Intensive task-switching training and single-task training differentially affect behavioral and neural manifestations of cognitive control in children

Sina A. Schwarze[a*], Corinna Laube[a,b], Neda Khosravani[a], Ulman Lindenberger[a,c], Silvia A. Bunge[d], Yana Fandakova[a,e]

[a] Center for Lifespan Psychology, Max Planck Institute for Human Development, Berlin, Germany
[b] Fresenius University of Applied Sciences, Berlin, Germany
[c] Max Planck UCL Centre for Computational Psychiatry and Ageing Research, Berlin, Germany, and London, UK
[d] Department of Psychology and Helen Wills Neuroscience Institute, University of California at Berkeley, Berkeley, USA
[e] Department of Developmental Cognitive Neuroscience, University of Trier, Trier, Germany

* Corresponding author: schwarze@mpib-berlin.mpg.de
Max Planck Institute for Human Development, Lentzeallee 94, 14195 Berlin, Germany

Running title: Task-switching training in children

Abstract

The ability to flexibly switch between tasks develops during childhood. Children's task-switching performance improves with practice, but the underlying processes remain unclear. We examined how nine weeks of task-switching training affect performance and task-related activation and connectivity as assessed by functional magnetic resonance imaging. Children (8–11 years) were pseudo-randomly assigned to three groups: high-intensity task switching (SW; n = 70), high-intensity single tasking (SI; n = 72), and passive control (n = 41). After three weeks, drift-diffusion modeling revealed faster evidence accumulation and more cautious responding in both training groups relative to the control group. At the end of training, these changes were maintained in the SW group only, that also showed activation decreases in dorsolateral prefrontal cortex. Functional connectivity increases associated with task-switching demands became less pronounced with practice in both training groups, with more persistent decreases in the SI group. We conclude that task-switching training altered performance by accelerating evidence accumulation and promoting more cautious responding. Faster evidence accumulation along with decreased task-related activations suggest increased processing efficiency in frontoparietal regions with training. More intense task-switching training helped maintain these changes, possibly by facilitating plastic change through the protracted mismatch between processing supplies and environmental demands.

Keywords: child development, drift-diffusion modeling, prefrontal cortex, task switching

1. Introduction

Executive functions describe a set of control processes supporting goal-directed behavior (Diamond 2013). Task switching, the ability to flexibly switch between different tasks, constitutes a key component of executive functions (Miyake et al. 2000; Miyake and Friedman 2012) and continues to improve across childhood (Cepeda et al. 2001; Crone et al. 2004; Reimers and Maylor 2005; Crone, Bunge, et al. 2006; Huizinga and van der Molen 2007; Weeda et al. 2014). Accordingly, a number of studies have aimed to improve children's task-switching abilities with training (Karbach and Kray 2009; Kray, Karbach, Haenig, et al. 2012; Zinke et al. 2012; Kray et al. 2013; Dörrenbächer et al. 2014; Karbach et al. 2017; Zuber et al. 2023). However, the mechanisms underlying training-related task-switching improvements in childhood are not yet well understood. The present study seeks to close this gap by examining changes in the cognitive and neural processes underlying task switching in children aged 8 to 11 years, an age period during which children continue to show major improvements in executive functions (Tervo-Clemmens et al. 2023).

1.1 Age differences in task-switching

To examine task switching in the laboratory, task-switching paradigms require individuals to perform two or more tasks in an intermixed fashion, such that each trial constitutes either a repeat of the previous task or a switch to a different one (cf. Koch and Kiesel 2022). The demand to switch to a different task elicits performance costs (i.e., switch costs), evident in lower accuracy and longer response times (RTs). Switch costs are assumed to reflect the updating of the relevant task set and inhibition of the no-longer relevant task set (e.g., Allport et al. 1994; Rogers and Monsell 1995; Meiran 1996; Mayr and Kliegl 2000; Wylie and Allport 2000). Blocks of trials involving task switches are referred to as *mixed blocks* and can be compared to *single blocks* in which participants perform the different tasks separately. The comparison of mixed and single blocks allows one to capture processes that are common to repeat and switch trials within mixed blocks (i.e., mixing costs), in particular the increased

demands to maintain and monitor multiple task sets (e.g., Rubin and Meiran 2005; Pettigrew and Martin 2016). Compared to young adults, children show greater mixing and switch costs, with switch costs approaching adult levels around age 10, while age differences in mixing costs continue to be evident up to adolescence (Cepeda et al. 2001; Crone et al. 2004; Reimers and Maylor 2005; Crone, Bunge, et al. 2006; Huizinga and van der Molen 2007; Manzi et al. 2011).

Cognitive processes involved in task switching can be assessed in a more granular manner using drift-diffusion models (Ratcliff 1978; for a review see Schmitz and Voss 2012). Specifically, drift rates – the speed of evidence accumulation for the correct response – are generally greater on repeat compared to switch trials, thus allowing a participant to reach a decision for the correct response more quickly on repeat trials (Schmitz and Voss 2012). The boundary-separation parameter, also referred to as the decision threshold, has been associated with response caution. It has been suggested to capture interindividual differences in strategy during task switching as well as intraindividual differences between conditions, such that boundary separation is greater on switch than on repeat trials, especially when switches are unpredictable (Karayanidis et al. 2009; Schmitz and Voss 2012). Finally, the non-decision time parameter reflects the encoding of cues and stimuli and preparatory processes, including the reconfiguration of the task set, which are thought to be more demanding on switch than repeat trials (Schmitz & Voss, 2012). Studies have further suggested that the non-decision time parameters additionally capture processes after the decision has been made, reflecting the continuous processing of the stimuli (Resulaj et al. 2009; Schroeder and Verrel 2014). Note however that these post-decision aspects of the non-decision time parameter have not been systematically examined in task-switching studies.

To date, drift-diffusion parameters during task switching have rarely been examined in developmental studies. Weeda and colleagues (2014) investigated drift-diffusion parameters on showed that children become more efficient at accumulating evidence for the correct response between ages 7 and 15 years, reflected in increased drift rates with age.

Compared to 7–11-year-olds, 15-year-olds showed smaller boundary separation, suggestive of less cautious responses, and more efficient stimulus encoding and response selection, indexed by lower non-decision time. All parameters approached adult levels between ages 11 and 15 years, indicating that most developmental changes in evidence accumulation, response caution, and preparatory processes during task switching mature during late childhood to mid-adolescence (Weeda et al. 2014; see also Schuch and Konrad 2017). Notably, studies to date only investigated drift-diffusion parameters for switch and repeat trials within mixed-task blocks and did not include a single-task condition. The contributions of these processes to developmental improvements in mixing costs are thus unknown. This constitutes a significant gap in our understanding of task-switching development, since mixing costs show greater improvements in late childhood than do switch costs (Cepeda et al. 2001; Reimers and Maylor 2005), and thus greater potential for training-related improvements.

1.2 Task-switching training

Task-switching abilities can be improved with training across the lifespan (Kray and Lindenberger 2000; Cepeda et al. 2001; Minear and Shah 2008; Berryhill and Hughes 2009; Strobach et al. 2012; von Bastian and Oberauer 2013; Dörrenbächer et al. 2014). During task-switching training, participants typically train switching between tasks over the course of several sessions, with studies consistently showing improved performance on the trained tasks (Kray and Dörrenbächer 2020). By comparing performance improvements with task-switching training to an active control group that practices the same tasks in a single-task condition, studies have demonstrated that it is specifically switching between tasks as opposed to repeated practice of the task rules that leads to improved performance (Minear and Shah 2008).

In studies with adults, mixing costs were substantially reduced or even eliminated upon training (Berryhill and Hughes 2009; Strobach et al. 2012), while switch costs were mostly reduced but remained present after training (Kray and Lindenberger 2000; Cepeda et

al. 2001; Strobach et al. 2012). This pattern of results suggests that the demands on task-set maintenance and monitoring processes associated with mixing costs (Rubin and Meiran 2005; Pettigrew and Martin 2016) can be met more effectively with training, resulting in comparable performance in mixed- and single-task blocks. From a developmental perspective, these results stress the potential of training to mitigate age differences in task switching, which are particularly pronounced with respect to the ability to maintain and monitor multiple task sets (Cepeda et al. 2001; Reimers and Maylor 2005).

Indeed, task-switching training in children leads to improvements in both mixing and switch costs (Cepeda et al. 2001; Karbach and Kray 2009; Kray, Karbach, Haenig, et al. 2012; Zinke et al. 2012; Kray et al. 2013; Dörrenbächer et al. 2014; Karbach et al. 2017; Zuber et al. 2023). Some studies showed even greater training gains in children than adults (Cepeda et al. 2001; Karbach and Kray 2009; Karbach et al. 2017) suggesting that task switching abilities may be especially malleable while they are still developing (cf. Wass et al. 2012; Kühn and Lindenberger 2016).

While these studies demonstrate that children approach adult levels of task-switching performance upon training, it is unclear whether neural activation patterns associated with task switching also become more adult-like or whether children improve their performance by strengthening different, potentially child-specific activation patterns. Moreover, varying switching demands during training, in combination with the opportunity to train the task rules during single tasks, may be particularly beneficial in children, as they may have additional difficulties in representing the different task-relevant rules (Karbach and Kray 2009).

1.3 Changes in neural processes with training

Task switching has been associated with increased fMRI activation in frontoparietal brain regions (for recent meta-analyses, see Worringer et al. 2019; Zhang et al. 2021), in particular in the inferior frontal junction (IFJ; cf. Derrfuss et al. 2005), the superior parietal lobe (SPL), and the dorsolateral prefrontal cortex (dlPFC), along with functional connections among them (Yin et al. 2015; Dajani et al. 2020). Training studies of task switching or dual

tasking in adults suggest that activation in these regions decreases with training (Dux et al. 2009; Jimura et al. 2014; Garner and Dux 2015). These results obtained for task-switching training are consistent with training studies of executive functions in general, which also showed decrements in brain activation with training (Landau et al. 2004; Landau et al. 2007; Dux et al. 2009; Schneiders et al. 2011; Jimura et al. 2014). At the same time, a substantial number of executive-function training studies has also reported training-related increases in activation (Olesen et al. 2004; Erickson et al. 2007; Westerberg and Klingberg 2007; Jolles et al. 2010; Schweizer et al. 2013; Buschkuehl et al. 2014). As a result, the overall picture of training-induced quantitative changes in fMRI activation is mixed (Landau et al. 2004; Kelly and Garavan 2005; Buschkuehl et al. 2012; Hsu et al. 2014; Constantinidis and Klingberg 2016). Decreased activation has been interpreted as improved efficiency of rule processing in frontoparietal regions, while increased activation has been interpreted as stronger involvement of the corresponding brain regions in task execution (Poldrack 2000; Kelly and Garavan 2005; Kelly et al. 2006). Additionally, connectivity among frontoparietal regions has been found to increase with cognitive training, both at rest (Jolles et al. 2013; Mackey et al. 2013; Guerra-Carrillo et al. 2014) and during task performance (Kundu et al. 2013; Thompson et al. 2016).

