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A diffusion model analysis of developmental changes in children's task switching

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ABSTRACT

This study aimed to investigate the underlying processes of the development of cognitive flexibility between childhood and young adulthood. We performed a diffusion model analysis on the reaction time and accuracy data from four age groups (7-, 11-, 15-, and 21-year-olds), who performed a task-switching task. We decomposed the data into processes related to the reconfiguration of the cognitive system to a new goal (i.e., task-set reconfiguration) and processes related to the interference of the previous task (i.e., task-set inertia). The developmental patterns of both processes indicated a relatively early maturing mechanism, associated with task-set inertia, and a later maturing mechanism, relating to task-set reconfiguration. This pattern of results was interpreted in terms of the development of the neural mechanisms involved in task switching, that is, the (pre-)supplementary motor area and the ventrolateral prefrontal cortex.

Introduction

Cognitive flexibility refers to the ability to flexibly adjust behavior to the changing demands of the environment and is a key component of human behavior (e.g., Miller & Cohen, 2001; Monsell, 2003).

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Cognitive flexibility can be examined using experimental tasks that require flexible switching between task demands. A particularly useful task is the task-switching paradigm (for a review of adult literature on task switching, see Monsell, 2003; see also Kiesel et al., 2010; Vandierendonck, Liefooghe, & Verbruggen, 2010). The task-switching paradigm requires the participant to make a choice between two response alternatives such as deciding between the shape (e.g., circle, triangle) and color (e.g., yellow, blue) of a stimulus. The shape and color tasks are presented in mixed blocks, allowing the comparison of performance on task repetitions and task alternations. In adults, longer response latencies and increased error rates are typically observed on trials that require a task switch (e.g., a shape–color sequence of trials) compared with repeating trials (e.g., a shape–shape sequence of trials). The difference in performance between task-switch trials and task-repeat trials is referred to as switch costs (Monsell, 2003).

Two major theories have been invoked for the explanation of switch costs. One account suggests that switch costs can be attributed to the reconfiguration of the task set (De Jong, 2000; Meiran, 1996; Rogers & Monsell, 1995). More specifically, it is assumed that once a task set is implemented, it stays active until it has been replaced by another task set. Consequently, it has been argued that task-switching costs arise from an executive or control process that reconfigures the cognitive system such that the relevant task set is active for execution (e.g., Rogers & Monsell, 1995). The other account asserts that, once implemented, a task set persists and interferes with new task-set configurations. This residual activation of a task set from the recent performance of a task, dubbed "task-set inertia," may interfere with the performance of the new task. This account assumes that switch costs reflect interference from the previous task at the level of stimulus–response associations, stimulus–stimulus associations, or response–response associations (e.g., Allport, Styles, & Hsieh, 1994; Wylie & Allport, 2000).

One line of evidence for an executive control process account comes from studies showing that at least part of the task-switching costs, "residual switch costs", persist even when participants have ample time between trials to prepare for the upcoming task. It is hypothesized that residual switch costs reflect the time taken by executive control processes, which must await stimulus presentation and, therefore, are insensitive to the preparation interval (e.g., Monsell, Yeung, & Azuma, 2000). In contrast, the "task carryover" account is supported by findings showing that switching from a difficult task to an easy task takes longer to complete than vice versa. This observation is consistent with the notion that the time needed for a task switch is determined primarily by the nature of the previous task. Thus, it is argued that greater inhibition is required to the easy task set when performing the difficult one, and this inhibition carries over to the next trial requiring the performance of the easy task. Overcoming this inhibition prolongs the selection of the appropriate response (e.g., Allport et al., 1994). An alternative explanation of the "task carryover effect" concerns the effect of inhibitory control when switching between tasks (for a review, see Koch, Gade, Schuch, & Philipp, 2010). This account assumes the involvement of an inhibitory mechanism that reduces the activation of the current task in order to switch to a different task. Evidence for the effect of inhibition during task switching was obtained in negative priming studies (e.g., Koch et al., 2010) and in n – 2 repetition costs (e.g., Mayr & Keele, 2000).

Initially, task-switching costs have been explained in terms of single factor models, emphasizing either task-set inertia or task carryover effects. More recently, most authors seem to entertain accounts of task-switching costs based on a plurality of causes (cf. Monsell, 2003, p. 137). Thus, Ruthruff, Remington, and Johnston (2001) proposed that both top-down and bottom-up processes might be active during a task switch; the former are required for programming mental operations involved in the upcoming task, whereas the latter are required for the actual execution of these operations. Similarly, Mayr and Kliegl (2003) suggested the existence of two processing stages during a task switch; the first processing stage is associated with the retrieval of task rules from long-term memory, and the second relates to the automatic application of rules to the stimulus at hand.

