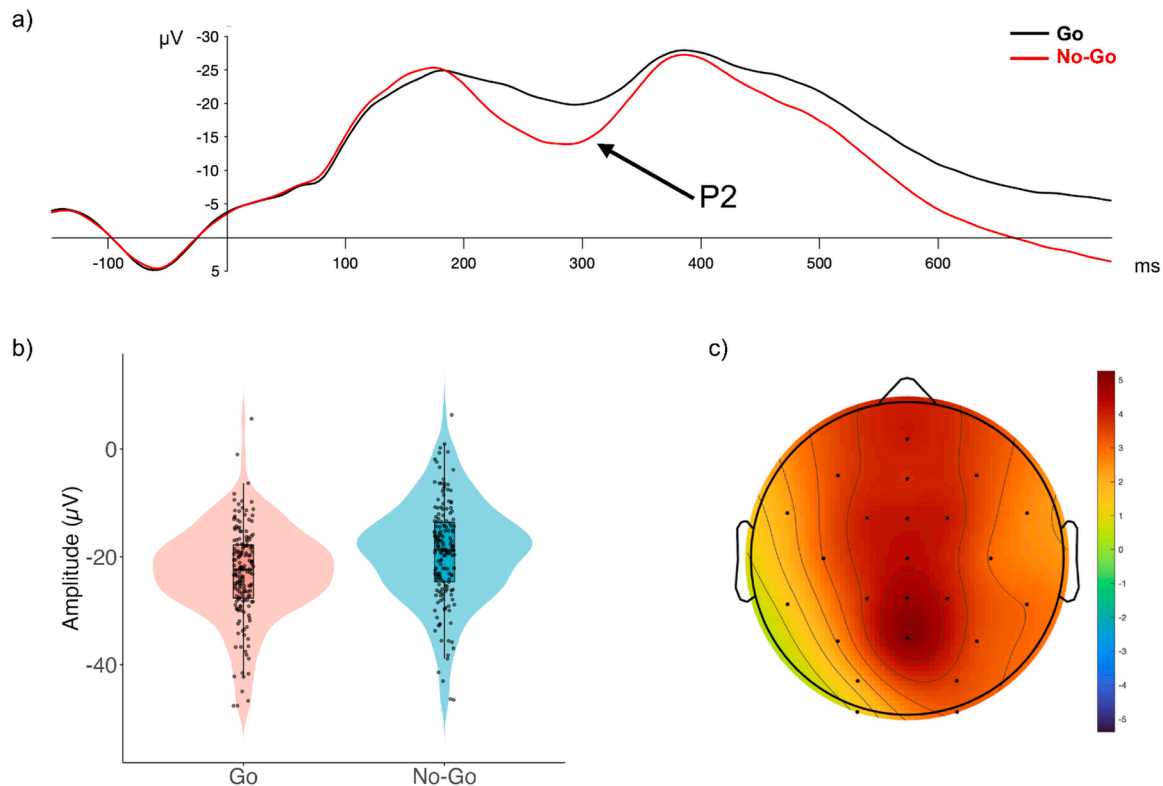


Fig. 3. a) Grand average ERP plot for the P2 channel cluster (FCz, FC1, FC2, Cz, C3, C4, CPz, CP1, CP2) for correct Go (black waveform) and No-Go (red waveform) trials. Amplitude in microvolts is plotted on the y-axis; negative values are plotted upward by convention. Time in milliseconds is plotted on the x-axis; 0 ms corresponds to the stimulus onset. b) Mean amplitudes measured from the P2 channel cluster for Go (pink) and No-Go (blue) conditions. Each dot represents a participant's ERP score, and the shaded areas illustrate the spread of the data. c) Scalp topography of the difference in mean amplitude between conditions (No-Go minus Go) during the P2 time window (229–397 ms post-stimulus), illustrating the spatial distribution of the condition effect.

extract P2 mean amplitude scores: FCz, FC1, FC2, Cz, C3, C4, CPz, CP1, CP2 (see Table 1 for a summary of P2 measurement specifications). This cluster was selected to capture the broad fronto-central distribution of the P2 observed in the scalp topography of the current sample.