Neuroimaging studies of age differences in task switching have shown that children recruit similar brain regions as adults, albeit less adaptively modulating task-related activation with increasing switching demands (Bunge and Wright 2007; Velanova et al. 2008; Wendelken et al. 2012; Mogadam et al. 2018; Engelhardt et al. 2019; Kupis et al. 2021; Zhang et al. 2021; Schwarze et al. 2023; but see Crone, Donohue, et al. 2006; Morton et al. 2009). To date, no studies have investigated the changes in neural processes associated with task-switching training in childhood. Based on the existent cognitive training literature, we hypothesized two alternative patterns of neural change. First, with training, children may show reduced activation in frontoparietal brain regions, similar to one of the training-related patterns observed in adults (Landau et al. 2004; Landau et al. 2007; Dux et al. 2009; Schneiders et al. 2011; Jimura et al. 2014). Such a pattern has been previously

demonstrated with attention training in children: investigating the time course of activation using electroencephalography, Rueda et al. (2012) showed faster recruitment of the attention network after training.

Second, cognitive training in children may have similar effects on neural processes as age-dependent maturation (Jolles and Crone 2012), such that with training, children's brain activation becomes increasingly similar to the activation seen in adults (Rueda et al. 2005; Jolles et al. 2012). For task switching, such a pattern would be reflected in more pronounced increases of brain activation with greater task-switching demands (e.g., Wendelken et al. 2012; Schwarze et al. 2023). Consistent with this hypothesis, studies have reported more adult-like connectivity patterns with working-memory training in children (Astle et al. 2015; but see Jolles et al. 2013) and a combined executive function training in adolescents (Lee et al. 2022). Note that training-induced increases in activation reported in previous studies in adults (Olesen et al. 2004; Erickson et al. 2007; Westerberg and Klingberg 2007; Jolles et al. 2010; Schweizer et al. 2013; Buschkuehl et al. 2014) may be indistinguishable from activation increases due to more adult-like activation with training.

Alternatively or additionally, children may also show qualitative changes by recruiting additional or different brain regions to meet increased demands on task-switching upon training (Buschkuehl et al. 2012; Jolles and Crone 2012). This would speak to fundamentally different training effects in children compared to adults, potentially due to the continuing development of the underlying neural circuitry (Galván 2010).

1.3 Present study

The goal of the present study was to shed light on the cognitive and neural processes supporting training-induced improvements in task switching in children aged between 8 and 11 years. To this end, we leveraged computational approaches to model cognitive processes during task switching (cf. Reinhartz et al. 2023) in combination with the examination of neural processes in two groups that trained with different dosages of task-switching over nine weeks. To elucidate trajectories of change beyond pre- and post-training measures (cf.

Lindenberger and Lövdén 2019; Lövdén et al. 2020), participants performed task switching in the MRI scanner or MRI simulator on two occasions during the training period in addition to the pre- and post-training sessions. We expected task-switching performance to improve with training in both groups, resulting in increasing drift rates, decreasing boundary separation, and decreasing non-decision times during mixed blocks, with changes potentially happening on different trajectories in the different training groups. Specifically, we expected less extensive or slower changes in children who trained smaller doses of task switching. We further sought to test the hypotheses regarding neural changes outlined above. All hypotheses were preregistered (https://osf.io/by4zq/).

To briefly preview the results, drift rates and boundary separation increased for both groups after the first three weeks of intensive training, indicating both faster evidence accumulation and more cautions responses, respectively. The observed increases in drift rate and boundary separation were greater for the intensive task-switching group, particularly in the mixed blocks. The high-intensity task-switching group maintained these increases for the rest of training, while the initial increases in the high-intensity single-tasking group returned to pre-training levels by the end of training.

On the neural level, children in the high-intensity task-switching training group showed decreased activation in the dlPFC across conditions. Functional connectivity among frontoparietal regions was higher on repeat than on single trials and decreased in both training groups. These changes were more pronounced in the intensive single-tasking group towards the end of training. Taken together, these results provide first insights into the dynamics of training-related change in the cognitive and neural processes supporting task switching in childhood and suggest that with training, children became more efficient in dealing with the demands of task switching.

2. Materials and Methods

Hypotheses and plans for analysis were preregistered before the start of data analysis at https://osf.io/by4zq/.

2.1 Research participants and study overview

A total of 183 children aged between 8 and 11 years (M = 9.95 years, SD = 0.70) were pseudo-randomly assigned to one of three groups: two training groups and a passive control group. An overview of the study design is depicted in Figure 1A.

The two training groups practiced for nine weeks on a tablet at home for a total of 27 training sessions (30–40 min per session). In each session, participants completed a task-switching training game. A high-intensity task-switching (SW) training group (N = 70, 35 girls; age: M = 9.85 years, SD = 0.65) completed 17% single-task blocks and 83% mixed-task blocks per training game. A high-intensity single-tasking (SI) training group (N = 72, 34 girls; age: M = 9.83 years, SD = 0.68) trained on 83% single-task blocks and 17% mixed-task blocks per training game. The stimuli and rules in each game were identical between the two training groups such that the groups differed only in their relative demands on task switching (see section 2.2). The passive control (PC) group (N = 41, 20 girls; age: M = 10.34 years, SD = 0.72) did not perform any training games.

In addition to at-home training, both training groups performed four sessions of a task-switching paradigm (described in section 2.3) in the MRI scanner or MRI simulator: before training (pre-test, session A), after approximately 3 weeks of training (session B), after approximately 6 weeks of training (session C), and again after approximately 9 weeks, after the training was completed (post-test, session D). No MRI data were collected for the MRI simulator participants, who performed the task-switching paradigm in a mock scanner that looked just like the MRI scanner. The PC group performed the same task-switching paradigm in the MRI scanner at sessions A and D, while sessions B and C only included structural scans.

All participants were screened for MRI suitability, had no history of psychological or neurological diseases, and spoke German as their primary language. All participants who provided MRI data were right-handed. Parents and children provided informed written consent. All participants were reimbursed with 10€ per hour spent at the laboratory. The training groups received an additional bonus of 40€ for the completion of all training games and MRI/MRI-simulator sessions. Additionally, children in the training groups received a toy as a reward for their performance on the training games (see details below). The study was approved by the ethics committee of the Freie Universität Berlin and conducted in line with the Declaration of Helsinki.

Behavioral analyses were based on the four (for the SW and SI group) or two (for the PC group) sessions of the experimental task-switching paradigm performed in the MRI scanner or simulator. To ensure that participants included in the analyses performed this paradigm meaningfully, we excluded data in a session-specific manner based on preregistered performance criteria. Specifically, if a child performed below 50% accuracy in the run of single blocks (run 1, see below for more details on the paradigm) in a given session of the task-switching paradigm or below 35% accuracy in either of the two runs of mixed blocks (run 2 and 3) their data of that session were excluded from analyses. Additionally, we excluded 4 participants (2 from each training group) from all analyses because they did not complete at least half of the 27 training games. Based on these criteria, behavioral analyses included 160 children at session A (SW = 60 [9 excluded based on session-specific performance], SI = 64 [6], PC = 36 [4]), 115 at session B (SW = 57 [6 excluded], SI = 58 [6]), 115 at session C (SW = 54 [7 excluded], SI = 61 [4]), and 133 at session D (SW = 47 [11 excluded], SI = 57 [7]), PC = 29 [5]).

Of the children included in behavioral analyses, we additionally excluded children from neuroimaging analyses based on in-scanner head motion. fMRI volumes with framewise displacement (Power et al. 2012) above 0.4 mm were labeled as low-quality (cf. Dosenbach et al. 2017). If any of the fMRI runs of a specific session exceeded 50% of low-quality volumes, the session was excluded for that participant. Thus, fMRI analyses included

87 children at session A (SW = 32 [3 excluded], SI = 30 [7], PC = 25 [2]), 55 at session B (SW = 33 [2 excluded], SI = 22 [6]), 55 at session C (SW = 31 [4 excluded], SI = 24 [4]), and 72 at session D (SW = 24 [4 excluded], SI = 24 [4]), PC = 24 [1]).

Note that 2 of the 4 participants who were excluded from all analyses due to having completed too few training games were included in the neuroimaging analysis for session A, on which we defined the regions of interest (ROIs). Very few participants left the study after session A, i.e., dropout was minimal: SW = 3, SI = 4, PC = 7.

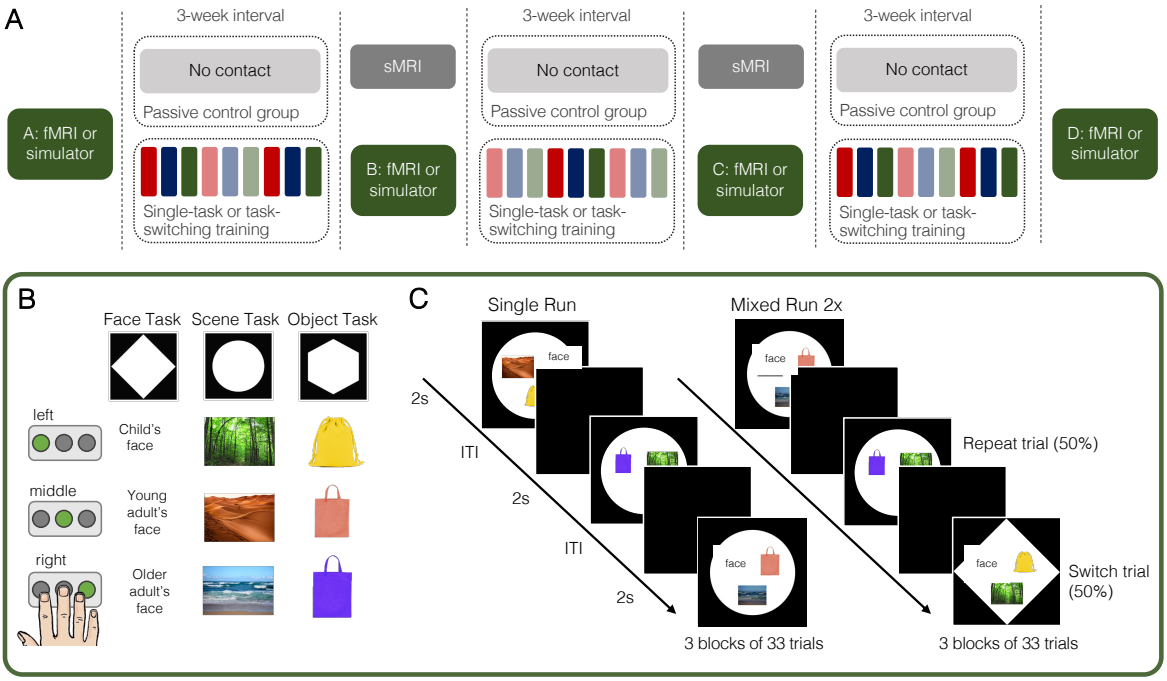

Figure 1. Outline of study design and experimental task-switching paradigm. (A) The timeline of training and assessment across the nine weeks for the three groups. fMRI or simulator indicates that the main task-switching paradigm (see B and C) was performed in the MRI scanner or MRI simulator, sMRI indicates structural scan. The colored bars indicate the training games: opaque colored bars indicate one of the three repeating games and translucent bars indicate one of the unique games, with the color indicating which of the repeating tasks matched the structure of the unique task. (B) The task-switching paradigm that all groups completed in the fMRI scanner or simulator. The shape cue indicated one of the three tasks. As indicated by three exemplar stimuli of each task, participants selected one of three buttons based on the face's age in the Face Task, the type of environment in the Scene Task and the color of the object in the Object Task. (C) Showing 3 sequential trials of the

single and mixed blocks; in the single run depicted here, participants performed the scene task on every trial. In the mixed task, the shape cues (and therefore tasks) repeated on some trials and switched on others. ITI: inter-trial interval. Image credits: Young and old adult faces were taken from the FACES collection (Ebner et al. 2010). B & C: Adapted from Schwarze et al. (2023), Figure 1, under CC.BY 4.0.

