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Understanding and Supporting Inhibitory Control: Unique Contributions from Proactive Monitoring and Motoric Stopping to Children's Improvements with Practice

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Abstract

Children struggle to stop inappropriate behaviors. What interventions improve inhibitory control, for whom, and why? Prior work suggested that practice proactively monitoring for relevant signals improved children's inhibitory control more than practice with motoric stopping. However, these processes were not clearly dissociated. This study tested 162 7- to 9-year-old children (89 female, 72 male, 1 unreported; 82% White) on the stop-signal task, following monitoring or stopping-focused practice. Both methods improved inhibitory control, supported generalization, and interacted ($\eta_p^2 = 0.20$-0.73). Practice approaches differentially impacted variability ($\eta_p^2 = 0.01$-0.09). Only monitoring benefits showed signs of depending upon proactive control ($\eta_p^2 = 0.02$). These findings highlight unique contributions of attentional and stopping processes to inhibitory control, suggesting possibilities for tailored interventions.

Keywords: inhibitory control; motoric stopping; context monitoring

Understanding and Supporting Inhibitory Control: Unique Contributions from Proactive Monitoring and Motoric Stopping to Children's Improvements with Practice

As we move through our lives, we often face situations in which we must interrupt an action. This is especially salient during childhood. Whether children are stopping themselves from petting a dog who suddenly snarls as they reach a hand out or interrupting chasing a ball once reaching a busy street, the ability to inhibit an ongoing or prepotent behavior is essential to their daily functioning. This type of inhibitory control, considered one type of response inhibition, develops across childhood (Carver et al., 2001; Davidson et al., 2006; Lo et al., 2013; Tillman et al., 2008; Zhong et al., 2014). It predicts a range of important life outcomes from educational attainment to criminality (Blair & Razza, 2007; Nigg et al., 2006; Thorell et al., 2004) and is impaired in a variety of developmental and neuropsychiatric disorders (Alderson et al., 2007; Geurts et al., 2014; van Velzen et al., 2014; Wright et al., 2014). As such, there is considerable motivation to both better understand response inhibition and develop effective methods to support it (Berkman et al., 2014; Diamond & Lee, 2011; Majid et al., 2015; Smid et al., 2020; Thorell et al., 2009).

Theories of response inhibition have emphasized the importance of a motoric stopping process – the stopping of a reach to pet a dog or a step into a busy street, for example. In the Stop-Signal Task designed to investigate such processes (Logan & Cowan, 1984), participants perform a primary action, such as pressing a button on the left or right to match the side of the screen where a stimulus appears. On some trials, a signal appears after the stimulus, and participants are instructed to not respond. These stop-signal trials can require interrupting a planned or ongoing behavior. They activate prefrontal cortical regions, including the right inferior frontal gyrus (rIFG; Aron et al., 2004, 2014) and elicit an event related potential (ERP) component, the Stop P3 (Smith et al., 2008). These neural patterns have been interpreted as the engagement of motoric stopping processes, like a brake.

However, attentional processes also play an important role in response inhibition (Chatham et al., 2012; Salinas & Stanford, 2013; Verbruggen et al., 2014; Wessel & Aron, 2017; Winter & Sheridan, 2014). For example, stopping a reach to pet a dog could be supported by detecting signals that a dog who initially appeared friendly now seems unfriendly and unsafe to pet. Stopping chasing a ball into a street requires children to detect that they have left the playground and reached the road. In the same way, stopping a button press in the Stop-Signal Task requires detecting the stop signal. Moreover, people proactively monitor for relevant signals in the environment in anticipation of their appearance to support detection of the signals and successful response inhibition. Such proactive monitoring may, in fact, be the controlled process that engages prefrontal regions, as evidenced in modified versions of the Stop Signal Task (Chatham et al., 2012; Dodds et al., 2011; Elchlepp & Verbruggen, 2017; Hampshire et al., 2010; Sharp et al., 2010). In one study, participants were instructed to respond to signals not by stopping, but by completing their target action and then repeating it. Participants showed the same rIFG activation and "Stop" P3 in these modified tasks as in the Stop-Signal Task. Crucially, the rIFG activation was sustained across trials including before the appearance of the signal, suggesting that these neural patterns reflect controlled proactive monitoring for signals relevant for behavior, in anticipation of the signals' appearance, rather than merely reactive detection of signals or stopping per se (Chatham et al., 2012; Swick & Chatham, 2014; cf Aron et al., 2014).

The discovery that proactive monitoring is critical to mature response inhibition raises the possibility that developments in proactive monitoring drive the developments in response inhibition observed across childhood. That is, as children increasingly watch in anticipation of signals in the environment that are relevant to how they should act (such as a dog turning unfriendly or reaching a busy street), they improve in their abilities to stop themselves from behaving inappropriately. An extended developmental time course for proactive monitoring seems likely, given that early in development (3-5 years) children tend to engage control reactively in the moment as needed, and become more efficient and systematic in engaging control proactively, in advance of needing it, across the middle childhood years and beyond (Andrews-Hanna et al., 2011; Blackwell & Munakata, 2014; Chatham et al., 2009; Chevalier et al., 2015, 2020; Lucenet & Blaye, 2014; Vallesi & Shallice, 2007; Waxer & Morton, 2011). This developmental shift in the temporal dynamics of control highlights that limitations in proactive monitoring may contribute to limitations in children's response inhibition. Attempts to support children's proactive monitoring might thus improve their response inhibition.

Indeed, in children, proactive monitoring practice appears to lead to greater benefits to response inhibition than practice with motoric stopping (Chevalier et al., 2014). To test this idea, 7-9-year-old children performed the primary action of pressing a button on the left or right to match the side of the screen where a stimulus appeared. On some trials, a signal appeared after the stimulus. In the monitoring practice condition, children were instructed to respond to the signal by completing their action and then doing it again (i.e. 'go-again'). They thus received practice with monitoring for a stimulus but not practice with motoric stopping. This practice activity built upon tasks that elicited proactive monitoring for signals in adults, with the idea that children with some capacity for proactive control would also engage in proactive monitoring and then experience associated benefits to their response inhibition. In the stopping practice condition, children were instructed to not respond when a highly salient signal appeared. They thus received practice with stopping an ongoing or planned action and minimal practice with monitoring because of the clear and obvious signal. Children who practiced either primarily stopping or primarily monitoring showed better response inhibition on a subsequent Stop-Signal Task compared to children in an active control condition, who were exposed to the same stimuli during practice, but practiced neither stopping nor monitoring. Moreover, children who practiced primarily monitoring showed better response inhibition than children who practiced primarily stopping. These findings highlighted the underemphasized role of attentional processes like proactive monitoring in response inhibition, and their potential for supporting improvements in inhibitory control.

The current study builds on this work and theorizing to test three important remaining questions for understanding the processes underlying response inhibition and interventions that may improve it. First, what are the unique contributions from monitoring and stopping practice to response inhibition, and how do they interact? Prior work pitted stopping and monitoring accounts against one another to test the most direct comparison: primarily monitoring practice with minimal stopping versus primarily stopping practice with minimal monitoring (Chevalier et al., 2014). As a result, the observed benefits may have been driven by specific combinations of monitoring demands and actions, such as the combination of monitoring and going again, rather than benefits of monitoring per se. This contrast thus did not dissociate benefits of monitoring or stopping practice, nor did it allow a test of their potential interaction. The current study achieves this by using a full 2x2 factorial design, with monitoring practice (high or low demand) crossed with action type (stop or go-again). We predict that this design will show independent benefits to response inhibition from monitoring practice and from stopping practice, and will reveal how they interact.

Second, do benefits from practice generalize to novel stimuli? Prior work used similar stimuli across monitoring practice and the Stop-Signal Task in order to test the first question of whether practice monitoring for a specific stimulus would lead to later benefits in response inhibition, even in the face of learning an action mapping (going again) that would later be incorrect. In contrast, the stimuli differed across stopping practice and the Stop-Signal Task, to minimize any contributions from monitoring for specific stimuli and to isolate benefits from stopping practice (Chevalier et al., 2014). The current study tests whether monitoring practice generalizes to novel stimuli at test. We predict that practice with monitoring will generalize to novel stimuli, which would be a critical step toward supporting inhibitory control in the real world. In addition, this design allows us to test whether prior findings reflected the differences in generalization demands after monitoring and stopping practice. Practice and test stimuli will differ in the same way across stopping and monitoring practice, allowing a more direct comparison.