During the second time window we selected based on the temporal PCA results (475–643 ms), we observed a later-occurring positive-going deflection in the ERP waveform across posterior channels, matching the characteristics of a P3b ERP component in cognitive control tasks (Peters et al., 2023; St. John et al., 2019; see Fig. 4 for the grand average plot, mean amplitude plot, and scalp topography for P3b). A posterior cluster was created for P3b, including the following channels: Pz, P3, P4, PO3, PO4 (see Table 1 for a summary of P3b measurement specifications). This cluster was selected to capture the posterior scalp distribution observed in the current sample and is consistent with the scalp distribution of the P3b reported in prior research with children (Peters et al., 2023; St. John et al., 2019).

For the P2 and P3b channels of interest, preliminary analyses were conducted to identify potential univariate mean amplitude outliers; no outliers were identified. Therefore, all selected channels across participants were included in their respective clusters. Descriptive statistics for Go and No-Go accuracy, overall behavioral task performance (indexed by d'), Go and No-Go ERP trial numbers, ERP mean amplitude for the Go and No-Go waveforms, and data quality (indexed by aSME), are reported in Table 2.

3.2. *T-tests comparing go and no-go mean amplitudes*

Paired samples *t*-tests revealed that the ERPs in the No-Go condition were more positive in amplitude compared to the ERPs in the Go condition, both for P2, $t(170) = 7.87$, $p < 0.001$, $d = 0.43$, and P3b, $t(170) = 12.77$, $p < 0.001$, $d = 0.74$.

3.3. *Correlations between child characteristics, behavioral performance, and ERP scores*

Zero-order correlations among child age, sex, behavioral performance, and ERP mean amplitude scores are reported in Table 3. There was a significant negative correlation between age and P2 No-Go mean amplitude, indicating that older children exhibited attenuated (less positive) P2 No-Go mean amplitudes than younger children. Similarly, there was a significant negative correlation between age and P3b mean amplitude in both Go and No-Go conditions, indicating that older children displayed attenuated (less positive) P3b mean amplitudes. Age was not significantly correlated with any other ERP scores or behavioral performance. Sex was not significantly correlated with any ERP measure or behavioral performance. P2 amplitudes were not associated with behavioral performance. P3b Go and No-Go mean amplitudes both displayed a significant positive correlation with behavioral performance, such that larger (more positive) P3b mean amplitudes were associated with better task performance.

3.4. *ERP scores and behavioral performance*

Additionally, we conducted separate multiple linear regression analyses to examine the associations between ERP scores and behavioral performance, accounting for child age and sex. Given that temporal PCA was conducted separately for Go and No-Go conditions, the analyses focused on ERP scores extracted from the Go and No-Go conditions.

Table 1
ERP measurement specifications.

ERP component	Time window	Channel cluster
P2	229–397	FCz, FC1, FC2, Cz, C3, C4, CPz, CP1, CP2
P3b	475–643	Pz, P3, P4, PO3, PO4

Note. ERP time windows are measured in milliseconds (ms).

However, to facilitate comparison with prior research and provide transparency, mean amplitudes were also extracted from the difference wave (No-Go minus Go) and used in exploratory analyses examining associations with age, sex, and behavioral performance (see Supplementary Table 3 for difference wave descriptives and Supplementary Tables 4 and 5 for difference wave correlations and regression analyses). For the regression models, behavioral performance was regressed onto Go and No-Go mean amplitudes separately, given the high inter-correlations among these variables. The results of these regression tests are reported in Table 4. Controlling for age and sex, P2 mean amplitudes were not related to behavioral performance. In contrast, controlling for age and sex, larger (more positive) P3b No-Go mean amplitudes were related to better behavioral performance. However, P3b Go mean amplitudes were not related to behavioral performance.