2.2 At-home training

Children in the SW and SI groups received a tablet after their first MRI or MRI simulator session and were instructed to complete three training games per week for nine weeks (i.e., 27 games in total; Figure 1A). The training games on the tablet were programmed using Unity (Version 5.6.1; Unity Technologies). Completion of the games was self-paced; however, a new game only became available 24 hours after the completion of the previous game. Three games were repeated every other week in the same order (i.e., 5 repetitions of each of the 3 games across training). One of the repeating games was identical to the paradigm performed in the MRI-scanner/-simulator sessions. Each repetition of the three games was interspersed with three unique games that were performed only once (for a total of 12 unique games). The unique games were designed to have the same rule structure as one of the repeating games, while using different stimuli. Each game started with task instructions followed by 3 practice blocks of 15 trials each, during which feedback was provided. No feedback was given during the rest of the game.

Two thirds (i.e., 18) of the training games consisted of 486 trials, one third (i.e., 9) consisted of 485 trials, resulting in a minimally different number of single trials performed at each game (see Supplementary Table 1 for details). In each game, the SW group completed 17% single-block trials and 83% mixed-block trials, while the SI group completed 83% single-block trials and 17% mixed-block trials. For both groups, mixed blocks included 50% repeat and switch trials with unpredictable cues that appeared simultaneously with the target. For all games, each trial lasted up to 3 s and responses had to be given within this period, with stimuli presentation ending when a response was given. There was a 50 ms

interval between response and presentation of the next trial. After each block, children could decide independently when to start the next block by pressing a button. Each game lasted between 30 and 40 minutes.

To encourage the completion of the games, children received stars at the end of each game block that were converted into coins at the end of each game. Children could trade the coins for toys at any of the MRI/MRI-simulator sessions, with a greater number of coins allowing children to receive larger toys. The number of stars received after each block depended on accuracy, with bonus points being awarded for faster responses compared to the previous blocks as long as performance did not drop below 80% accuracy for the SW group and 90% accuracy for the SI group. On average, children in the SW and SI group completed 25.2 (SD = 3.52) and 25.4 (SD = 3.02) training games, respectively (no difference between groups: $t = 0.00$, $p = 1$).

2.3 Experimental task-switching paradigm

For the training groups, all four laboratory sessions included a task-switching paradigm (see Schwarze et al. 2023, for detailed paradigm description) that participants performed in the MRI scanner or simulator. Particpants were familiar with the paradigm from an assessment session completed prior to the first MRI-scanner/-simulator session, and two practice blocks completed in the MRI simulator right before the actual task. The task-switching paradigm consisted of three tasks: the Face Task, the Scene Task, and the Object Task. Participants had to perform the task cued by the shape of the background, based on previously learned rules linking each shape with one of the three tasks (Figure 1B). Specifically, the Face Task required the presented face to be categorized by age (child, young adult, older adult), the Scene Task required the presented scene to be categorized by its location (forest, desert, ocean), and the Object Task required the presented object to be categorized by color (yellow, red, purple). Responses were given via button press with three fingers of the right hand. The stimuli and the task cue appeared at the same time. The arrangement of the target images varied randomly on each trial independent of the categorization rule. In each

session, participants performed 3 runs of 99 trials each (Figure 1C). Every trial lasted 2 s, followed by a fixation cross (1–6s, jittered) along with an extended fixation period (20 s) after every 33 trials. In the first run (i.e., single run), tasks were presented sequentially in a single-task manner. In runs two and three (i.e., mixed runs), the three tasks were intermixed with a switch rate of 50% and switches were unpredictable. The first trial of each run was excluded from all analyses. At each session, the experimental paradigm was performed in the MRI scanner after an initial T1-weighted scan during which participants watched a muted cartoon. The PC group followed the same protocol for their sessions A and D, while sessions B and C only included structural scans. For comparability, children who performed the task in the MRI simulator also watched a muted cartoon accompanied by scanner noise before they completed the task. Performance in this task-switching paradigm did not differ between children in the MRI-scanner and MRI-simulator group at any of the sessions.

2.4 Behavioral analyses

Trials with response times (RTs) below 200 ms and above 3000 ms, and trials with no responses, were excluded from analyses. Accuracy was calculated as the percentage of correct responses across all given responses for each condition. Median RTs were based on correct trials only. Outliers were defined as accuracy or RT values differing by more than 3.5 SD from the condition- and session-specific mean across all groups, and were removed from analyses of accuracy and RTs separately. To further examine training-related changes in the cognitive processes underlying task switching while accounting for potential speed–accuracy tradeoffs, we applied drift-diffusion modeling for the two training groups across the four laboratory sessions (Ratcliff 1978). Drift-diffusion models have previously been applied to task-switching paradigms in young adults (Schmitz and Voss 2012), children (Weeda et al. 2014; Schuch and Konrad 2017) and older adults (Ging-Jehli and Ratcliff 2020). Drift-diffusion parameters (i.e., drift rate, boundary separation, and non-decision time) were estimated for each group and session using a hierarchical drift-diffusion models (HDDM) in the HDDM toolbox (Version 0.9.8; Wiecki et al. 2013).

Specifically, the HDDM was fitted to correct and incorrect trials, with outlier probability set to 5%. Since all three parameters (boundary separation, drift rate, and non-decision time) have been associated with different cognitive processes during task switching (cf. Schmitz & Voss, 2012), the model of interest allowed all three parameters to vary between conditions and groups across sessions. Compared to models fixing one or multiple parameters, the model of interest proved a better fit to the data. Individual-specific estimates were averaged across all iterations (N = 5000) of the model and used for subsequent analyses of training-related change described below (cf. Katahira 2016).

All analyses were performed using Bayesian linear mixed models with the *brms* package in R (Bürkner 2017). Reported effects are based on 95% credible intervals (CI), meaning that we can make a statement with 95% probability (cf. Bürkner 2017; see also Morey et al. 2016).

2.4.1 Changes from pre- to post-training: Accuracy and RTs

For accuracy and RTs, we examined change in the SW and SI groups relative to the PC group from the pre-test (session A) to post-training (sessions D). Deviating from the preregistration, we included the SW and SI groups separately in these models, as opposed to combining them, to capture differences for each training group. More specifically, group (SW, SI, and PC, with PC as reference level), session (A vs. D), and condition (single vs. repeat vs. switch) were modeled as fixed effects, allowing for interactions among them. Models included random intercepts and slopes for individual participants. We started with a full model that included all interactions between fixed effects and compared this to models with fewer interaction terms, using leave-one-out cross-validation in the *loo* package (Vehtari et al. 2022). Across all analyses, the model including all interaction terms either outperformed or did not differ from the models with fewer interaction terms (see Supplementary Table 2).

2.4.2 Changes across all four sessions: HDDM parameters

To test for differences in change between the two training groups in the course of training, we compared HDDM parameters between the SW and SI groups across all four sessions. Change across more than two sessions is not necessarily linear; to describe these trajectories as precisely as possible, we thus opted to model the four sessions of the present study as a factor with four levels (sessions A, B, C, and D). In the results reported below, we compare each of the sessions B, C, and D against the pre-test session A to test whether the training completed up to that point was associated with improved performance relative to before the start of training. Group (SW vs. SI), session (B vs. A, C vs. A, D vs. A), and condition (single vs. repeat vs. switch) were modeled as fixed effects allowing for interactions among them with random intercepts and slopes for individual participants. Across all analyses, the models including all interaction terms outperformed or did not differ from the models with fewer interaction terms (see Supplementary Table 2).

We opted to analyze HDDM parameters using linear mixed models for consistency with all remaining analyses. An alternative approach for testing differences in HDDM parameters is the pairwise comparison of the posterior distributions of a parameter, for instance, testing whether the posterior distributions of a parameter differ between the SW and SI group at a specific session. These analogous, preregistered analyses revealed the same pattern of results as the mixed models reported below (see Supplementary Table 3).

2.4 fMRI data acquisition and preprocessing

As reported by Schwarze et al. (2023), structural and functional MR images were collected on a 3-Tesla Siemens Tim Trio MRI scanner. Functional runs consisted of 230 whole-brain echo-planar images of 36 interleaved slices (TR = 2000 ms; TE = 30 ms; 3 mm isotropic voxels). The imaging protocol included functional imaging during the performance of the task-switching paradigm on all four sessions for the SW and SI group and on the first and last MRI session for the PC group. Structural MRI scans were acquired for all groups at all

four sessions (220 slices; 1 mm isotropic voxels; TR = 4500 ms; TE = 2.35 ms; FoV = 160 ×198 x 220).

Preprocessing was performed using fMRIprep (Version 20.2.0; Esteban et al. 2019). For a detailed description see the fMRIprep documentation (https://fmriprep.org/en/stable/). Briefly, functional images were co-registered to individual anatomical templates using FreeSurfer (Greve and Fischl 2009). The anatomical template was created from anatomical scans across all sessions, removing scans that were of poor quality based on the MRIQC classifier (Version 0.15.2; Esteban et al. 2017) and additional visual inspection. Images were slice-time corrected (using AFNI; Cox and Hyde 1997), realigned (using FSL 5.0.9; Jenkinson et al. 2002), resampled into MNI152NLin6Asym standard space with an isotropic voxel size of 2 mm, and spatially smoothed with an 8mm FWHM isotropic Gaussian kernel using SPM12 (Functional Imaging Laboratory, University College London [UCL], UK).

2.5 fMRI data analysis

2.5.1 General linear models (GLM)

GLM analyses were performed using SPM12 software (Functional Imaging Laboratory, UCL, UK). For each participant, we estimated an event-related GLM for each session. Each stimulus presentation was coded as an event with zero duration, and convolved with a canonical hemodynamic response function (HRF). Separate regressors were included for correct single, correct repeat, and correct switch trials. Incorrect trials, trials with no responses, and the first trial of each run were modeled in a nuisance regressor. Data were high-pass filtered at 128 s. To minimize head motion artifacts, we included the amount of framewise displacement per volume in mm (Power et al., 2012), realignment parameters (three translation and three rotation parameters), and the first six anatomical CompCor components (as provided by fMRIprep; Behzadi et al. 2007) as regressors of no interest. The first five volumes of each run were discarded to allow for stabilization of the magnetic field. Temporal autocorrelations were estimated using first-order autoregression. To identify

regions that showed activation associated with mixing demand, we compared activation on repeat trials in mixed blocks to single-block trials (repeat > single) across all three groups at session A (N = 89; voxel-level $p < .001$, FDR-corrected at cluster level). To identify regions modulated by switch demand, we compared activation on switch to repeat trials in the mixed blocks (switch > repeat) across all three groups at session A (N = 89; voxel-level $p < .001$, FDR-corrected at cluster level).