Finally, who benefits most from practice? Prior work demonstrates that intervention effects in executive function and with children tend to be compensatory, with individuals who initially perform worse benefitting more (Jaeggi et al., 2008; Karbach & Unger, 2014; Loveden et al., 2012; Rueda et al., 2006; Traut et al., 2021). The current study includes an individual difference measure of children's proactive control, the AX-continuous performance task (AX-CPT), to test the possibility that proactive control supports and thus correlates with benefits from high monitoring demand practice. We predict that variations in children's benefits from high monitoring demand practice will relate to variations in their proactive control, because of the importance of engaging control in advance of needing it in order to watch in anticipation of signals in the environment. Given that intervention effects in executive function and with children tend to be compensatory, we predict that less proactive children will benefit more from high monitoring demand practice relative to more proactive children. Such findings could provide insight into the types of practice that will be most effective for particular individuals. The current study also includes an individual difference measure of children's response inhibition abilities, the Anti-saccade task, in order to measure children's baseline performance prior to practice. In this computerized task, children must stop themselves from looking at a flashing cue in order to report the identity of a number that appears briefly after the cue on the opposite side of the screen. This allowed us to assess successful randomization of participants to groups.

We view the following analyses as confirmatory because of the way that they build on and extend prior relevant findings: testing benefits from high monitoring demand practice, benefits from stopping practice, and compensatory effects in the benefits of high monitoring demand practice. Testing the interaction between monitoring practice and stopping practice was exploratory given the novelty of this question.

Method

Participants

162 participants between the ages of 7 – 9 years old were enrolled in the study (89 female, 72 male, and 1 unreported; mean age 8.22 years; age range 7.01 – 8.99 years). This age range was selected based on prior work with inhibitory control practice and Stop-Signal Testing (Chevalier et al., 2014). Participants were primarily from families living within the Boulder County, Colorado area with most parents reporting at least a college degree (94%). Participants were predominantly White (82%); the remainder of participants were Asian (5%), Black or African American (<1%), American Indian/Alaskan Native (<1%) or declined to report race (11%). Participants were predominantly not Hispanic or Latino (80%); the remainder were

Hispanic or Latino (6.2%) or declined to report ethnicity (13.5%). Children with diagnosed attentional disorders were excluded and parents were asked to complete questionnaires on ADD and ADHD-type behaviors (Strengths and Difficulties Questionnaire (SDQ); Goodman, 2005) to further screen for atypical attentional development. Informed consent was obtained from a parent or legal guardian and child verbal assent was obtained prior to participation. Families received monetary compensation for transportation while children received an age appropriate book or toy. The local Institutional Review Board approved all study procedures.

148 participants completed the primary task of interest, the inhibitory control practice task, with 36 to 38 participants in each group (see Table 1). 14 children were excluded from the group analysis due to failure to complete the inhibitory control practice task (n = 9, typically resulting from the child becoming frustrated with the task and declining to continue), failure to complete the Stop-Signal Task test or missing test data (n = 3), disclosure of disqualifying disorder post-administration (n = 1), or technical issues during task administration (n = 1). There were no group differences in drop-out rates ($\chi^2 = 1.659$, p = 0.1977, Supplemental Table 1) and no difference in age between participants who were excluded and participants who were kept (Welch two-sample t-test = 0.302, p = 0.7666). An additional 2 participants were excluded from individual differences analyses for either failure to complete (n = 1) or technical error during AX-CPT (n = 1).

Power

A sample size of 160 participants was targeted, to provide sufficient statistical power to detect effect sizes comparable to the moderate effects evidenced by Chevalier and colleagues (2014) (Cohen's $d = 0.61$, requiring $n = 35$ per cell for 80% power), while accounting for loss of participants.

Design

For the inhibitory control practice task, a between subjects 2 x 2 design was implemented. The factor of *monitoring demand* included high and low demand and the factor of *action type* included stop and go-again actions. Participants were pseudo-randomly assigned to one of the four resulting groups, with efforts made to ensure an equal distribution of gender and age across each of the groups.

Procedure

Children were individually tested during a single 1.5-hour testing period. All tasks were administered on a single computer and responses for all tasks, including individual differences measures, recorded via keyboard button presses. All participants were administered the same task ordering to minimize carryover differences between participants for individual differences analyses. Task order was as follows: AX-CPT, Anti-saccade, inhibitory control practice, and Stop-Signal Test. Children chose a sticker between each task. Participants were provided a ~5-minute break between Anti-saccade and inhibitory control practice; additional breaks were provided as needed.

Individual Differences Tasks

AX-CPT

Children performed a child-adapted version of AX-CPT to measure their proactive profiles (Chatham et al., 2009). Trials consisted of two sequentially presented stimuli, a cue (A or B) and a probe (X or Y), with a brief intervening delay. The majority of trials (70%) comprised A-X trials in which participants were instructed to perform a target response (i.e., button-press corresponding to a smiley face) once they had been shown the complete cue-probe trial pair. The remainder of trials were divided equally between three non-target cue-probe pairings (A-Y, B-X, and B-Y; each comprising 10% of total trials), for which participants were instructed to perform a non-target response (i.e., a button-press corresponding to a frowny face). Cue and probe stimuli consisted of images of cartoon characters (SpongeBob SquarePants and Blue) and fun objects (a watermelon and a Slinky), respectively. Cues were presented for 500ms and probes for an initial 6000ms, adjusted to 150% of participants' average response times on the previous 8 trials. Participants received feedback via a score bar tracking progress and an image of a clock with an auditory bell for responses that were too slow (i.e., exceeded the length of the probe). Participants completed a demo phase consisting of 4 trials; trials and instructions were repeated for incorrect responses. Participants then completed a total of 120 test trials (4 blocks of 30 trials).

Participants' proactive control was assessed in terms of a Proactive Behavioral Index (PBI), calculated as $(AY - BX) \div (AY + BX)$ (Braver et al., 2009). Response times were used because of the greater variability in response times compared to accuracy across participants. A positive PBI reflects greater slowing on AY than BX trials, as would be expected with proactive control, whereas a negative PBI reflects greater slowing on BX than AY trials, as would be expected with reactive control. As in prior studies using this paradigm with children of this age (Chatham et al., 2009), PBI was calculated using accurate trials after trimming responses made <200ms after the probe. This trimming led to the exclusion of 2.8% of trials. Further exclusions (e.g., for long reaction times) were not performed to minimize researcher degrees of freedom in analyzing reaction time data (Morís Fernandez & Vadillo, 2020; Simmons, Nelson, & Simonsohn, 2011); the inclusion of fast trials produced qualitatively the same results.

Anti-saccade

Children performed a standard Anti-saccade task to measure their baseline response inhibition abilities. At the start of the task, children were seated ~60cm from a computer screen and instructed to focus on a fixation cross presented at the center of the screen. On each trial, following a variable delay (1500ms - 3500ms), a black square flashed either to the right or left of the fixation cross (350, 375, or 400ms), followed by the brief (<200ms) presentation of a probe (single digit, 1-9) which was then obscured. Children were asked to report which number appeared on each trial, which was then recorded by the experimenter. Between each trial a 'Ready?' screen appeared which the experimenter progressed forward by clicking the space bar. The first task block consisted of "pro-saccade" trials in which the cue and probe were presented in the same location (16 trials). The remaining blocks consisted of "anti-saccade" trials in which the cue and probe were presented on opposite sides of the screen, requiring participants to inhibit their prepotent looking action when the cue appeared in order to be able to report the probe. Participants completed a practice block (6 trials), followed by 54 test trials (3 blocks of 18 trials). Systematic verbal encouragement was provided. Response inhibition was assessed in terms of participants' accuracy of probe report during the anti-saccade trial blocks.

Inhibitory Control Practice & Testing.

Practice Phase

Children were told that they would be helping ‘Mike’ the air traffic controller land planes (similar to Chevalier et al., 2014). They were instructed to look at an air traffic control tower at the center of the screen and to watch for planes that would appear either to the left or right of the tower. To help Mike land the planes, they were told to press a button on the same side of the screen on which the plane appeared. Accurate responses were followed by positive feedback and the appearance of a successfully ‘landed’ plane at the bottom of the screen; inaccurate responses resulted in negative feedback. Participants were administered two demonstrations followed by 24 No-signal practice trials. During this practice block, participants’ mean reaction times were calculated to be used for assigning time pressure later in the task.

Following this practice, all participants received two demonstrations of Signal trials for their condition and two No-signal trials, after which they were administered a combined No-signal trial and Signal trial practice block (24 trials) followed by six test blocks comprised of both trial types (12 Signal trials, 36 No-signal trials). A response time limit of 1.5 x participants’ mean response time from practice was implemented on all No-signal trials for all groups during these blocks, with all participants experiencing feedback if they did not respond within the time limit (Figure 1). This was to deter the adoption of a general slowing strategy. For all groups, signals appeared after a variable delay of 20%, 30%, 40%, or 50% of the child’s mean reaction time for practice Signal trials, but the stimuli for Signal trials differed between groups.