4. Discussion

The current study aimed to characterize the morphology, timing, and amplitude of earlier- and later-occurring ERPs in young children elicited during a cognitive control task (Go/No-Go) that used more naturalistic stimuli. Two latent ERP components were identified, consistent with the morphology, timing, and scalp distribution of the frontocentral P2 and posterior P3b components. Both the P2 and P3b components displayed larger (more positive) mean amplitudes for the No-Go than for the Go stimuli, suggesting stronger neural responses when infrequent, complex, and more naturalistic visual stimuli that conflict with task goals are presented. Additionally, exploratory analyses revealed that age was negatively associated with P2 mean amplitudes for the No-Go condition and with P3b mean amplitudes for both the Go and No-Go conditions, such that older children displayed attenuated (less positive) amplitudes. Child sex was not associated with P2 or P3b mean amplitudes. Lastly, more positive P3b mean amplitudes in the No-Go condition, but not the Go condition, were associated with better behavioral performance, whereas P2 mean amplitudes were not related to behavioral performance. Collectively, these results provide insight into the nature of earlier- and later-occurring neural responses that support the detection and evaluation of goal-conflicting more naturalistic stimuli in young children.

4.1. *Earlier-occurring ERPs*

We did not observe an N2 component in the present study using complex, more naturalistic visual stimuli, which contrasts findings of Go/No-Go studies with children that used simpler visual stimuli embedded on monochromatic backgrounds (Abdul Rahman et al., 2017; Isbell et al., 2019). One possibility relating to the lack of an N2 reported here is that the No-Go stimuli in the present task do not deviate robustly from the global stimulus context (Daffner et al., 2000). Specifically, the Go stimuli included unique, non-repeating real animal photographs, while the No-Go stimuli consisted of a sub-category deviation (i.e., orangutans) within the larger “animal” context. Consequently, this design may not have generated sufficient contextual conflict to elicit the N2. Additionally, many Go/No-Go tasks are designed with a single or a small set of Go stimuli and one No-Go stimulus, with each presented repeatedly with varying frequency (Isbell et al., 2019). In contrast, in the present task, each Go trial included a novel animal photo (i.e., no repeating Go stimuli), and the No-Go trials consisted of three repeating orangutan photographs. Therefore, although the overall probability of Go trials was higher compared to the No-Go trials, the No-Go stimuli were repeated more frequently compared to the unique, non-repeating Go stimuli. Given that the N2 is enhanced for low-frequency stimuli (Nieuwenhuis et al., 2003), it is possible that the repetitive nature of the No-Go stimuli compared to individual Go stimuli does not elicit a typical N2 amplitude modulation (i.e., more negative amplitudes for No-Go stimuli compared to Go stimuli). Consistent with this, in similar