2.5.2 ROI definition and analyses

ROIs were defined on the repeat > single contrast and switch > repeat contrast across all children at session A described above. To ensure anatomical specificity, we anatomically restricted activation-based ROIs in the dlPFC, SPL, and precuneus using the middle frontal gyrus, SPL, and precuneus regions of the Harvard-Oxford atlas, respectively (thresholded at 30%; Makris et al. 2006). The IFJ was restricted based on coordinates from a meta-analysis of task switching (Derrfuss et al. 2005), as no anatomical mask is available for this functionally defined region associated with task-switching (cf. Richter and Yeung 2014). We extracted activation parameters for these ROIs using Marsbar (Brett et al. 2002).

We performed Bayesian linear mixed models to investigate whether activation in the ROIs changed with training and differed between training groups. First, we explored trajectories of training-related change in activation across all four sessions in the two training groups. As for the analyses of HDDM parameters described above, models included fixed effects of group (SW vs. SI), session – modeled as a factor with four levels (A, B, C, D) –, and condition. Condition included repeat vs. single for models of activation in ROIs defined by the repeat > single contrast, and switch vs. repeat for activation in ROIs defined by the switch > repeat contrast. Random intercepts of participant and random slopes of session were also included in all models.

In a second step, to test whether changes in task-related activation were training-related, we compared the SW and SI groups to the PC group on sessions A and D, for which data from all groups was available. Models included fixed effects of group (SW vs. PC, SI vs.

PC), session (A vs. D), and condition (repeat vs. single; switch vs. repeat) and their interactions, as well as random intercepts of individuals and random slopes of session. Results of these analyses are included in the main results for ROIs that showed changes in the two training groups across all four sessions; detailed model outputs for all ROIs are reported in Supplementary Tables 9 and 11.

To test for training-related changes in the adult task-switching network, we additionally defined ROIs from 53 adults (20–30 years) who performed the same task-switching paradigm at a single timepoint (see Schwarze et al. 2023 for details). Results for these preregistered ROI analyses are reported in Supplementary Tables 4–6, and were generally consistent with the results reported below.

2.5.3 Whole-brain longitudinal analyses

Since the ROI-based analysis is biased towards the activation patterns observed in session A, we additionally performed longitudinal whole-brain analyses to test for training-related changes outside the ROIs, as well as how these differed between groups. We constructed mixed ANOVAS in SPM with group as a between-participant factor and session as a within-participant factor. Specifically, we tested for differences between the SW and SI groups and the PC group comparing sessions A and D, and for differences between the SW and SI groups across all four sessions. The input contrast images included the repeat > single contrast to investigate changes in modulation of activation with mixing demand, and the switch > repeat contrast for changes in modulation of activation with switch demand. There were no significant clusters showing changes in activation with training at the predefined threshold ($p < .001$, uncorrected), neither when comparing sessions A and D nor when testing for any effects across all sessions.

2.5.4 Psychophysiological interactions

To examine training effects in task-related functional connectivity, we conducted gPPI (generalized psychophysiological interaction) analyses (McLaren et al. 2012) using the

CONN toolbox (Version 20b; Whitfield-Gabrieli and Nieto-Castanon 2012). gPPI can be used to model how connectivity strength differs between conditions, thus making it possible to investigate how brain networks are flexibly adapting to task demands. gPPI parameters were estimated separately for each condition, that is, correct single, correct repeat, and correct switch trials (McLaren et al. 2012). The main effect of the three conditions and the nuisance regressors from the activation GLM were regressed out of the fMRI timeseries before analysis. We calculated ROI-to-ROI gPPI for connections among ROIs associated with mixing demand, identified by the repeat > single contrast (i.e., bilateral IFJ, bilateral SPL, and left dlPFC). In a separate but identical model, we calculated ROI-to-ROI gPPI for connections among the ROIs associated with switch demands, identified by the switch > repeat contrast (i.e., left IFJ, bilateral SPL, bilateral precuneus).

The gPPI models provided two connectivity parameters for each connection between any two ROIs representing connectivity estimates in both directions. Therefore, we first tested whether the direction had an effect on the connectivity parameter. We modeled estimated connectivity for each connection with a linear mixed model including the direction, condition, session, and training group as fixed effects, allowing for all interactions and including random intercepts of individuals and random slopes of session. We compared this model to one without any interactions involving seed region. As model comparisons indicated better fit for models without interaction effects of seed region, we averaged parameters across directions for each connection to be used in the subsequent analysis.

Individuals' condition-specific gPPI parameters (averaged across directions) for each connection and session were analyzed using Bayesian linear mixed models to examine differences in the changes of these parameters between the SW and SI groups. Specifically, mirroring the models of activation above, we tested whether connectivity values among the ROIs associated with mixing demands (defined on the basis of the repeat > single contrast) changed across sessions (i.e., session B, C, and D compared to A as the reference level). In addition to the fixed effect of session, models included fixed effects for group (SW vs. SI) and condition (repeat vs. single) and random intercepts of participant and connection, as

well as random slopes for session. For the connectivity parameters among the ROIs associated with switch demand, we tested the same model, except that the condition levels consisted of switch vs. repeat.

Additionally, to characterize whether key task-switching regions changed connectivity to brain regions outside of the ROIs defined by brain activation, we analyzed seed-to-voxel PPIs. Here, we used a seed in the left IFJ and in the left SPL, based on their prominent roles in task switching (e.g., Kim et al. 2012; Richter and Yeung 2014) and our analyses of age differences in task switching between children and adults (Schwarze et al. 2023). Results of these seed-to-voxel analyses and further preregistered connectivity analyses are reported in Supplementary Results 1–3.

3. Results

3.1 Training-related improvements in accuracy and RTs in the SW group

To examine changes in task-switching performance with training, we first examined changes in accuracy and RT between sessions A to D (for analyses of accuracy and RTs across all sessions, see Supplementary Table 7). Here, we were primarily interested in differences between the training groups and the control group. To this end, we predicted accuracy and RT by fixed effects of group (SW, SI, and PC), condition (single, repeat, switch), and session (A vs. D). Across all models, the models including all interactions fit best or did not differ from the best fitting model (see Supplementary Table 2), suggesting that training-related changes in performance differed between groups and conditions. To further characterize how the groups changed with training, we used the PC group as the reference to evaluate change in each training group relative to the control group. There were no differences in accuracy or RTs among the three groups at session A prior to training.

For both accuracy (Figure 2A) and RTs (Figure 2B), we observed mixing costs (i.e., lower accuracy and longer RTs on repeat than single trials) and switch costs (i.e., lower accuracy and longer RTs on switch than repeat trials) across both sessions and all groups (see Table 1 for model estimates).

RT switch costs decreased from session A to D across all groups due to faster RTs on switch trials. Compared to the PC group, the SW group showed increasing accuracy and decreasing RTs from session A to D across conditions. Compared to the PC group, the SI group maintained higher single-task accuracy across sessions A and D, but did not differ in the repeat or switch conditions (see Supplementary Figure 1 for condition-specific changes). Taken together, the SW group – but not the SI group – showed a greater training-related increase in accuracy and decrease in RTs relative to the PC group. The lack of interactions between session and condition on accuracy change suggests that improvements were similar across all conditions.

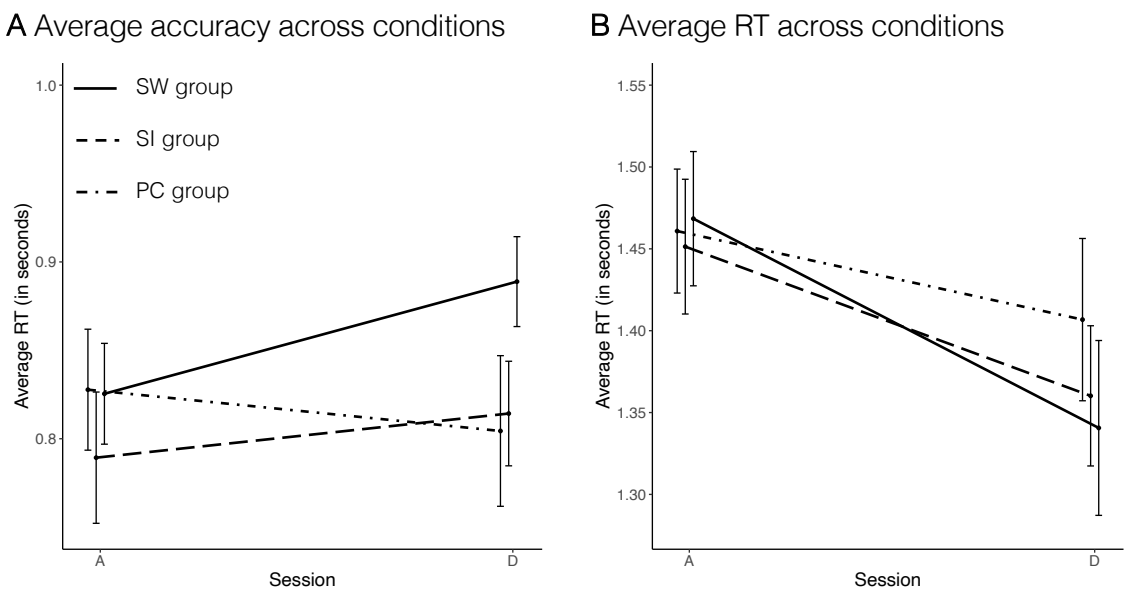

Figure 2: Training-related changes in overall performance. Accuracy (A) and RTs (B) averaged across conditions. Overall performance improved from session A to D in accuracy and RTs in the task-switching (SW) training group (blue) relative to the passive control (PC) group (green). The single-task (SI) training group is shown in red. Error bars denote 95%-confidence intervals.

Table 1: Model outputs for accuracy and RT. Models included condition (single, repeat, switch; with repeat as the reference level), session (A, D; with A as the reference level), and group (SW, SI, PC; with PC as the reference level) as fixed effects, and random intercepts for individuals and random slopes for sessions. Note that because the PC group was defined as a reference level, the model output only includes the comparisons of the SW group to the PC group and of the SI group to the PC group. Bold values indicate estimates whose 95%-CI did not include zero. Est.: Estimate.