Conditions differed in monitoring demand and action type on Signal trials, crossed in a 2x2 design (Figure 1). In Low Monitoring Demand conditions, signals took the form of a ‘thunderstorm’ that turned the background of the display black, showed clouds and lightning that spanned the screen, and made the sound of thunder. The visual signal remained on screen for the remainder of the trial; the auditory signal occurred once at the onset of the signal. In High Monitoring Demand conditions, signals took the form of a brief appearance of a small storm cloud beneath the airplane (100ms); the background screen remained white and no audio was presented. In Stopping practice conditions, children were instructed to withhold any action during Signal trials for the duration of the trial. In Go-again practice conditions, children were instructed to press the corresponding button again if a signal was presented. Similar to Chevalier et al. (2014), Signal trials for the Go-again groups included a first-press response time pressure of 1.0 x mean practice block response time and second-press response time pressure of 1.1 x mean practice block response time to a) make the Go-again condition approximately as challenging as the Stopping condition and to b) encourage children to respond while monitoring under high monitoring demand rather than sequence response and monitoring processes, given the benefits of simultaneous monitoring and responding for response inhibition. The time pressure is unlikely to lead to faster responses on Signal trials than on No-signal trials, because participants prepare their response before knowing whether a signal will appear. The time pressure is also unlikely to explain group differences in response inhibition, as discussed in the Results. Feedback was provided for responses that did not fall within the time limit. Negative feedback was presented for the Go-again groups if children press twice during No-signal trials. This was to deter the adoption of a constant go-again strategy.

To provide a stronger test of generalization from practice to test, this practice task differed from the comparable practice task in Chevalier et al. (2014) in two ways. First, the airplane stimuli appeared in the upper half of the screen instead of on the midline (whereas the target stimuli appeared on the lower half of the screen at test). Second, the signal in the High

Monitoring Demand condition appeared beneath the stimulus rather than as part of it (whereas the signal appeared as part of the stimulus at test).

Stop-Signal Task

Children were asked to help a baby monkey get bananas (similar to Chevalier et al., 2014). During No-Signal trials children saw a yellow banana appear on either the left or right side of the screen and were asked to press the button on the congruent side. On Signal trials, all children saw the banana turn brown and were instructed to stop and withhold any action to prevent the baby monkey from getting a brown banana (Figure 2). The stop-signal delay (SSD) was adjusted based on a staircase procedure, with the delay increasing by 50ms after successful trials and decreasing by 50ms after unsuccessful trials (Verbruggen & Logan, 2009). This process ensures that participants produced the 50% accuracy levels on at least one level of SSD for Signal trials, necessary for modeling stop-signal reaction time (SSRT). Participants continued to receive feedback for accurate and inaccurate responses as they did during practice. Response inhibition on the Stop-Signal Task is measured in terms of stop-signal reaction times (SSRTs) – an estimation of how quickly participants inhibited the ongoing action of responding once the stop signal appeared. SSRT is calculated by the procedures discussed below, with shorter SSRT indicating faster stopping and better response inhibition. The only difference between this 'Monkey Game' and that administered by Chevalier et al. (2014) was that the banana appeared in the lower half of the screen instead of on the midline of the screen, to more strongly test generalization from practice to test. Participants completed one block of No-signal trials (24 trials), one practice block of No-signal trials and Signal trials (24 trials) and 3 test blocks of 36 No-signal and 12 Signal trials each.

[FIGURES 1 & 2 ABOUT HERE]

Results

Estimation of SSRT Distribution Parameters

Performance during the Stop-Signal Test was measured through estimations of participants' SSRT distribution parameters using all available trial data from accurate trials. Estimation of SSRT distribution parameters was performed using a hierarchical Bayesian ex-Gaussian estimation approach implemented in the software BEESTs (Matzke, Dolan, et al., 2013; Matzke, Love, et al., 2013). As opposed to estimating mean SSRTs through the standard race model approach (Logan & Cowan, 1984), Bayesian Parameter Estimation (BPE) procedures allow for estimation of multiple characteristics of participants' SSRT distribution. This includes participants' modal SSRT, μ (mu), the dispersion or spread of SSRTs, σ (sigma), and the degree of positive skew of SSRT distributions, τ (tau). Participants can show similar (or even identical) measures of central tendency that obscure different reaction time distributions (Balota & Yap, 2011). Estimating the complete distribution of participants' SSRTs provides a more complete picture of response inhibition processes - how quickly participants inhibit, how consistent that inhibition is, and how often participants make prolonged stops. While ex-Gaussian distribution parameters cannot reliably be mapped onto specific cognitive processes, unlike parameters from mathematical models of cognition (Balota & Yap, 2011; Matzke & Wagenmakers, 2009), we can use analyses of these parameters to make inferences about how different aspects of performance are influenced by practice. As in prior work (Chevalier et al., 2014), we focus on the modal time for successful response inhibition (μ), as our main measure of inhibitory control, and consider implications of the measures of variability (σ), and skew (τ). Each parameter is measured in units of milliseconds (ms), where lower numbers indicate faster times.

The method implemented in BEESTs estimates parameters of the SSRT distribution by utilizing a survival analysis approach. The distribution of response times to Signal trials for which participants failed to inhibit themselves (i.e., the signal-response RT distribution) is assumed to be right-censored by a successful stopping process (i.e., no RT data for signal-responses are available for responses longer than a participant's stop process finishing time). Further, it is assumed that the complete signal-response RT distribution is identical to that of the known and complete go RT distribution (i.e., response on No-signal trials). Using these assumptions, the BPE approach estimates the distribution of finishing times that censor the observed data for that distribution – allowing for the parameters for each participant's SSRT distribution to be determined.

The four models were generated following the same procedures, providing parameters for SSRT distributions of each member of each group (Figure 3). Models were generated by calculating 3 Markov-chains with a 5,000 iteration burn-in and thinning every 5 iterations. Gelman-Rubin R Hat convergence diagnostics were calculated for each parameter estimate for each participant and were all approximately 1, suggesting that none of the four models experienced a failure to converge. The use of a hierarchical, as opposed to an individual, estimation approach allows for increased accuracy in estimates by pooling information from the whole group to estimate parameters for individual members (Matzke, et al., 2013). Groups for the hierarchical modeling were derived from the full 2x2 design creating four separate groups for parameter estimation.

[FIGURE 3 ABOUT HERE]

Preliminary Analyses

To assess successful randomization of participants to the four practice conditions, we tested for group differences in age, Anti-saccade accuracy, and AX-CPT performance. No differences were observed in age or AX-CPT performance. However, participants assigned to the Low Monitoring Demand condition performed worse on Anti-saccade than those assigned to the High Monitoring Demand condition, ($F(1, 144) = 4.215$, $p = 0.042$, $\eta_p^2 = 0.03$). As such, all subsequent models controlled for Anti-saccade performance.

Group Effects

All analyses were conducted in an R environment for statistical computing (R Core Team, 2017). We conducted a series of ANCOVAs testing for main effects of action type (stop versus go-again) and monitoring demand (high versus low demand) and their interaction, on each parameter of the SSRT and Go RT distributions (Equation 1). To account for the failure of randomization between Monitoring levels, all models included a Baseline Response Inhibition (Anti-saccade accuracy) covariate. To account for likely effects of age on response inhibition abilities, Age was included as covariate. Age and Baseline Response Inhibition were correlated ($r = 0.55$, $p < 0.0001$) and below commonly accepted cut-offs for mutual inclusion within our models (O'Brien, 2007). Additionally, each model was checked for tolerance and squared multiple correlation values; all were within acceptable parameters (Judd, McClelland, & Ryan, 2017; Tabachnick & Fidell, 2013). Moreover, the addition of the age covariate to all group and individual differences models made no qualitative difference to results.

(Equation 1)

$$\textit{Distribution Parameter} \sim \beta_0 + \beta_1(\textit{Monitoring Condition}) + \beta_2(\textit{Action Condition}) + \beta_3(\textit{Monitoring*Action}) + \beta_4(\textit{Baseline Response Inhibition}) + \beta_5(\textit{Age}) + e$$

Both Stopping and High Monitoring Demand practice benefited modal SSRT, and the two types of practice interacted. Participants in Stopping conditions demonstrated faster modal SSRTs (*M* = 204.4ms; *SD* = 8.1ms) than those in Go-again conditions (*M* = 223.2ms; *SD* = 23.4ms) ($F(1, 142) = 79.858$, $p < 0.001$, $\eta_p^2 = 0.36$) (Figure 4c). Participants in High Monitoring Demand conditions also showed faster modal SSRTs (*M* = 207.5ms, *SD* = 13.4ms) than those in Low Monitoring Demand conditions (*M* = 220ms; *SD* = 23ms) ($F(1, 142) = 34.978$, $p < 0.001$, $\eta_p^2 = 0.198$) (Figure 4b). Action type and monitoring demand interacted ($F(1, 142) = 83.824$, $p < 0.001$, $\eta_p^2 = 0.371$) (Figure 4a), indicating that their effects were not additive. Instead, the benefit of monitoring or stopping practice was greater when the other demand was low. That is, the benefit of monitoring practice was greater in Go-again conditions ($t(1, 142) = 10.452$, Cohen's $d = 32.53$, $p < 0.0001$) than in Stopping conditions ($t(1, 142) = 6.03$, Cohen's $d = 9.82$, $p = 0.1002$), and the benefit of stopping practice was greater in Low Monitoring Demand conditions ($t(1, 142) = 12.669$, Cohen's $d = 38.784$, $p < 0.0001$) than in High Monitoring Demand conditions ($t(1, 142) = -0.223$, Cohen's $d = -0.669$, $p = 0.9961$). Finally, in contrast with prior work (Chevalier et al., 2014), children in the High Monitoring Demand and Go-again group did not differ significantly from children in the Low Monitoring Demand and Stopping condition ($t < 2.1$).