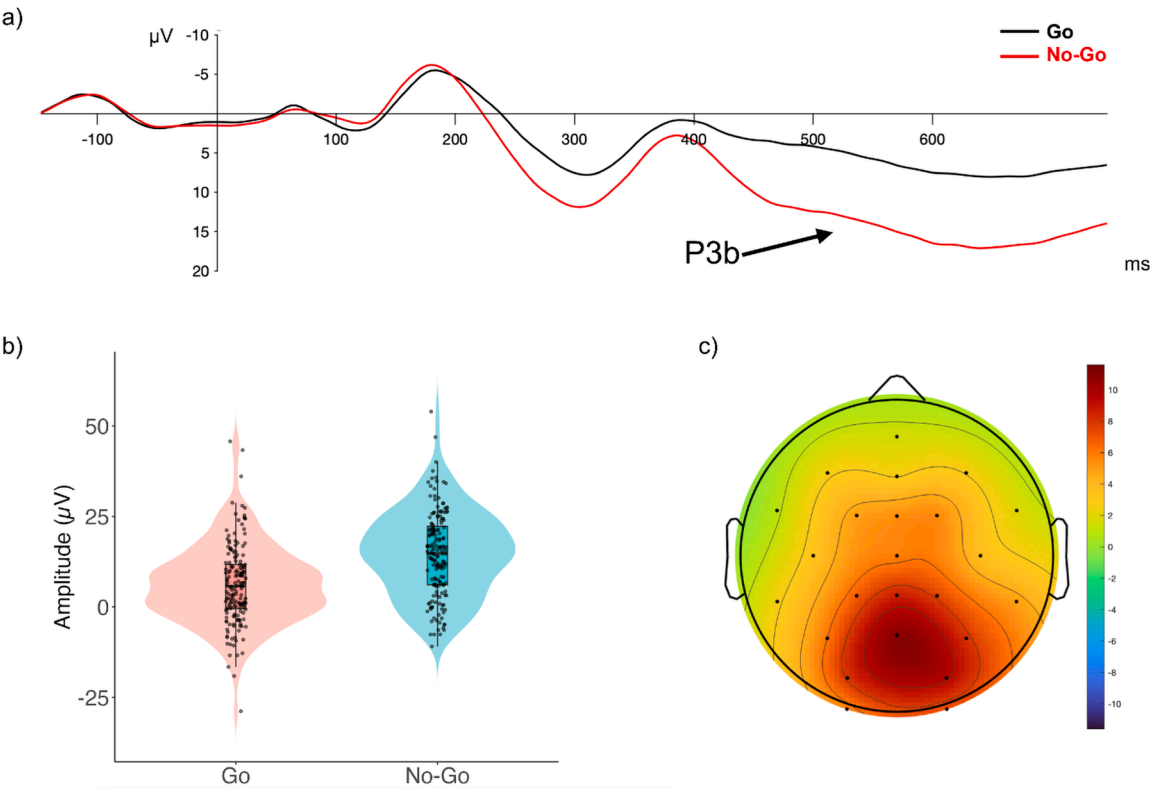


Fig. 4. a) Grand average ERP plot for the P3b channel cluster (Pz, P3, P4, PO3, PO4) for correct Go (black waveform) and No-Go (red waveform) trials. Amplitude in microvolts is plotted on the y-axis; negative values are plotted upward by convention. Time in milliseconds is plotted on the x-axis; 0 ms corresponds to the stimulus onset. b) Mean amplitude measured from the P3b channel cluster for Go (pink) and No-Go (blue) conditions. Each dot represents a participant's ERP score, and the shaded areas illustrate the spread of the data. c) Scalp topography of the difference in mean amplitude between conditions (No-Go minus Go) during the P3b time window (475–643 ms post-stimulus), illustrating the spatial distribution of the condition effect.

Table 2
Descriptives for behavioral and ERP measures.

Variables	Mean	SD	Min	Max
Go accuracy (%)	89.88	9.39	57.08	99.58
No-Go accuracy (%)	61.13	16.43	20.00	93.75
d'	1.75	0.71	-0.02	3.57
Go trial numbers	171.60	37.77	61.00	223.00
No-Go trial numbers	58.19	13.93	22.00	80.00
P2 Go mean amplitude	-23.02	8.59	-47.63	5.60
P2 No-Go mean amplitude	-19.18	9.23	-46.52	6.31
P3b Go mean amplitude	6.09	11.01	-28.84	45.73
P3b No-Go mean amplitude	14.60	11.80	-10.96	54.00
P2 Go aSME	4.20	2.21	1.77	16.13
P2 No-Go aSME	4.15	1.46	1.92	8.87
P3b Go aSME	4.66	2.53	1.84	22.63
P3b No-Go aSME	4.55	1.68	1.96	11.10

Note. d' -prime (d') was used to index overall Go/No-Go behavioral performance. Higher d' values indicate better performance. ERP time-window mean amplitude scores are for correct trials and are measured in μ V. aSME: analytic standardized measurement error. Higher aSME values denote lower data quality.