Effect	Accuracy			RT		
	Est.	CI		Est.	CI	
Intercept	**0.81**	0.77	0.86	**1.47**	1.41	1.52
condition: single vs. repeat	**0.13**	0.1	0.16	**-0.28**	-0.32	-0.23
condition: switch vs. repeat	**-0.07**	-0.11	-0.04	**0.26**	0.22	0.3
session: D vs. A	-0.02	-0.07	0.03	-0.02	-0.09	0.04
group: SW vs. PC	0.01	-0.04	0.07	0	-0.07	0.07
group: SI vs. PC	-0.02	-0.08	0.03	-0.01	-0.08	0.06
condition (single vs. repeat) x session (D vs. A)	-0.05	-0.1	0.01	0.01	-0.05	0.07
condition (switch vs. repeat) x session (D vs. A)	0.03	-0.02	0.08	**-0.08**	-0.14	-0.02
condition (single vs. repeat) x group (SW vs. PC)	-0.04	-0.08	0	0.02	-0.03	0.07
condition (switch vs. repeat) x group (SW vs. PC)	-0.02	-0.06	0.02	0.01	-0.04	0.06
condition (single vs. repeat) x group (SI vs. PC)	-0.03	-0.07	0.01	0.03	-0.03	0.08
condition (switch vs. repeat) x group (SI vs. PC)	-0.01	-0.05	0.03	-0.01	-0.06	0.05
session (D vs. A) x group (SW vs. PC)	**0.08**	0.02	0.14	**-0.09**	-0.18	-0.01
session (D vs. A) x group (SI vs. PC)	0.03	-0.03	0.09	-0.07	-0.15	0.01
condition (single vs. repeat) x group (SW vs. PC) x session (D vs. A)	0.01	-0.05	0.08	0.06	-0.02	0.14
condition (switch vs. repeat) x group (SW vs. PC) x session (D vs. A)	0.02	-0.04	0.08	-0.01	-0.08	0.07
condition (single vs. repeat) x group (SI vs. PC) x session (D vs. A)	**0.07**	0.01	0.13	0.05	-0.02	0.13
condition (switch vs. repeat) x group (SI vs. PC) x session (D vs. A)	-0.01	-0.07	0.05	-0.01	-0.09	0.07

3.2 Hierarchical drift-diffusion models across all four sessions

For a more detailed understanding of the training-related changes in the cognitive processes contributing to task switching, we analyzed HDDM parameters (Wiecki et al. 2013) across all four sessions in the SW and SI groups. There were no differences between the SW and SI groups in any of the HDDM parameters at session A. We predicted different HDDM parameters (drift rate, boundary separation, and non-decision time) by training group (SW vs. SI), condition (single, repeat, and switch), and session (A, B, C, and D). In all analyses, the models including all interactions fit best or did not differ from the best fitting model (see Supplementary Table 2), suggesting that the SW and SI groups differed in changes in HDDM parameters across conditions. To characterize group differences in change, session A was set as the reference level, and the other three sessions (i.e., sessions B, C, D) were compared to this reference. For clarity, we focus on effects showing a probability of 95% below (see Supplementary Table 8 for complete model outputs).

3.2.1 Condition effects across sessions.

Across sessions and groups, drift rates were lower on switch than on repeat trials (switch vs. repeat: est. = –0.28; 95%-CI –0.39, –0.18) and lower on repeat trials than on single trials (single vs. repeat: est. = 0.69; 95%-CI 0.58, 0.81), indicating faster evidence accumulation for the correct response on trials with lower mixing and switch demands (Figure 3A). Boundary separation parameters were greater for single compared to repeat trials (single vs. repeat: est. = 0.10; 95%-CI 0.01, 0.18), and for repeat compared to switch trials (switch vs. repeat: est. = –0.17; 95%-CI –0.25, –0.09), suggesting that participants were more cautious on single-task blocks than on repeat trials within mixed blocks, and more cautious on repeat trials than on switch trials (Figure 3B). Non-decision time was shorter for single compared to repeat trials (single vs. repeat: est. = –0.1; 95%-CI –0.13, –0.06), and for repeat than for switch trials (switch vs. repeat: est. = 0.22; 95%-CI 0.17, 0.27), showing that preparation time was shorter on trials with lower mixing and switch demands (Figure 3C). Thus, with increasing mixing (repeat vs. single) and switch (switch vs. repeat) demands, children were

slower at accumulating evidence for the correct response, followed a less cautious response strategy, and took longer to prepare the response.

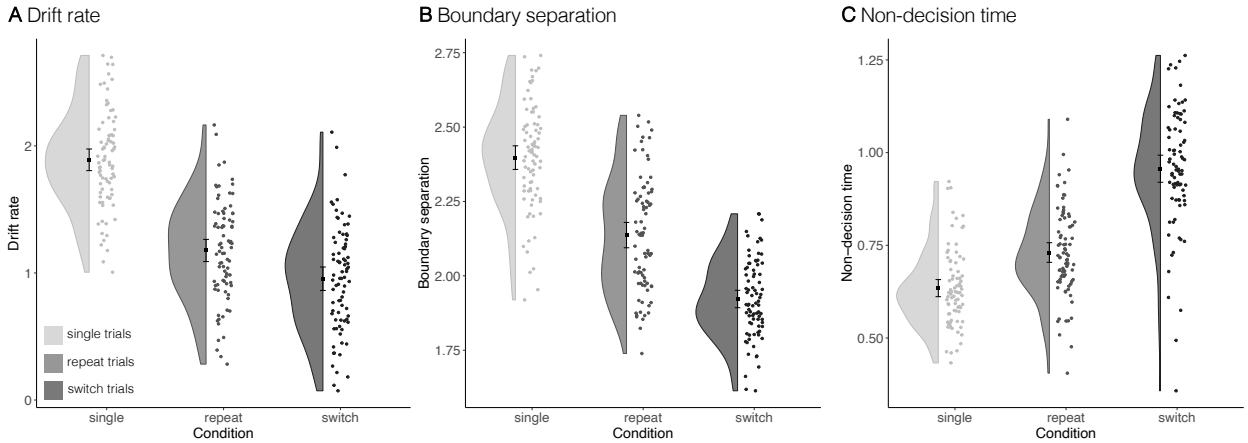

Figure 3: Condition differences in hierarchical drift-diffusion model parameters. Showing (A) drift rate, (B) boundary separation, and (C) non-decision time for single trials (light green), repeat trials (light blue), and switch trials (purple) across sessions and groups. Scatters show individuals' parameter values averaged across sessions. Error bars denote 95%-confidence intervals. Note that parameter values were averaged across sessions within individuals for visualization purposes only; no analyses were calculated on these averaged data.

3.2.2 Training-related increases in drift rates in the SW group

Across training groups and task conditions, drift rates increased from session A to B (est. = 0.27; 95%-CI 0.13, 0.41) and remained higher on session C compared to A (est. = 0.28; 95%-CI 0.13, 0.43; Figure 4A). Of note, these overall effects of training were further qualified by interactions with group and condition.

First, across groups, increases early in training were larger for single than for repeat trials (Session [B vs. A] x condition [single vs. repeat]: est. = 0.29; 95%-CI 0.13, 0.44) whereas the maintenance of increased drift rates later in training was more pronounced for switch than repeat trials (session [D vs. A] x condition [switch vs. repeat]: est. = 0.15; 95%-CI 0.01, 0.29). Second, the SW group benefited more from training in the first three weeks of training: drift rate increases from A to B were greater in the SW group compared to the SI group (session [B vs. A] x group [SW vs. SI]: est. = 0.24; 95%-CI 0.04, 0.45). These initial

differences in drift rate between the SW and SI groups were especially pronounced for repeat and switch trials relative to single trials (session [B vs. A] x condition [single vs. repeat] x group [SW vs. SI]: est. = –0.30; 95%-CI –0.52, –0.08; no interaction for difference between repeat and switch trials). Third, a further benefit of SW compared to SI training became evident at session D: compared to the SI group, the SW group maintained increased drift rates at session D compared to A across conditions (session [D vs. A] x group [SW vs. SI]: est. = 0.34; 95%-CI 0.1, 0.58).

Taken together, both training groups showed an increase in evidence accumulation after the first three weeks of training, with the SW group showing greater increases than the SI group. Of note, the SW group – but not the SI group – maintained these improvements at the end of training.

3.2.3 Greater boundary separation in the SW group

Changes in boundary separation were qualified by interactions with condition and group, suggesting differences in training-related changes between groups and conditions (Figure 4B). First, the SW group showed greater increases in boundary separation than the SI group from session A to B across all conditions (session [B vs. A] x group [SW vs. SI]: est. = 0.20; 95%-CI 0.06, 0.32). The SW group maintained these condition-independent increases at session D to a greater extent than the SI group (session [D vs. A] x group [SW vs. SI] = est. = 0.22; 95%-CI 0.07, 0.36). Second, relative to session A, boundary separation parameters on single trials were higher in session B (session [B vs. A] x condition [single vs. repeat]: est. = 0.53; 95%-CI 0.42, 0.65) and session C (session [C vs. A] x condition [single vs. repeat]: est. = 0.26; 95%-CI 0.14, 0.37). This change was further qualified by an interaction with group (session [B vs. A] x condition [single vs. repeat] x group [SW vs. SI]: est. = –0.23; 95%-CI –0.40, –0.06), indicating that the difference in boundary-separation increase between single and repeat trials was particularly pronounced in the SI group.

Thus, response caution increased within the first three weeks of training, with similar increases across conditions for the SW group and specific increases for single trials in the SI

group. At the end of training, the SW group showed greater maintenance of the increased boundary separation than the SI group.

3.2.4 Decrease of non-decision time across the SW and SI groups

Across both training groups, non-decision time decreased with training, such that non-decision times at sessions B, C, and D were lower than at session A (B vs. A: est. = –0.05; 95%-CI –0.08, –0.02; C vs. A: est. = –0.07; 95%-CI –0.11, –0.04; D vs A: est. = –0.08; 95%-CI –0.11, –0.05; Figure 4C). Decreases were particularly pronounced for single trials relative to repeat trials at session B (session [B vs. A] x condition [single vs. repeat]: est. = –0.06; 95%-CI –0.1, –0.01). Thus, across training groups, non-decision time decreased, suggesting reduced preparation time with training.