[FIGURE 4 ABOUT HERE]

The dispersion of the SSRT distribution (σ) was affected by action type, such that participants in Stopping conditions showed tighter distributions than those in Go-again conditions ($F(1, 142) = 374.398$, $p < 0.001$, $\eta_p^2 = 0.725$) (Figure 5c). Dispersion was not significantly affected by monitoring demand ($F(1, 142) = 2.23$, $p = 0.1376$, $\eta_p^2 = 0.015$) (Figure 5b), but monitoring demand and action type interacted ($F(1, 142) = 47.35$, $p < 0.001$, $\eta_p^2 = 0.250$)

(Figure 5a). Specifically, stopping led to tighter distributions in the context of high monitoring demand (*M* = 48.4ms, *SD* = 3.5ms) than low monitoring demand (*M* = 58.3ms, *SD* = 5.16ms) ($t(1, 142) = 6.03$, Cohen's $d = 9.82$, $p < 0.001$), but this pattern flipped for the Go-again groups, with going again leading to tighter distributions in the context of low monitoring demand (*M* = 72.4ms, *SD* = 8.2ms) than high monitoring demand (*M* = 79.1ms, *SD* = 9.8ms) ($t(1, 142) = -3.725$, Cohen's $d = -6.30$, $p = 0.0016$). The skew of the SSRT distribution (τ) was not significantly affected by action type, monitoring demand, or their interaction (all $Fs < 1.77$). Age was a trending covariate for SSRT dispersion only ($F(1, 142) = 3.488$, $p = 0.064$, $\eta_p^2 = 0.011$), such that older children demonstrated tighter SSRT distributions than younger. For complete model results see Supplemental Table 2.

[FIGURE 5 ABOUT HERE]

Go RTs were largely unaffected by action type, monitoring demand, or their interaction ($Fs < 1.49$) with one exception: Action type influenced Go RT skew ($F(1, 142) = 6.265$, $p = 0.013$, $\eta_p^2 = 0.042$). Participants in the Stopping conditions had less skew than participants in the Go-again conditions. These findings highlight that the time pressure imposed in Go-again conditions is unlikely to explain group differences in response inhibition (e.g., given that the time pressure imposed on going during training did not lead to faster going during test). Age was a significant covariate for the Go RT mode ($F(1, 142) = 4.824$, $p = 0.029$, $\eta_p^2 = 0.033$) and dispersion ($F(1, 142) = 4.874$, $p = 0.029$, $\eta_p^2 = 0.033$), such that older children demonstrated shorter modal going times and tighter distributions. For complete model results, see Supplemental Table 3.

Individual Differences

We conducted a series of ANCOVAs to test for effects of individual differences in proactive control and interactions with action type and monitoring demand factors on each parameter of the SSRT and Go RT distributions, again controlling for a covariate of Baseline Response Inhibition (Anti-saccade accuracy) and Age (Equation 2).

(Equation 2)

$$\textit{Distribution Parameter} \sim \beta_0 + \beta_1(\textit{Monitoring Condition}) + \beta_2(\textit{Action Condition}) + \beta_3(\textit{Proactive Control}) + \beta_4(\textit{Monitoring*Proactive Control}) + \beta_5(\textit{Action*Proactive Control}) + \beta_6(\textit{Monitoring*Action*Proactive Control}) + \beta_7(\textit{Baseline Response Inhibition}) + \beta_8(\textit{Age}) + e$$

Proactive control showed trending interactions with monitoring demand for both modal SSRT ($F(1,136) = 3.19$, $p = 0.076$, $\eta_p^2 = 0.023$) (Figure 6a) and skew of the SSRT distribution ($F(1,136) = 3.356$, $p = 0.069$, $\eta_p^2 = 0.024$) (Figure 6b). These trends were driven by more proactive participants showing numerically larger modal SSRTs ($r = 0.15$, $p = 0.1891$) in the High Monitoring Demand condition, while proactive control showed no relation with modal SSRT in the Low Monitoring Demand condition ($r = -0.10$, $p = 0.3941$), and more proactive participants showing numerically larger SSRT skew in the High Monitoring Demand condition ($r = 0.17$, $p = 0.1554$), while more proactive participants showed numerically smaller SSRT skew in the Low Monitoring Demand condition ($r = -0.20$, $p = 0.0968$). Proactive control did not show a relation with any SSRT parameters alone or in interaction with action type (all Fs < 0.66), highlighting the potential specificity of the relationships with monitoring demand. However, differences between the trending and non-significant effects did not reach statistical significance

(Fs < 1.49). We return to this issue in the Discussion. For complete model results, see Supplemental Table 4.

[FIGURE 6 ABOUT HERE]

Proactive control did not show any interactions with action type or monitoring type on Go RTs (Fs < 0.62). This finding highlights that the time pressure imposed in Go-again conditions is unlikely to explain group differences in response inhibition (e.g., given that the time pressure imposed on going during training did not lead to faster going during test). However, proactive control showed a main effect on Go RT mode ($F(1,136) = 3.963$, $p = 0.049$, $\eta_p^2 = 0.028$) and dispersion ($F(1, 136) = 8.758$, $p < 0.01$, $\eta_p^2 = 0.06$), with a trending effect on skewness ($F(1,136) = 3.561$, $p = 0.061$, $\eta_p^2 = 0.026$). More proactive participants demonstrated faster modes and tighter distributions with shorter tails. For complete model results see Supplemental Table 5.

Discussion

By separately targeting monitoring and stopping practice, we were able to reveal distinct effects of these attentional and action experiences on children's inhibitory control. First, stopping and monitoring practice each improved response inhibition on their own, and the two types of practice interacted, such that benefits from practicing both together were no greater than benefits from practicing one alone. Second, stopping practice decreased the variability in stop-signal reaction times, and stopping and monitoring practice interacted. Third, children's individual differences in proactive control showed trends of relating only to monitoring practice, but not to stopping practice. We interpret each of these findings in turn and discuss their relation to prior work and implications for future directions.

Improvements to Inhibitory Control

Participants who practiced a task emphasizing either stopping or high monitoring demand showed better inhibitory control than their go-again or low monitoring demand counterparts. The benefits of each type of practice generalized to novel stimuli: practicing in the context of landing planes in possible storms generalized to a context of feeding bananas to a monkey. Thus, what children learned from practice went beyond monitoring or stopping for a particular stimulus.

Stopping and monitoring practice interacted, such that participants who did not practice stopping or monitoring performed the worst, but participants who practiced both stopping and monitoring performed no better than participants who practiced only stopping or monitoring. That is, individuals who should have received the best of both worlds did not reap double the benefit. This is unlikely to reflect a ceiling effect, given that participants actually performed marginally *worse* after practice with stopping and high monitoring demand than after stopping alone ($t(142) = -2.311$, $p=0.1002$, Cohen's $d = -6.923$). One possibility is that the cognitive load associated with simultaneously stopping and monitoring reduced what children could learn from this practice.

These findings extend and inform prior work, which suggested that the benefits of monitoring practice are greater than those for stopping practice (Chevalier et al., 2014). This prior work used similar stimuli across practice and test for the monitoring condition, so our work shows the first generalization of monitoring practice to novel stimuli. Future work should test whether benefits from practice generalize more broadly to real-world inhibitory control situations as well as with a more expansive demographic population (see Nielsen et al., 2017). Moreover, the present work shows that when generalization demands are equated across monitoring and stopping practice, practice with going again and high monitoring demands does not lead to significantly greater benefits than practice with stopping and low monitoring demands, contrary to the pattern found in prior work. Our finding suggests that the earlier result was driven by the differences in generalization demands between conditions. Specifically, while children can generalize practice to novel stimuli, they benefit most when similar stimuli are used across practice and test - an important consideration for developing methods of practicing response inhibition for real-world situations. Finally, prior work tested only those two conditions to pit monitoring and stopping accounts against one another, so our work is the first to reveal main effects of and interactions between the two types of practice. Stopping practice or monitoring practice improves inhibitory control, but their simultaneous combination does not yield additional benefits.