versions of the Zoo Game comprising unique Go stimuli and repeating No-Go stimuli administered to 3- to 5-year-old and 4- to 10-year-old children, an N2 component was observed but N2 amplitudes did not differ between Go and No-Go conditions (Grabell et al., 2017; Lewin et al., 2023). In a similar version of the Zoo game administered to 4- to 11-year-old children, an atypical N2 pattern was reported, in which Go amplitudes were more negative relative to No-Go amplitudes (Xu et al., 2025). Together with the lack of an N2 in the present study, these findings raise the possibility that Go/No-Go tasks comprising continuously changing more naturalistic visual stimuli may engage neural processes associated with cognitive control that differ from those

observed in traditional paradigms that consist of simpler and more repetitive stimulus presentations.

Instead of an N2, we observed a robust P2 component that displayed larger (more positive) amplitudes for the No-Go than for the Go stimuli, which may reflect how cognitive control is engaged in response to continuously changing real-world visual information rather than repetitive streams of simple visual stimuli. In particular, this may reflect a greater allocation of attentional resources to infrequent targets during an early stimulus evaluation stage (Potts, 2004; Gajewski et al., 2008; Nijs et al., 2010), which may be especially salient when categorizing conflicting, complex naturalistic stimuli that contain subtle category differences. This result is consistent with the findings of previous adult Go/No-Go studies using photographs as stimuli (Moretta and Buodo, 2021; Liu et al., 2020). However, compared with research on adult populations (Liu et al., 2020; Moretta and Buodo, 2021), the P2 component observed in the current study with kindergartners was characterized by relatively later and more prolonged latency. In addition, the P2 was broadly distributed across frontal and centroparietal channels, which contrasts with prior studies with adults that reported more focal P2 scalp distributions (Liu et al., 2020; Moretta and Buodo, 2021). Our timing and scalp distribution findings align with prior studies that observed later latencies and broader scalp distributions of various neural responses associated with cognitive control in young children (Coch et al., 2005; Hampton Wray et al., 2017; Isbell et al., 2016; Mehnert et al., 2013), which may reflect the ongoing maturation of brain regions and networks underlying cognitive control across childhood (Fiske and Holmboe, 2019).

The P2 effect in the current study, characterized by more positive amplitudes elicited by No-Go than by Go stimuli, adds to the mixed literature on earlier-occurring ERPs during versions of the Zoo Game with more naturalistic visual stimuli. Specifically, a P2 component was

Table 3

Zero-order correlations.

Variables	1	2	3	4	5	6	7
1. Age	–						
2. Sex	-0.11	–					
3. d'	-0.02	0.15	–				
4. P2 Go mean amplitude	-0.10	-0.11	-0.03	–			
5. P2 No-Go mean amplitude	-0.16*	-0.10	0.00	0.74***	–		
6. P3b Go mean amplitude	-0.25**	0.01	0.16*	0.45***	0.36***	–	
7. P3b No-Go mean amplitude	-0.15*	-0.06	0.20**	0.25**	0.43***	0.71***	–

Note. Sex: 0 = male, 1 = female. d' was used to index overall Go/No-Go behavioral performance. Higher d' values indicate better performance. ERP waveform measures are taken from correct trials and are expressed in μ V.

* $p < 0.05$ ** $p < .01$ *** $p < 0.001$.**Table 4**

Summary of regression analyses for behavioral performance (d') predicted by P2 and P3b mean amplitudes controlling for child age and sex.