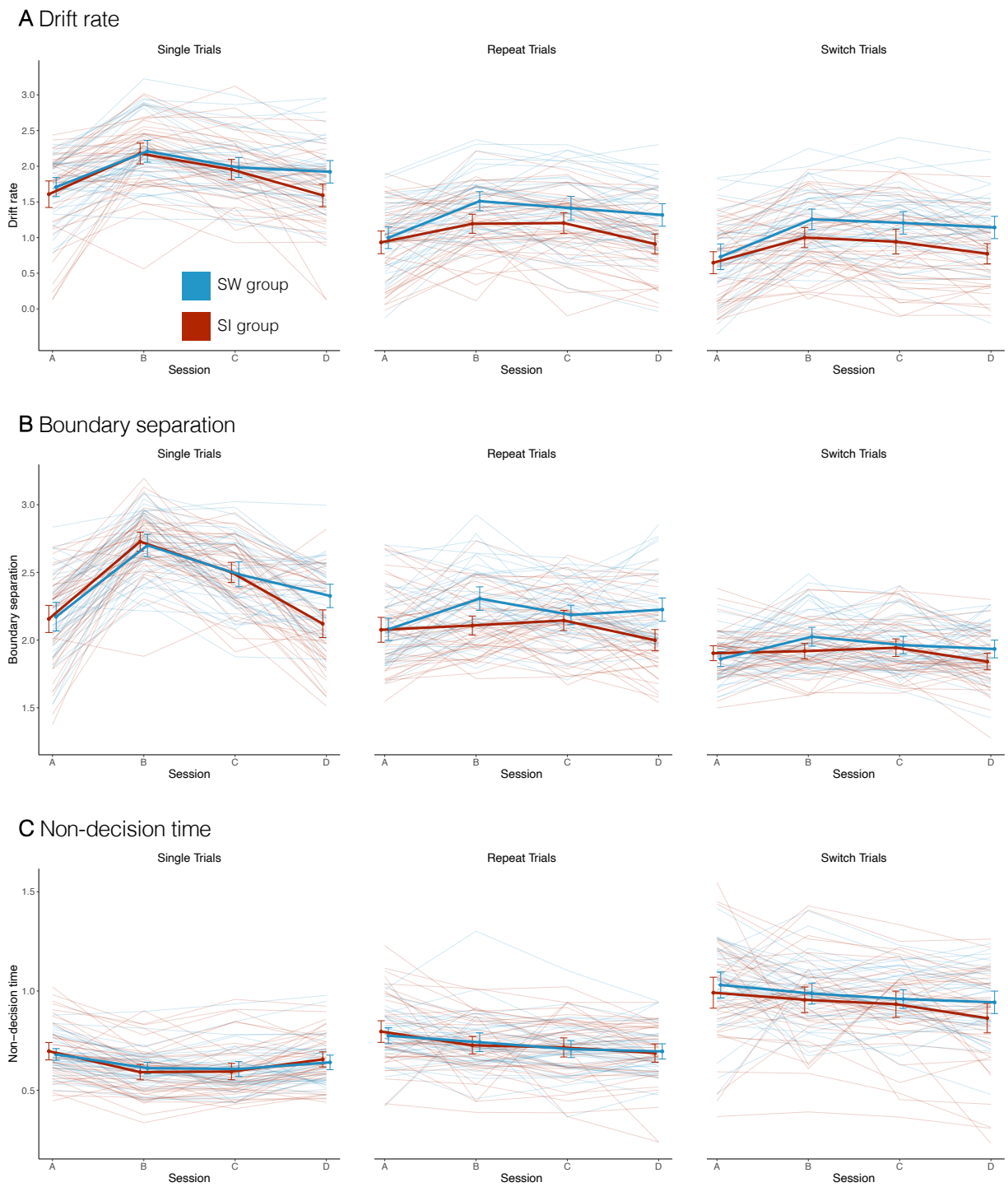

Figure 4: Training-related changes in hierarchical drift-diffusion model parameters. Showing (A) drift rate, (B) boundary separation, and (C) non-decision time for single trials (left panels), repeat trials (central panels), and switch trials (right panels). The SW group is depicted in blue, and the SI group in red. Thin lines show individual trajectories colored according to training group. Error bars denote 95%-confidence intervals.

3.3 Changes in activation and connectivity associated with mixing demands

Whole-brain activation across all children at session A revealed stronger activation for repeat > single trials in multiple frontal and parietal regions, including the bilateral IFJ, bilateral SPL, and left dlPFC (Figure 5A). Accordingly, we investigated training-related change in activation and ROI-to-ROI connectivity in the following ROIs: left and right IFJ, left and right SPL, and left dlPFC. First, in line with the behavioral analyses above, we tested whether activation and connectivity changed at any of the sessions during or at the end of training (i.e., sessions B, C, D) relative to the pre-test session A. Second, to test whether these changes were indeed related to training, we compared changes in the training groups to the PC group, focusing on sessions A and D where data from all groups were available.

3.3.1 Reduced frontoparietal activation with training in the SW group

Within each ROI, we analyzed activation parameters for the effects of session (B, C, and D compared to A as the reference level) and interactions with group (i.e., differences between SW and SI groups). Below, we report effects involving session and interactions of session with group (see Supplementary Tables 9 and 10 for an overview of all effects).

In the right SPL (Figure 5B), activation on repeat trials decreased such that the difference between single and repeat trials decreased with training across both groups. The decrease in activation for repeat trails became evident at session C (est. = –1.06; 96%-CI: –2.03, –0.1) and remained evident at session D (est. = –1.15; 95%-CI: –2.09, –0.19). While a descriptively similar pattern was evident in the left SPL, the data did not support the effect with 95% probability. Comparison to the PC group for sessions A and D caution the interpretation of these changes as related to the training program: the decreases in repeat activation from session A to D became evident across all three groups (est. = –1.19; 95-%CI: –2.15, –0.22) and neither the SW nor the SI group differed reliably from the PC group at session D (all 95%-CI include zero).

Compared to session A, activation in the left dlPFC (Figure 5B) decreased across both single and repeat conditions for the SW group but not the SI group (group [SW vs. SI] x

session [D vs. A]: est. = –0.87; 95%-CI: –1.79, –0.01). Descriptively, the left IFJ showed a similar effect as the dlPFC, but we did not find evidence for the effect with the predefined criterion of 95% probability. Comparison to the PC group for sessions A and D provided support that this change was specific to the SW group: compared to the PC group, the SW group showed lower activation in the left dlPFC and left IFJ across conditions at session D compared to A (left dlPFC: est. = –1.48; 95-%CI: –2.47, –0.5; left IFJ: est. = –0.84; 95-%CI: –1.6, –0.07).

To summarize, the dlPFC and SPL showed decreases in activation across sessions. The effects in the dlPFC were observed across the single and repeat conditions and were only present in the SW group. In the SPL, the differences between single and repeat trials decreased in both training groups as well as in the PC group and were therefore unlikely to be related to the intensive training manipulation in the study.

3.3.2 Decreased task-based connectivity in the SI training group

To test whether task-based connectivity among the ROIs (i.e., left IFJ, left SPL, left dlPFC, right IFJ, right SPL) showed training-related changes, we analyzed connection-specific PPI parameters for the effects of session (B, C, and D compared to A) and interactions with group (i.e., differences between SW and SI groups).

Across sessions, connectivity was greater for repeat than for single trials (repeat vs. single: est. = 1.91; 95%-CI: 1.46, 2.38), indicating that regions interacted more closely in response to mixing demands. As shown in Figure 5C, this condition difference was influenced by training. Specifically, connectivity for the repeat condition decreased with training (condition [repeat vs. single] x session [B vs. A]: est. = –0.75; 95%-CI: –1.46, –0.05; C vs. A: est. = –2.17; 95%-CI: –2.85, –1.49; D vs. A: est. = –1.57; 95%-CI: –2.25, –0.88), with especially pronounced decreases in the SI group towards the end of training (condition [repeat vs. single] x group [SW vs. SI] x session [C vs. A]: est. = 2.14; 95%-CI: 1.23, 3.05; [D vs. A]: est. = 1.41; 95%-CI: 0.47, 2.36). Comparison to the PC group for sessions A and D indicated that this late change was specific to the SI group: compared to the PC group, the

SI group showed lower connectivity on repeat trials at session D compared to A (condition [repeat vs. single] x group [SI vs. PC] x session [D vs. A]: est. = –1.58; 95%-CI: –2.60, –0.58).

In summary, connectivity among frontoparietal ROIs during task repeats decreased with training across both groups, suggesting less upregulation of connectivity in the mixed- vs. single-task context over time. Towards the end of training (i.e., sessions C and D) this decrease was particularly pronounced for the SI group relative to the SW group.

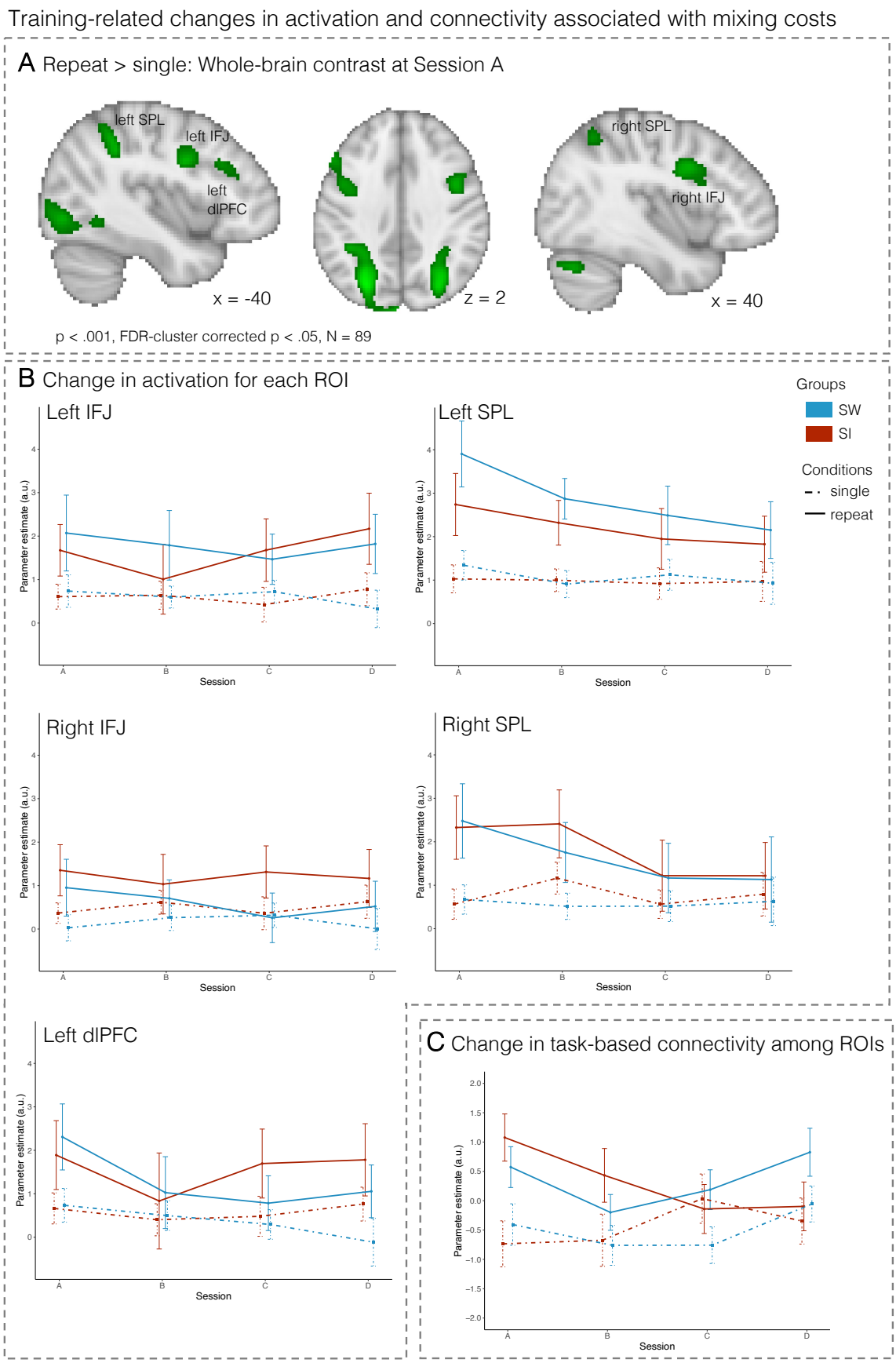

Figure 5: Training-related changes in activation and connectivity associated with mixing costs. (A) Brain regions showing greater activation on repeat than on single trials at session A across all

children (N = 89; $p < .001$, FDR-cluster corrected $p < .05$). (B) Change in activation for each ROI. (C) Change in connectivity (i.e., PPI parameters across all connections) among these ROIs. The SW group is shown in blue and the SI group is shown in red. Error bars denote 95%-confidence intervals.