Decreases to Inhibitory Control Variability

The variability (dispersion) of participants' inhibitory control was affected both by action type and by an interaction between action type and monitoring demand. First, stopping practice decreased the variability of inhibitory control compared to going-again. Stopping practice may lead to tighter SSRT distributions by making people more consistent in their execution of the motoric stopping process of inhibitory control. Practice going-again may also lead to wider SSRT distributions by making people less consistent in their execution of the motoric stopping process. This would occur if go-again practice causes participants to sometimes activate the incorrect responses.

In addition, these tendencies to sometimes activate the incorrect action mapping could be exaggerated in the context of high monitoring practice due to heightened responsiveness to cues, leading to the observed interaction between action type and monitoring demand on inhibitory control variability. Specifically, a heightened responsiveness to cues imparted by high monitoring demand practice could amplify mistaken go-again behaviors following go-again practice, leading to greater variability difference between stopping and going again under high monitoring demand compared to low monitoring demand. This could explain why high monitoring demand practice did not decrease variability in inhibitory control compared to low monitoring demand practice overall: consistency benefits from high monitoring demand practice when paired with stopping were cancelled out by consistency impairments from high monitoring demand practice when paired with going again. This pattern suggests that practice with high monitoring led to a higher responsiveness to cues, while practice with stopping both improved the execution of the motoric stopping process and ensured the correct action mapping when a signal appeared.

The difference in effects of high monitoring demand practice and stopping practice on variability might also reflect stopping being a more automatic process, leading to more consistent effects on subsequent behavior after practice, whereas monitoring may be more controlled and thus subject to variations in attention across both practice and test (e.g., Chatham et al., 2012; Hampshire et al., 2010). If stopping is a more automatic process, then opportunities to practice stopping may consistently lead to stopping behavior and this repeated practice reduces variability. In contrast, if monitoring is a more controlled process, then opportunities to practice monitoring may only support monitoring behavior when participants are sufficiently attentive and engaging control, and this inconsistent practice leads to greater variability.

These findings extend and inform prior work, which showed greater variability following go-again and high monitoring practice compared to stopping and low monitoring practice (Chevalier et al., 2014). We replicate those findings, and extend them via our 2x2 design to determine that the contrast between practice stopping and going again influences variability in inhibitory control, and this contrast is heightened under conditions of high relative to low monitoring demand.

Relation to Proactive Control

Individual differences in proactive control seem to have mattered for the effects of monitoring practice on inhibitory control and its variability, but individual differences in proactive control did not relate to the effects of stopping practice. This finding is broadly consistent with the idea that monitoring is more related to control processes than stopping is (Chatham et al., 2012). While further work is needed to probe the specific interactions observed, we speculate that they may reflect compensatory effects. Less proactive participants may benefit more from monitoring practice than more proactive participants, who may already be inclined to approach an inhibitory control task proactively. In addition, after practicing monitoring and going again, more proactive participants may be more likely to reduce their monitoring when it is later mapped to a different target, stopping, based on their detection of and adjustment to the incompatibility between actions. This could explain why more proactive participants showed numerically larger SSRTs and greater skew after high monitoring demand practice. Low monitoring demand practice should not relate to proactive control, so this condition may provide more insight into participants' baseline relations, with more proactive participants showing numerically less skew as expected. More proactive participants would also be expected to show faster inhibitory control but this baseline relation may be masked by the influence of stopping practice.

To our knowledge, this is the first study to link individual differences in proactive control to effects of monitoring practice. Our findings extend prior work demonstrating compensatory effects in interventions targeting other aspects of executive functioning (e.g., Karbach & Unger, 2014; Traut et al., 2021), with individuals who perform worse at baseline benefitting more. This finding points to the possibility of optimizing practice to support inhibitory control based on individual profiles, for example, matching less proactive individuals to high monitoring practice, to yield faster inhibitory control and fewer lapses. Future work should track changes in inhibitory control from before practice to after practice, to better assess relations between individual differences and benefits from practice.

Limitations and Future Directions

We designed our study to minimize and address pre-existing differences between groups, via random assignment of participants to groups and the measuring of and controlling for Anti-saccade performance as a baseline measure of children's response inhibition. However, random assignment does not guarantee a lack of pre-existing differences (as indicated by the group differences in Anti-saccade performance), nor is the baseline Anti-saccade measure a pure or complete measure of all pre-existing differences that might be relevant to later performance on the Stop-Signal Task. Thus, an important direction for future work will be to use a pre-post design, measuring response inhibition via the same task (e.g., Stop-Signal) before and after practice, to more directly assess and address any pre-existing differences between groups. A pre-post design would further allow a more precise characterization of changes in response inhibition following practice. The current design demonstrates that benefits are greater after practice with stopping compared to practice with going again, greater after practice with high monitoring demand compared to low monitoring demand, and greater after practice with stopping or high monitoring demand when the other demand is low. However, the current design does not reveal how post-practice response inhibition compares to baseline. All practice conditions may have improved response inhibition relative to baseline, or some conditions may have improved response inhibition relative to baseline while others worsened it. For example, the go-again condition not only gives no practice with stopping; it gives double practice with a response that will later be incorrect (i.e., going in response to a signal). Thus, go-again practice might lead to worse response inhibition relative to baseline, while stopping and high monitoring demand practice lead to better response inhibition relative to baseline. A pre-post design would address such possibilities, while our design addresses benefits of different types of practice relative to one another.

While our findings with individual differences in proactive control suggest compensatory effects of practice and point toward the possibility of tailored intervention efforts, future work with larger samples will likely be necessary to detect statistically significant correlational interactions. In addition, our findings with proactive control correlations were consistent with our prediction that proactive control processes would relate to benefits from high monitoring demand practice. However, future work should address the processes underlying benefits from practice more directly, for example by using measures such as pupillometry or ERP during practice and test, to assess the control processes engaged. Such measures would also allow a more direct test of the assumptions behind our current approach. Specifically, when children who have some capacity for proactive control engage in practice activities like those that elicit proactive monitoring in adults, they too will engage in proactive monitoring (as assessed through pupillometry or ERP) and experience associated benefits to their response inhibition.

Finally, we note that while we designed our conditions to target separable components of monitoring and stopping, a full dissociation is not possible given that monitoring might not entail stopping, but stopping may entail monitoring even with attempts to minimize monitoring demands. Moreover, although our manipulations showed distinct effects, they also showed an interaction suggestive of an interdependence between monitoring and stopping mechanisms. Future work could explore such possibilities and related remaining questions for the field (Eichlepp et al., 2016; Swick & Chatham, 2014; Wessel & Aron, 2013; Wiecki & Frank, 2013), for example by testing novel empirical predictions generated by computational models incorporating independent versus interdependent monitoring and stopping mechanisms. These types of investigations could also further address relationships between the proactive attentional processes we emphasize and related processes such as working memory and their role in inhibition (Friedman et al., 2008; Munakata et al., 2011; Troller-Renfree et al., 2020; Wiemers & Redick, 2018).

Conclusion

Our findings highlight independent and interacting effects of attentional and action experiences – stopping and monitoring practice – on children's inhibitory control and its variability, and the role of individual differences in proactive control. These patterns suggest that monitoring may be more controlled than stopping, and practice might be effectively tailored based on individual differences. Future work to test such ideas will illuminate the mechanisms supporting inhibitory control and how best to harness them.

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Figures

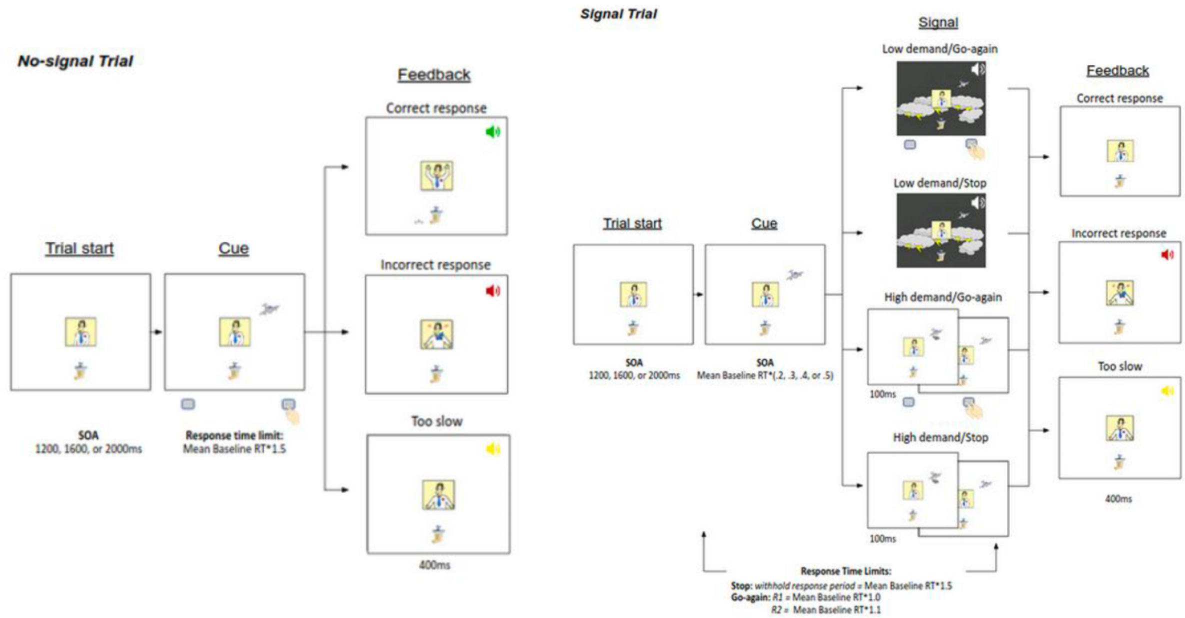

Figure 1. Schematic of No-Signal and Signal trials for inhibitory control practice, with stimuli shown in boxes and required responses shown below the boxes with finger icon.