Models	Variables	B	$SE\ B$	β	p	R^2
P2 Go						0.02
	Age	0.00	0.14	0.00	0.99	
	Sex	0.21	0.11	0.15	0.06	
P2 No-Go	P2 Go	0.00	0.01	-0.01	0.86	0.02
	Age	0.01	0.14	0.01	0.95	
	Sex	0.21	0.11	0.15	0.06	
P3b Go	P2 No-Go	0.00	0.01	0.02	0.76	0.05
	Age	0.08	0.14	0.04	0.58	
	Sex	0.21	0.11	0.15	0.05	
P3b No-Go	P3b Go	0.01	0.01	0.17	0.03	0.07
	Age	0.06	0.13	0.04	0.64	
	Sex	0.23	0.11	0.16	0.03	
	P3b No-Go	0.01	0.00	0.22	< 0.01*	

Note. ERP waveform measures were extracted from correct trials and are expressed in μ V. Sex: 0 = male, 1 = female. Bonferroni-corrected significance was evaluated at $p < .025$ (two regression tests per ERP component). Significant p -values are indicated by *.

reported in 7-year-old children, although differences between Go and No-Go conditions were not examined (Lamm et al., 2014). In contrast, studies with school-aged children did not report a P2 component (Grabell et al., 2017; Xu et al., 2025). As with the variability observed for N2 across studies, the mixed findings regarding the P2 may reflect subtle differences in task design. For example, previous studies using versions of the Zoo Game have differed in inter-stimulus intervals. In some task versions, trials ended with a button press (Grabell et al., 2017; Lamm et al., 2014; Xu et al., 2025), potentially resulting in shorter and more variable inter-stimulus intervals. Given that shorter intervals between stimulus presentations are associated with shorter ERP recovery periods (Polich, 2011), it is possible that earlier-occurring ERPs, such as the N2 and P2, are particularly sensitive to subtle temporal differences in task design. Alternatively, differences in participant characteristics may also contribute to the discrepancies in findings. The current sample consisted only of children in kindergarten, whereas previous samples consisted of younger children (Grabell et al., 2017), older children (Lamm et al., 2014), or broad age ranges (Lewin et al., 2023; Xu et al., 2025). Given that the transition to formal schooling is characterized by substantial development of cognitive control (Brod et al., 2017; Davidson et al., 2023; Morrison et al., 2019), differences in schooling experiences may contribute to variation in the earlier-occurring neural responses observed across studies. Nonetheless, the robust P2 effect observed in the current study demonstrates that earlier-occurring ERPs can be elicited during cognitive control tasks using more naturalistic visual stimuli, and underscores the need for future research to systematically examine how task design and

developmental factors contribute to variability in earlier-occurring ERP components.

4.2. Later-occurring ERPs

Consistent with our prediction, we observed larger (more positive) P3b amplitudes for the rare No-Go compared to frequent Go trials over posterior channels. These findings are consistent with prior studies with children that used Go/No-Go tasks that involve a range of stimuli, such as simple shapes, colored drawings of animals, and real photographs of animals (Abdul Rahman et al., 2017; Peters et al., 2023; St. John et al., 2019; Xu et al., 2025). The P3b has been associated with the updating or reactivation of stimulus-response mappings (Polich, 2011; Verleger, 2020) and initiation of response inhibition (Downes et al., 2017; Polich, 2011) following the identification and evaluation of conflicting stimuli. Such consistent findings regarding the P3b in Go/No-Go tasks across a variety of stimuli may suggest that later-occurring neural processes supporting cognitive control are less sensitive to variations in stimulus complexity than earlier-occurring neural processes. Consistent with prior studies with early childhood samples (Peters et al., 2023; St. John et al., 2019), the P3b in the current study was characterized by a posterior scalp distribution. However, P3b latency was relatively delayed and prolonged in our sample compared to prior work with young children (Peters et al., 2023; St. John et al., 2019). Given that ERPs are sensitive to task characteristics, such as task difficulty (Gajewski and Falkenstein, 2013), it is possible that the complex, more naturalistic stimuli used in the current study may have placed greater demands on stimulus evaluation and conflict resolution, potentially resulting in delayed and prolonged P3b latencies. Thus, although the P3b may index neural processes supporting cognitive control that are robustly elicited across stimulus contexts, the timing of these processes may differ across task characteristics.