3.4 Training-related changes in activation and connectivity associated with switch demand

Whole-brain activation across all children at session A indicated increased activation for switch than for repeat trials in the left IFJ, bilateral SPL, and bilateral precuneus. Accordingly, we investigated training-related changes in activation and ROI-to-ROI connectivity in the following ROIs: left IFJ, left and right SPL, and left and right precuneus (Figure 6A). First, we tested whether activation and connectivity had changed at any of the sessions during or at the end of training (i.e., sessions B, C, D) relative to the pre-test session A. Second, to test whether these changes were indeed related to training, we compared changes in the training groups to the PC group, focusing on sessions A and D, where data from all groups were available.

3.4.1 Transient changes in switch-related brain activation with training

We analyzed activation parameters for repeat and switch trials for the effects of session (B, C, D compared to A) and interactions with group (SW vs. SI group) in each ROI. Below, we report effects that involved session and interactions of session with group (see Supplementary Tables 11 and 12 for an overview of all effects).

Across both groups and conditions (Figure 6B), activation in the left IFJ decreased from session A to B (effect of session B vs. A: est. = –1.03; 95%-CI: –1.89, –0.20). In the right precuneus, activation increased from session A to B (effect of session B vs. A: est. = 0.95; 95%-CI: 0.21, 1.69). These changes returned to baseline towards the end of training as indicated by no differences of sessions C and D compared to A (all 95%-CI include zero). Accordingly, the training groups did not show any differences in activation compared to the PC group at session D in the IFJ and in the precuneus (all 95%-CI include zero). The right SPL showed an overall decrease in activation across switch and repeat trials from session A

to D in both groups (est. = –0.61; 95%-CI: –1.18, –0.06). The comparisons to the PC group did not show clear evidence that this change in the training groups differed from the PC group: the interactions of group and session did not become evident (95%-CI included zero).

To summarize, across groups, the IFJ and the precuneus showed early changes in activation between sessions A and B after three weeks of training, with increases in the right precuneus and decreases in the left IFJ across conditions. The right SPL showed slower decreases in overall activation that only became evident at the end of training at session D; however, a lack of difference to the PC group at session D caution against the interpretation of this decrease as related to the intensive training manipulation in the study.

3.4.2 Inconclusive results regarding changes in task-based connectivity with training

We next analyzed connection-specific PPI parameters among left IFJ, left SPL, left precuneus, right SPL, and right precuneus for the effects of session (B, C, D compared to A) and interactions with group (SW vs. SI group).

As shown in Figure 6C, connectivity for switch trials decreased from session A to B in the SI group, while the SW group showed an increase of connectivity for switch trials and a decrease for repeat trials (session [B vs. A] x group [SW vs. SI] x condition [switch vs. repeat]: est. = 1.77; 95%-CI: 0.76, 2.77). However, we did not observe clear differences in connectivity between switch and repeat trials across the two groups independent of training. Thus, the observed differences between groups in training-related changes cannot be meaningfully interpreted as changes in adaptively adjusted connectivity among regions based on switch demands. Compared to the PC group, the SW group also showed a different pattern of change from session A to D between conditions (session [D vs. A] x group [SW vs. PC] x condition [switch vs. repeat]: est. = 1.41; 95%-CI: 0.33, 2.49), but again the lack of condition effects across groups and sessions limits the interpretability of these findings. The SI group showed no compared to the PC group when comparing sessions A and D.

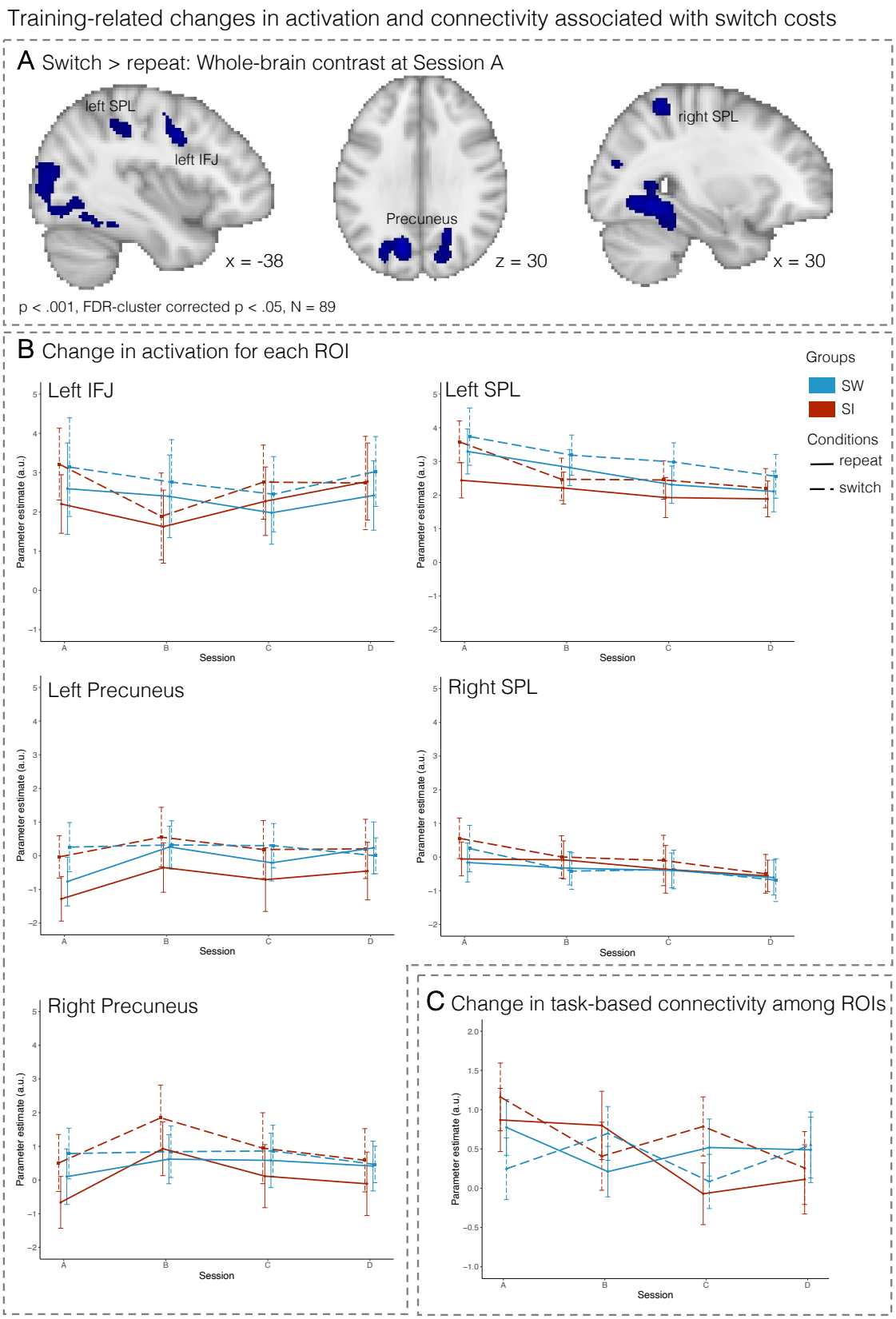

Figure 6: Training-related changes in activation and connectivity associated with switch costs. (A) Brain regions showing greater activation on switch than on repeat trials at session A across all children (N = 89; p < .001, FDR-cluster corrected p < .05). (B) Change in activation for each ROI. (C)

Change in connectivity (i.e., PPI parameters across all connections) among these ROIs. The SW group is shown in blue and the SI group in red. Error bars denote 95%-confidence intervals.

4. Discussion

In the present study we investigated behavioral and neuroimaging data of 8–11-year-olds to elucidate behavioral and neural changes as a function of different doses of task-switching training. We analyzed task performance in terms of drift-diffusion parameters, fMRI activation, and task-based functional connectivity before and after training, as well as twice during the nine-week training phase, to shed new light on the behavioral and neural changes that take place during task-switching training.

Comparing the pre- and post-training sessions, accuracy increased and RTs decreased with training across conditions in the group with the higher dose of task-switching training. These findings corroborate and extend previous findings demonstrating that task-switching performance in children can be improved with intensive training (Karbach and Kray 2009; Kray, Karbach, Haenig, et al. 2012; Zinke et al. 2012; Dörrenbächer et al. 2014; Karbach et al. 2017). We leveraged drift-diffusion modeling to provide a more detailed picture of how the different training schedules influenced cognitive processes during task switching. We observed rapid changes after three weeks (i.e., from session A to B) across all parameters in both training groups: the boundary-separation and drift-rate parameters increased, while non-decision time decreased. Children in the high-intensity task-switching group showed more pronounced increases in drift rate and boundary separation that were maintained for the duration of the training. The sustained increase in boundary separation in the high-intensity task-switching group is somewhat surprising, given that previous training studies have shown reductions in boundary separation (Reinhartz et al. 2023; Schmiedek et al. 2023). In our view, the combination of increasing drift rates with widening decision boundaries reveals that children were approaching the task in a more cautious manner with increasing practice. Additionally, both groups showed decreases in the non-decision time parameter with training. Thus, even small doses of task switching during training, in combination with extensively practicing the task rules separately, improved preparatory processes such as reconfiguration of the task set (Schmitz and Voss 2012) and more

efficient response execution in light of potentially conflicting or distracting information (cf. Resulaj et al. 2009; Schroeder and Verrel 2014).

On the neural level, we observed different patterns of changes in activation associated with mixing demands (i.e., repeat vs. single trials) and switch demands (i.e., switch vs. repeat trials). Activations associated with both single and repeat trials decreased in lateral prefrontal ROIs (i.e., left dlPFC and to a smaller extent, left IFJ) in the high-intensity task-switching group, but not in the high-intensity single-tasking group. Additionally, task-related activations on repeat trials decreased in the right SPL in both training groups, but also the PC group, resulting in a smaller difference between repeat and single conditions. In parallel, connectivity among frontal and parietal regions decreased with training for repeat trials, with more pronounced changes in the high-intensity single-tasking group than in the high-intensity task-switching group. Brain regions specifically associated with greater switch demands prior to training showed a rapid training-related change in activation in session B, but returned to baseline by the end of training.