Note. No-Signal trials began with the appearance of an air traffic controller. After a variable delay (stimulus onset asynchrony, SOA, of 1200, 1600, or 2000ms), a plane appeared on the left or right side of the screen. Participants pressed a button corresponding to the side of the screen the plane appeared on, under a response deadline of 1.5 times their mean baseline RT from the No Signal practice block. Visual and auditory feedback indicated whether the response was correct, incorrect, or too slow. No-Signal trials were the same across all conditions. Signal trials also began with the appearance of the air traffic controller followed by a plane appearing on the left or right side of the screen. After a variable delay (SOA of .2, .3, .4, or .5 times each participant's mean baseline RT), a signal appeared. The signal and required response differed across the 4 conditions as shown: Signals placed either low demands on monitoring (black screens with auditory stimulus) or high demands on monitoring (transient appearance of a small cloud without auditory stimulus). In response to the signal, children were instructed to either repeat their action (in Go-again conditions) or stop their action (in Stop conditions). The response deadline in Go-again conditions was participant's mean baseline RT for the first press and an additional 1.1 times their mean baseline RT for the second press. In Stop conditions, the response limit (i.e., time window during which participants should not respond) was 1.5 times participants' mean baseline RT from the appearance of the cue. As on No-Signal trials, visual and auditory feedback lasting 400ms indicated whether the response was correct, incorrect, or too slow.

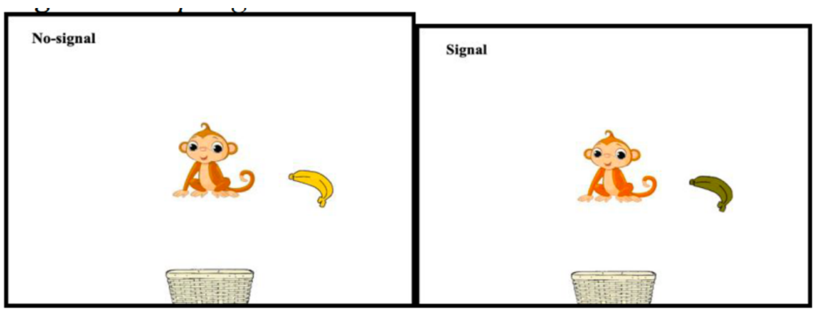

Figure 2. Stop-Signal Task schematic.

Note. Children were instructed to help feed a baby monkey by pressing the button corresponding to the side of the screen the banana appeared on (No-signal trials), and to withhold a response if the banana turned brown (Signal trials).

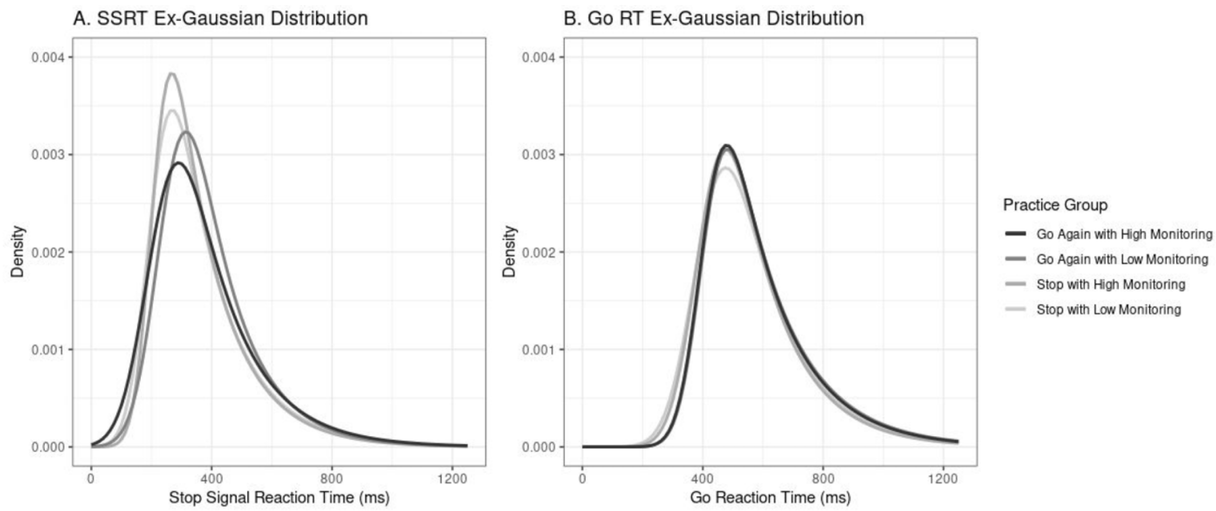

Figure 3. Stop Signal RT and Go RT Distributions.

Note. As addressed in targeted analyses below, **(A)** density curves for SSRT distribution functions based on average estimated parameters for each of the four groups demonstrate differences in the peak, width, and skew of distributions across groups, whereas **(B)** density curves for Go RT distribution functions based on average estimated parameters for each of the four groups show no differences.

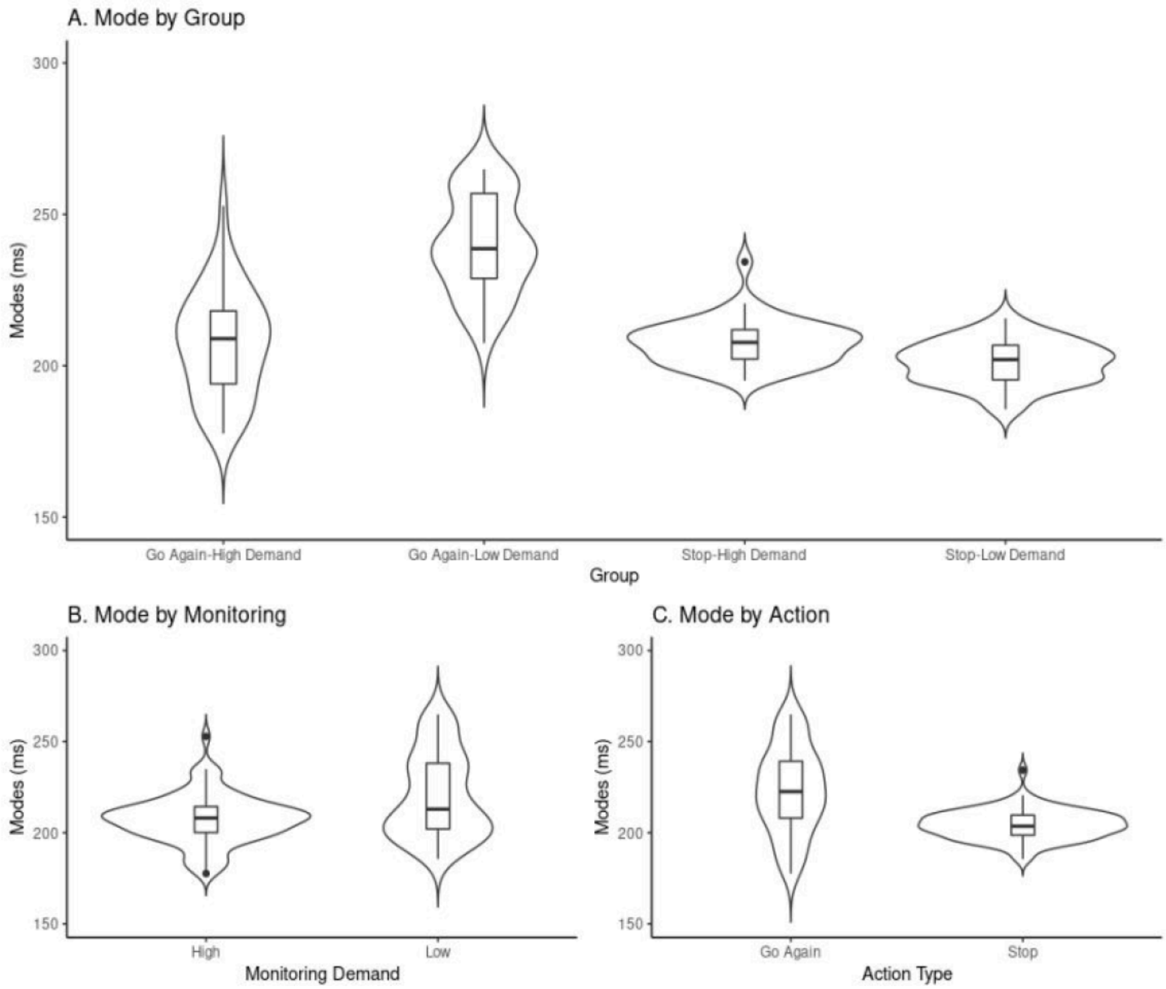

Figure 4. Modal Stop Signal RT by Condition.