4.3. Links with age, sex, and behavioral performance

In addition to characterizing the morphology, timing, and amplitudes of earlier- and later-occurring ERPs, the current study aimed to explore associations among ERP amplitudes, child characteristics (age and sex), and behavioral performance. Regarding age-related differences, we found that older children showed attenuated (less positive) P2 amplitudes in the No-Go, but not the Go, condition. Age-related reductions in P2 amplitudes during No-Go trials, which place greater demands on cognitive control, may reflect more efficient neural mechanisms supporting the early detection and evaluation of high-conflict, complex visual stimuli in older children. In contrast, age-related differences in earlier-occurring neural processes may not be apparent during the frequent and less demanding Go trials. This pattern differs from the P3b findings, in which greater age was associated with attenuated (less positive) P3b mean amplitudes in both the Go and No-Go conditions. This finding is consistent with a recent early childhood

longitudinal study that reported decreases in P3b mean amplitudes in both Go and No-Go conditions from preschool to first grade (Peters et al., 2023). Age-related reductions in both Go and No-Go P3b mean amplitudes may be driven by ongoing structural maturation of brain regions that give rise to the P3b, as developmental changes in synaptic density, myelination, and cerebral blood flow have been linked to the magnitude of observed ERP waveforms (Coch and Gullick, 2011). Together, these findings suggest that age-related differences in earlier-occurring neural processes may be more apparent under conditions of greater conflict, whereas age-related differences in later-occurring neural processes may be evident across conditions that vary in cognitive control demands.

In addition to age, we explored whether sex may be associated with ERP indices of cognitive control. We did not observe links between sex and any ERP measure, which is consistent with prior work that administered Go/No-Go tasks to young children (Lahat et al., 2010; Peters et al., 2023). It is possible that brain mechanisms involved in detecting and evaluating conflicting stimuli do not exhibit robust sex-related differences during this developmental period.

Lastly, we explored the links between ERP amplitudes and behavioral performance. After accounting for child age and sex, P2 amplitudes were not related to behavioral performance. The P2 has been suggested to reflect an early stimulus evaluation stage rather than response selection (Moretta and Buodo, 2021; Potts, 2004). Variability in this early evaluation stage may be less directly related to individual differences in behavioral task performance in early school years. In contrast, after accounting for child age and sex, larger (more positive) P3b No-Go, but not Go, amplitudes were associated with better behavioral performance. These findings may suggest that variability in later-occurring neural processes involved in evaluating and updating task-relevant stimulus-response mappings and response selection is more closely related to successful task performance during early school years.

4.4. Limitations and future directions

To determine the temporal dynamics of the earlier- and later-occurring ERP components, the present study adopted a data-driven analytic approach by conducting temporal PCA. Although temporal PCA helped identify ERP measurement time windows best suited for the current sample, this approach is not without limitations. For example, data-driven approaches can introduce potential bias due to sample characteristics (Luck and Gaspelin, 2017). An additional limitation of PCA is the potential conflation of PCA factors, in which multiple ERP components may be combined into a single PCA factor (Scharf et al., 2022). However, this was less of a concern in the current study as P2 and P3b morphologies were both temporally and spatially distinct, as demonstrated by the identified time windows and scalp topographies.

One strength of the current study is that the Go/No-Go task included real photographs of animals embedded over naturalistic backgrounds, which may more closely represent the complex visual information that children encounter in the real world (Sonkusare et al., 2019) and, therefore, provide a more ecologically valid context for examining the neural mechanisms supporting cognitive control. However, while complex, more naturalistic stimuli may better approximate real-world visual experiences, they also reduce experimenter control over potential perceptual confounds (Kappenman and Luck, 2011). Consequently, we cannot conclude with certainty that the P2 component observed in the current study was primarily attributable to the use of real photographs or to other perceptual stimulus features (e.g., naturalistic stimulus backgrounds). To better address this issue, future research directly comparing neural responses in Go/No-Go tasks that vary in stimulus complexity (e.g., simple line drawings versus visually rich photographs) would help disentangle the contributions of stimulus features to variability in ERP indices of cognitive control.