Taken together, more intensive task-switching training led to faster accumulation of information for the correct response while simultaneously promoting a more cautious response strategy. The accompanying neural analyses indicate that intensive task-switching training was associated with decreases in task-related activation in the prefrontal cortex (PFC) as well as in connectivity among PFC and parietal regions, presumably indicating more efficient task processing with training.

4.1 Training improves efficiency of processing in frontoparietal regions

Both training groups showed increases in drift rates with training, suggesting faster, more efficient evidence accumulation for the correct response (Radcliff, 1978). Higher drift-rate parameters have been associated with faster response selection during task switching (Schmitz and Voss 2012), potentially due to less interference from the previous stimulus-response (S-R) mapping (Weeda et al. 2014). Previous studies on the flexibility of task-set updating in children have suggested that such an interference from the previous S-R

mapping contributes to the costs of switching, especially in children (Hommel et al. 2011). Thus, with training, children might become better at resolving interference or selecting the correct S-R mapping more quickly. Furthermore, increased drift rates have been associated with more efficient extraction of high-quality information from the task (Ratcliff et al. 2012) along with increased efficiency of rule processing (cf. Schmitz and Voss 2012). Gains in evidence accumulation during perceptual decision making have been found to be positively associated with working memory gains on a completely different set of tasks (Schmiedek et al. 2023), pointing to a connection between drift rate and mechanisms supporting working memory. Increased efficiency with multitasking training has also been proposed by Dux and colleagues (2009), based on decreased activation in lateral PFC, which is consistent with the activation decreases that we observed specifically in the high-intensity task-switching group.

Specifically, activation in lateral prefrontal regions associated with mixing demands (i.e., repeat > single contrast), especially in the left dlPFC, showed a decrease across both conditions from the first to the second session. Notably, only the high-intensity task-switching group maintained these changes by the end of training. Previous studies in adults have associated such activation decreases with increased efficiency of rule processing (Kelly and Garavan 2005; von Bastian et al. 2022). Poldrack (2000) has suggested that a key contributor to training-related activation decreases are more precise neural representations of task sets that enable more efficient processes. Accordingly, Garner and Dux (2015) showed training-related performance improvements with dual-task training alongside reduced task-related activations and more distinct task-set representations in the PFC in adults.

The present results extend the observation that increased efficiency underlies training-related improvements in executive functions from adulthood (cf. von Bastian et al. 2022) to late childhood, by demonstrating decreases in frontal activation that were accompanied by increased drift rates with intensive task switching training. This observation is relevant in light of suggestions that training in children may speed up maturation with children becoming more adult-like in activation and connectivity patterns (Jolles et al. 2012;

Jolles and Crone 2012). Our previous work (Schwarze et al. 2023) showed the present task-switching paradigm elicited smaller upregulation of frontoparietal activation in (untrained) children compared to adults. This pattern indicates a potential for children's activation patterns to become more adult-like by condition-specific increases in activation. However, we did not observe such changes in any of the ROIs (see also Supplementary Results 3). Rather than showing more adult-like activation, children revealed a similar training-related change of decreasing PFC activation as previously reported in adults. Future studies are needed to elucidate how these training-related changes in neural processes depend on the targeted executive function (e.g., task-switching as opposed to working-memory training; Jolles et al. 2012; Astle et al. 2015) or the investigated age range (Rueda et al. 2005; Lee et al. 2022).

4.2 Rapid temporary changes in switch-related activation

Most changes of activation associated with switch costs were similar across training groups and relatively short lived, such that they became evident at the second session but were no longer present at the end of training. While this pattern matches the initial changes of the drift rate and boundary separation parameters, it does not match the maintenance of the later changes, especially in the high-intensity task-switching group.

In line with the well-established evidence that switch costs approach adult levels earlier than mixing costs do (Cepeda et al. 2001; Crone et al. 2004; Reimers and Maylor 2005; Crone, Bunge, et al. 2006; Huizinga and van der Molen 2007; Manzi et al. 2011), children in the present study showed smaller switch costs than mixing costs prior to training (see Schwarze et al. 2023). Thus, the different patterns of change observed for neural processes associated with mixing and switch costs may reflect differences in the mismatch between current ability and demands imposed on the cognitive control system during training (cf. Lövdén et al. 2010; Lövdén et al. 2020). According to this interpretation, the supply–demand mismatch was greater for mixing costs than for switch costs, leading to the

observed sustained changes in neural activation, whereas the relatively smaller mismatch for switch costs could be met by temporary changes of control processes.

4.3 Return to baseline performance and activation in the SI group

While we had predicted slower or less extensive behavioral improvements and neural changes with lower dosages of task switching, the high-intensity single-tasking group showed behavioral and neural changes as quickly and almost as extensively as the high-intensity task-switching group. However, the high-intensity single-tasking group returned to baseline levels of performance and dlPFC activation by the end of training. There are different potential explanations for the return to baseline with intensive single-task training. First, the lower doses of task switching in each training game (i.e., 17%) may not have posed enough demands to evoke sustained challenge to the task-switching networks to maintain the initial changes (Lövdén et al. 2010). Hence, the changes observed at the beginning of training may rather reflect the reconfiguration of existing resources, also referred to as flexibility (Lindenberger and Lövdén 2019; Lövdén et al. 2020; cf. Baltes 1987), than structural alterations of brain and behavior that would qualify as plasticity.

Second, the lower dosage of task-switching demands during training in the high-intensity single-tasking group may have favored adopting a strategy that is tailored to the demands of the single-task context, which, however, might be less well suited for task switching. Group differences in boundary separation are especially interesting to consider in light of such potential strategy differences. Specifically, boundary separation captures response caution, both on an individual level as well as on a trial level that is likely to correspond to the perceived risk of making an error (Schmitz and Voss, 2012). While both groups showed greater boundary separation for single trials at the second session, only the high-intensity task-switching group showed these increases for repeat and switch trials as well. The increased boundary-separation parameter may reflect greater control allocation to switch and repeat trials or the increased sensitivity to the cue and its changes within mixed blocks. With children in the high-intensity single-tasking group mainly practicing on the

relatively easier condition of single-task blocks, they may have adopted a different strategy for the allocation of control than the high-intensity task-switching group (Shenhav et al. 2013; see Steinbeis 2023 for a developmental perspective). This may have hindered them in correctly judging the required control on mixed blocks, in line with our observation that group differences in the increase in boundary separation were especially pronounced for repeat and switch trials as opposed to single trials. Such differences in control allocation might have been especially prominent in the second half of training, when children had become more familiar with the type of task-switching paradigm and the amount of cognitive control required for successful performance.

Another key difference between the two training groups may be related to the need to track changes in task demands indicated by changes in context. The ability to track changes in contexts continues to develop in late childhood (Waskom et al. 2014; Frick and Chevalier 2023) and contributes to the development of self-directed control (Frick et al. 2022). In the present training paradigm, the demands for context tracking were greater for the high-intensity task-switching group, in which participants performed more mixed blocks during training and thus faced more frequent switches of the cue. During the training games, the cue was always presented along with the target stimulus, effectively rendering it the context of the stimulus. Thus, the high-intensity task-switching group not only learned the mappings between each stimulus and the corresponding response, but also more intensively practiced tracking the context in which these were presented, which was crucial for successful task performance. In turn, the improved ability to track the context might have enabled more efficient rule implementation in the dlPFC (Hyafil et al. 2009; Ruge et al. 2013) and thus reduced activation in this region to a greater extent in this group than in the high-intensity single-tasking group.

Finally, children in the two training groups may have learned the rule structure differently, based on their experience with the tasks during training. Mixed blocks require the application of the rules in a hierarchical manner: mappings between a stimulus and a response are nested within a cue indicating which stimulus is relevant. While the ability to

identify and apply such hierarchical rule structures has been demonstrated in infants and toddlers (Werchan et al. 2015; Werchan et al. 2016), it is continually refined throughout childhood and adolescence (Kray, Karbach, and Blaye 2012; Unger et al. 2016). During the instruction phase of each training game, the hierarchical structure of each task was made explicit to both groups. Nonetheless, children in the high-intensity single-tasking group may have represented the mappings between stimulus and response separately from the cue, as the cue was only relevant at the beginning of a block. Such a flat rule structure could be more efficient when single-tasking, but ineffective in mixed blocks where the cue is crucial for successful performance on each trial (cf. Verbeke and Verguts 2023).

4.4 Limitations

We would like to acknowledge some important limitations of the present study. First, the sample size for the analyses of activation and connectivity is relatively small, limiting our ability to find smaller effects, especially for whole-brain analyses over time as they require complete datasets with currently available data-analysis pipelines. Thus, the reported training-related changes in activation and connectivity patterns should be interpreted with caution and seen as a starting point for further research. Additionally, changes in performance and brain function may happen at different time scales (Baykara et al. 2021). For example, the limited changes in activation associated with switch costs may be due to session B being too far into training to capture the potentially early onset of such changes. Also, in keeping with earlier work on task switching (Schmitz and Voss 2012; Schmitz and Voss 2014; Weeda et al. 2014; Schuch and Konrad 2017; Ging-Jehli and Ratcliff 2020), we did not estimate all possible parameters of the drift-diffusion model (Henrich et al. 2023), given the limited number of trials per condition and group. Finally, while we were able to demonstrate that different doses of task-switching during training (i.e., high-intensity task switching vs. high-intensity single tasking) were associated with differential changes in performance and activation patterns, it seems worthwhile to investigate the effects of other training regimes in future work. In particular, we recommend examining the effects of a

sequential training regime in which single-task training precedes task-switching training. Possibly, task-switching training is more effective if preceded by a training phase during which the decision rules governing each task have been firmly established.

4.5 Conclusion

In this study, we show that high-intensity task-switching training speeds up evidence accumulation, induces more cautious response strategies, and reduces activation and connectivity in frontal regions in children aged between 8 and 11 years. By comparing different doses of practicing switching between rules, we were able to demonstrate that greater experience with task switching is associated with more efficient rule processing in the PFC. In summary, we conclude that high-intensity task-switching may facilitate the efficient allocation of cognitive control, such as the continuous tracking of contextual information and the flexible, hierarchical representation of currently relevant tasks. Our findings provide initial evidence on the ways in which task-switching processes change with training at both behavioral and neural levels of analysis in late childhood. Future research can build on these findings by investigating which training regimes are most effective in promoting efficient task switching at different ages, with the aim to better understand the interplay between maturational and experiential factors and timescales in the ontogeny of cognitive control.

Funding:

This work was support by the Max Planck Institute for Human Development and by the DFG Priority Program SPP 1772 "Human performance under multiple cognitive task requirements: From basic mechanisms to optimized task scheduling" (Grant No. FA 1196/2-1 to Y.F.).

Acknowledgments:

During the work on their dissertations, S.A.S. and N.K. were predoctoral fellows of the International Max Planck Research School on the Life Course (LIFE; http://www.imprs-life.mpg.de) of the Max Planck Institute for Human Development, Berlin, Germany. The authors thank Theodoros Koustakas for support with the analyses and Julia Delius for editorial assistance and helpful comments. Communication regarding this article should be directed to S.A.S, schwarze@mpib-berlin.mpg.de, or Y.F., fandakova@uni-trier.de.

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