Note. Children showed faster modal SSRTs after: **(A)** practicing stopping compared to practicing going again, and **(B)** practicing high-demand monitoring compared to low-demand monitoring. **(C)** Action type and monitoring demand interacted, with greater benefit from monitoring or stopping practice when the other demand was low.

Figure 5. *Dispersion of Stop Signal RT by Condition*

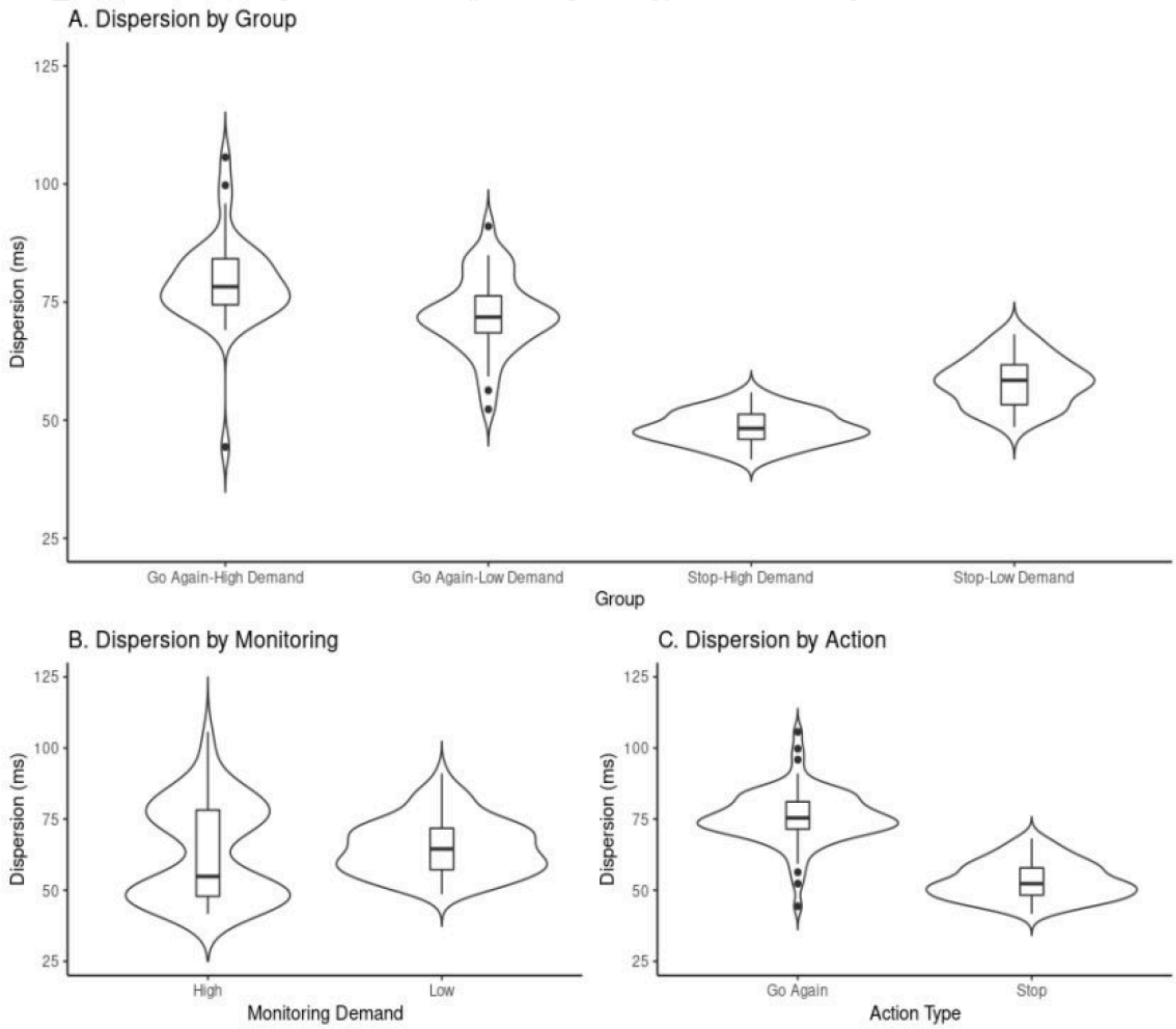

Figure 5. Dispersion of Stop Signal RT by Condition.

Note. Children showed tighter SSRT distributions after practicing stopping compared to practicing going-again **(C)**. This effect was greater if children practiced a high as compared to a low monitoring demand **(A)**, and there was no effect of monitoring demand alone **(B)**.

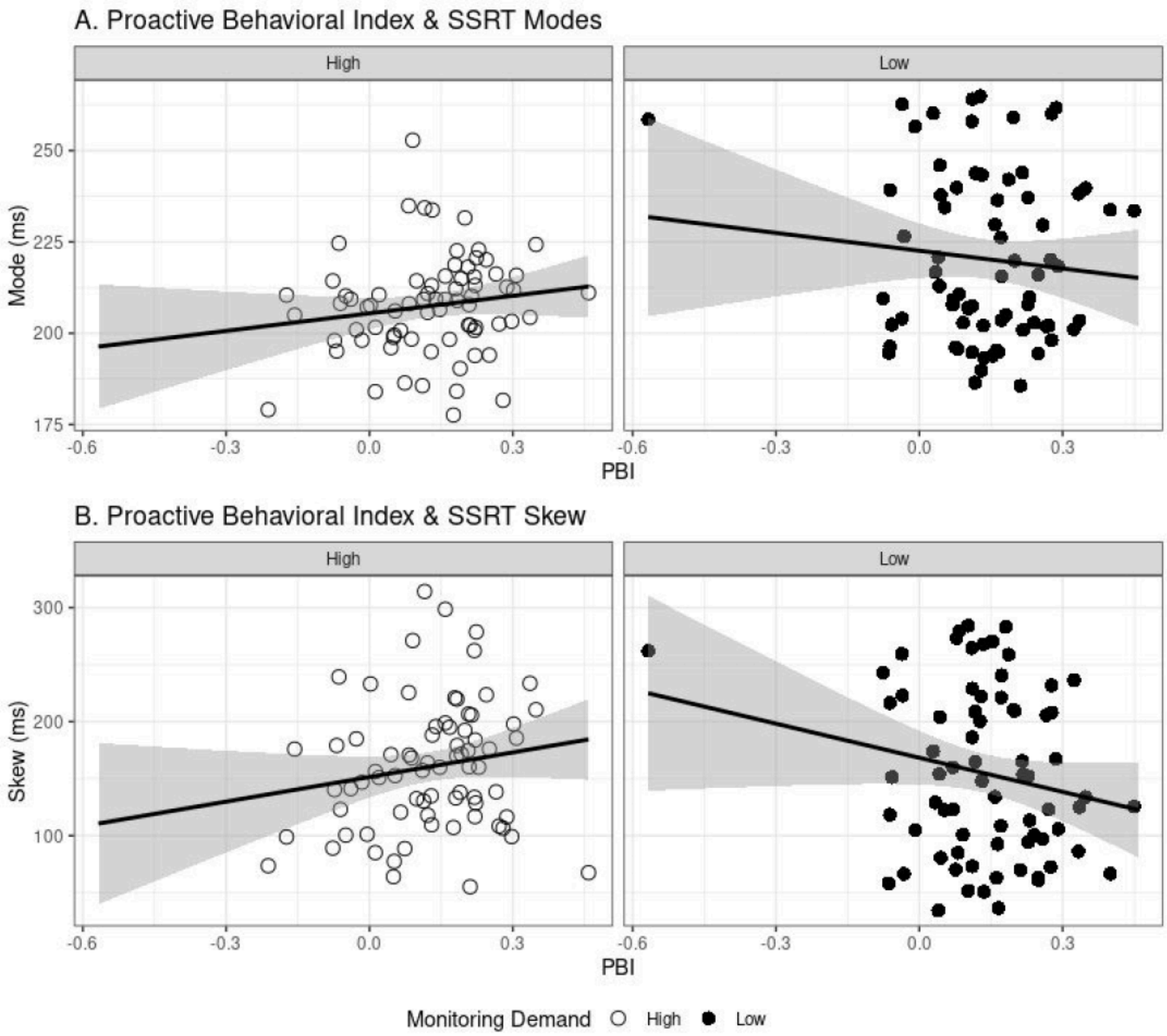

Figure 6. Proactive Control and Stop Signal RT.