Another strength of the current study is the school-based EEG data collection from a relatively large sample of children. This allowed for greater inclusivity of children from schools with diverse socioeconomic

characteristics, which can increase the representativeness of the sample. However, due to the study's original design, parent surveys for participant sociodemographic information were not administered concurrently. To better assess the representativeness of the sample and examine child and family characteristics, future school-based EEG studies should aim to collect sociodemographic information while making efforts to minimize the burden on participating families and schools.

Our research adds to the growing body of research that EEG systems can be successfully mobilized for data collection in more naturalistic settings without compromising feasibility or data quality (Xu et al., 2022). However, aspects of the school environment, such as noise or children's familiarity with the setting, may have influenced children's task performance or data quality in ways that differ from those in more controlled lab environments. As such, some of the discrepancies between the current findings and prior lab-based studies, such as the absence of an N2 component, may partially reflect differences in testing contexts, task designs, and sample characteristics. Future research directly comparing ERPs elicited during the same task in school and lab settings would help clarify the extent to which the testing environment contributes to variability in neural responses observed during cognitive control tasks. Despite these limitations, the present study indicates that in-school data collection, which greatly increases the inclusion of representative populations, can be successful when using tasks with more naturalistic stimuli.

5. Conclusion

The present study aimed to characterize earlier- and later-occurring neural indices of cognitive control elicited during a Go/No-Go task consisting of real photographs of animals embedded in natural backgrounds, administered in the first year of formal schooling, a period of substantial growth in cognitive control. Regarding the earlier-occurring ERP morphology, instead of the commonly reported N2 in Go/No-Go tasks, we observed the P2 component, characterized by a broad fronto-central positive-going deflection which was larger (more positive) in amplitude for the No-Go compared to the Go stimuli. The later-occurring ERP morphology was consistent with the frequently observed posterior P3b, though the latency was relatively delayed and prolonged compared to studies using less complex stimuli. Additionally, links between age and ERP amplitudes varied across components and conditions, with older children demonstrating attenuated P2 amplitudes for only No-Go stimuli and attenuated P3b amplitudes for both Go and No-Go stimuli. Furthermore, only larger P3b No-Go mean amplitudes were associated with better behavioral task performance, suggesting that individual differences in successful task performance may be more closely related to variability in later-occurring cognitive control processes than earlier-occurring neural responses indexed by the P2. Together, our findings provide insight into ERP indices of brain functions supporting cognitive control when children are tasked with detecting and evaluating complex, more naturalistic visual stimuli that more closely resemble their everyday visual environments. Furthermore, our study adds to the growing evidence that developmental cognitive neuroscience research can be conducted in more naturalistic settings, such as public schools, with relatively large samples of children, broadening the socioeconomic diversity and representativeness of child participants.

CRedit authorship contribution statement

Dylan M. Richardson: Writing – review & editing, Writing – original draft, Visualization, Software, Formal analysis, Data curation, Conceptualization. **Amanda N. Peters:** Writing – review & editing, Visualization, Conceptualization. **Nicholas E. Waters:** Writing – review & editing, Supervision, Project administration, Investigation, Data curation, Conceptualization. **Jennie K. Grammer:** Writing – review & editing, Resources, Methodology, Funding acquisition, Data curation,

Conceptualization. **Amanda Hampton Wray:** Writing – review & editing, Validation, Data curation, Conceptualization. **Elif Isbell:** Writing – review & editing, Writing – original draft, Validation, Supervision, Software, Resources, Formal analysis, Data curation, Conceptualization, Methodology.

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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.

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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.2026.101817.

Data availability

Due to the language used in the original parent consent forms, we cannot publicly share the data. However, EEGLAB/ERPLAB scripts and R code used in this study are publicly available on OSF: https://osf.io/2dfyh/overview?view_only=04b47da8a0014bbe855e264009c2b5fe.

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