Note. Children's variations in proactive control marginally interacted with monitoring demand practice: **(A)** More proactive children showed numerically longer modal SSRTs in the High Monitoring Demand group only. **(B)** More proactive children showed numerically larger SSRT skew (τ) in the High Monitoring Demand group, but numerically smaller SSRT skew in the Low Monitoring Demand group.

Table 1

Table 1. *Summary Statistics by Group*

Variable				
Action Type	Stop		Go-again	
Monitoring Demand	Low	High	Low	High
N	37	38	36	37
Age	7.74 (0.68)	7.81 (0.68)	7.73 (0.65)	7.78 (0.68)
Individual Differences				
Anti-saccade	0.35 (0.16)	0.37 (0.18)	0.30 (0.14)	0.40 (0.20)
AX-CPT	0.14 (0.11)	0.12 (0.13)	0.14 (0.17)	0.13 (0.13)
Stop Signal Reaction Time				
Mode (μ)	200.95 (7.19)	207.74 (7.68)	239.62 (15.97)	207.21 (17.59)
Dispersion (σ)	58.28 (5.16)	48.41 (3.49)	72.36 (8.23)	79.11 (9.79)
Skew (τ)	158.89 (80.63)	151.54 (62.38)	149.25 (64.85)	167.86 (49.12)
Go Reaction Time				
Mode (μ)	391.95 (57.91)	396.67 (59.28)	405.55 (61.62)	404.02 (89.96)
Dispersion (σ)	80.28 (46.94)	73.69 (46.53)	63.39 (36.57)	63.62 (52.02)
Skew (τ)	171.44 (35.87)	163.82 (29.5)	184.88 (41.03)	180.41 (39.01)

Note. Summary statistics by group for age, individual differences measures, stop-signal reaction time (SSRT) and go reaction time (GoRT) distributions.

Supplemental Table 1

Participant dropout by group during Inhibitory Control practice task

Group	Stop	Go Again
Low Monitoring	4	2
High Monitoring	1	2

Supplemental Table 2

Group Analysis of Stop Signal Reaction Time Parameters

Stop Signal Reaction Time Parameter	DF_1	DF_2	MeanSq	F	p	η_p^2
Mode (μ)						
Monitoring Demand	1	142	5872	34.977	<0.001	0.198
Action Type	1	142	13405	79.857	<.0001	0.360
Monitoring*Action	1	142	14071	83.823	<0.001	00.371
Anti-saccade	1	142	16	0.095	0.7577	0.001
Age	1	142	245	1.462	0.2286	0.692
Dispersion (σ)						
Monitoring Demand	1	142	110.7	2.2303	0.1375	0.015
Action Type	1	142	18587.8	374.39	<0.001	0.725
Monitoring*Action	1	142	2350.9	47.351	<0.001	0.250
Anti-saccade	1	142	88.9	1.790	0.1830	0.012
Age	1	142	173.2	3.488	0.0638	0.024
Skew (τ)						
Monitoring Demand	1	142	2554	0.615	0.4338	0.004
Action Type	1	142	249	0.060	0.8067	0.000
Monitoring*Action	1	142	7359	1.774	0.1849	0.012
Anti-saccade	1	142	3709	0.894	0.3458	0.006
Age	1	142	6822	1.645	0.2017	0.011

Supplemental Table 3

Group Analysis of Go Reaction Time Parameters

Go Reaction Time Parameter	DF_1	DF_2	MeanSqr	F	p	η_p^2
Mode (μ)						
Monitoring Demand	1	142	5142	1.496	0.2232	0.010
Action Type	1	142	2241	0.652	0.4206	0.005
Monitoring*Action	1	142	350	0.102	0.7499	0.001
Anti-saccade	1	142	74378	21.649	<0.001	0.132
Age	1	142	16572	4.823	0.0296	0.033
Dispersion (σ)						
Monitoring Demand	1	142	211	0.123	0.7256	0.001
Action Type	1	142	8235	4.826	0.0296	0.033
Monitoring*Action	1	142	1573	0.921	0.3386	0.006
Anti-saccade	1	142	19992	11.717	<0.001	0.076
Age	1	142	8316	4.874	0.0288	0.033
Skew (τ)						
Monitoring Demand	1	142	131	0.114	0.7355	0.001
Action Type	1	142	7180	6.264	0.0134	0.042
Monitoring*Action	1	142	593	0.517	0.4730	0.004
Anti-saccade	1	142	11769	10.268	0.0016	0.067
Age	1	142	2588	2.257	0.1351	0.016

Supplemental Table 4

Individual Differences in Proactive Control (PBI) and Stop Signal Reaction Time Parameters

Stop Signal Reaction Time Parameter	DF_1	DF_2	MeanSq	F	p	η_p^2
Mode (μ)						
Monitoring Demand	1	136	4929	29.529	<.0001	0.178
Action Type	1	136	6260	37.502	<0.001	0.216
PBI	1	136	18	0.106	0.7444	0.001
Monitoring*Action	1	136	8972	53.749	<0.001	0.283
Monitoring*PBI	1	136	533	3.192	0.0762	0.023
Action*PBI	1	136	1	0.007	0.9312	0.000
Monitoring*Action*PBI	1	136	310	1.859	0.1748	0.013
Anti-saccade	1	136	7	0.043	0.8357	0.000
Age	1	136	268	1.608	0.2069	0.012
Dispersion (σ)						
Monitoring Demand	1	136	40.5	0.990	0.3214	0.002
Action Type	1	136	9172.0	224.010	<0.001	0.692
PBI	1	136	26.3	0.643	0.4239	0.000
Monitoring*Action	1	136	813.4	19.864	<0.001	0.091
Monitoring*PBI	1	136	7.6	0.186	0.6666	0.000
Action*PBI	1	136	2.2	0.053	0.8166	0.001
Monitoring*Action*PBI	1	136	93.3	2.278	0.1335	0.003
Anti-saccade	1	136	45.8	1.118	0.2921	0.001
Age	1	136	203.6	4.972	0.0273	0.011
Skew (τ)						
Monitoring Demand	1	136	1804	0.447	0.5047	0.003
Action Type	1	136	1663	0.412	0.5218	0.003
PBI	1	136	85	0.021	0.8844	0.000
Monitoring*Action	1	136	732	0.181	0.6708	0.001
Monitoring*PBI	1	136	13536	3.356	0.0691	0.024
Action*PBI	1	136	1412	0.350	0.5550	0.003
Monitoring*Action*PBI	1	136	3215	0.797	0.3735	0.006
Anti-saccade	1	136	5830	1.445	0.2313	0.011
Age	1	136	8326	2.064	0.1530	0.015

Supplemental Table 5

Individual Differences in Proactive Control (PBI) and Go Reaction Time Parameters

Go Reaction Time Parameter	DF_1	DF_2	MeanSq	F	p	η_p^2
Mode (μ)						
Monitoring Demand	1	136	1398	0.410	0.5225	0.003
Action Type	1	136	2203	0.647	0.4223	0.005
PBI	1	136	13479	3.962	0.0485	0.028
Monitoring*Action	1	136	8917	2.621	0.1077	0.019
Monitoring*PBI	1	136	139	0.040	0.8403	0.000
Action*PBI	1	136	650	0.191	0.6627	0.001
Monitoring*Action*PBI	1	136	13121	3.857	0.0515	0.028
Anti-saccade	1	136	74320	21.849	<0.001	0.138
Age	1	136	13445	3.952	0.0488	0.028
Dispersion (σ)						
Monitoring Demand	1	136	240	0.146	0.7022	0.001
Action Type	1	136	6950	4.257	0.04097	0.030
PBI	1	136	14295	8.757	0.00363	0.060
Monitoring*Action	1	136	9133	5.595	0.0194	0.040
Monitoring*PBI	1	136	44	0.026	0.8698	0.000
Action*PBI	1	136	1018	0.623	0.4310	0.005
Monitoring*Action*PBI	1	136	8227	5.040	0.0263	0.036
Anti-saccade	1	136	20623	12.634	0.0005	0.085
Age	1	136	5910	3.620	0.0591	0.026
Skew (τ)						
Monitoring Demand	1	136	64	0.058	0.8095	0.000
Action Type	1	136	6291	5.736	0.0179	0.040
PBI	1	136	3905	3.560	0.0612	0.026
Monitoring*Action	1	136	676	0.616	0.4338	0.005
Monitoring*PBI	1	136	3	0.003	0.9564	0.000
Action*PBI	1	136	676	0.616	0.4336	0.005
Monitoring*Action*PBI	1	136	4	0.003	0.9511	0.000
Anti-saccade	1	136	13587	12.389	<0.001	0.083
Age	1	136	2705	2.466	0.1186	0.018