The notion of multiple mechanisms involved in task switching has stimulated research aimed at identifying the mechanisms active in a particular paradigm as well as their temporal dynamics during the task switch (for a review, see Vandierendonck et al., 2010). Recently, Schmitz and Voss (2012) applied diffusion modeling for isolating mechanisms involved in different task-switching paradigms. Diffusion modeling (Ratcliff, 1978) takes into account both latency and accuracy of reaction time (RT) data and allows for decomposing the effects on both in meaningful underlying constructs. The diffusion model assumes that, in speeded two-choice tasks, stimulus processing consists of a noisy accumulation of evidence over time. When the evidence is hitting a predefined boundary, a response is emitted (see Fig. 1). The diffusion model decomposes the two-choice process into a set of informative parameters. Drift rate (v) quantifies the speed of information processing, reflecting stimulus difficulty and the processing ability of the participant. Boundary separation (a) quantifies response caution and, thus, captures the speed–accuracy trade-off; Starting point (z) quantifies a priori bias for one of the response options. Non-decision time (*Ter*) quantifies time used for encoding the stimulus and executing the response.

Recently, a number of studies applied diffusion modeling to different task-switching paradigms (e.g., Karayanidis et al., 2009; Madden et al., 2009; Mansfield, Karayanidis, Jamadar, Heathcote, & Forstmann, 2011; Schmitz & Voss, 2012). Using the classical diffusion model (Ratcliff, 1978), Schmitz and Voss (2012) examined task-switching processes with several variants of the alternating runs paradigm and the explicit cueing paradigm. They observed higher drift rates for repeat trials than for switch trials, which was interpreted as evidence for beneficial carryover effects from the previous trial to the current trial. Drift rates were also higher when advance task cues helped participants to prepare for the upcoming task, which was interpreted to suggest a higher task readiness. On this account, task readiness can be influenced by preparation effects (i.e., more complete activation of the new relevant task set) and inertia effects (i.e., carryover effects from the previous trial) (Koch & Allport, 2006). Boundary separation was adjusted on a trial-to-trial basis. More specifically, it was found that participants set boundaries lower (i.e., exercised less caution) when advance information, indicating that the upcoming trial involved task-set repetition, was given provided that there was sufficient time to prepare for the upcoming task. Finally, it was observed that the non-decision parameter was increased on task-switch trials when advance preparation was not possible. This observation was interpreted to suggest that the non-decision parameter may reflect higher order processes (e.g., top-down biasing of relevant task components). In brief, Schmitz and Voss's (2012) study demonstrates that diffusion modeling provides a valuable tool for decomposing switch costs in psychologically relevant constructs. More specifically, these authors demonstrated that differences in non-decision time between task-repeat and task alternation trials reflect task-set reconfiguration processes, whereas differences in drift rate provide a manifestation of task readiness shown to be influenced by inertia effects (Schmitz & Voss, 2012). The results converge with earlier findings and allow for an interpretation of diffusion model parameters in terms of components of task switching. This in turn allows us to assess developmental change in the alleged components underlying task switching.

The goal of the current study was to apply diffusion modeling to developmental change in task switching. Early studies examining developmental change in executive functions revealed that young

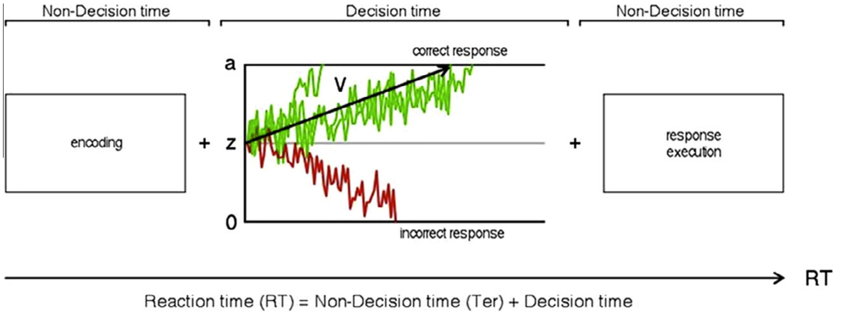

Fig. 1. A schematic representation of the diffusion model. The model decomposes performance data for correct and incorrect responses (RT and accuracy) into decision processes and non-decision processes. The decision process starts at point z, where information is accumulated until a response boundary (0 [incorrect response] or a [correct response]) is reached, after which a response is initiated. The mean rate of information accumulation (drift rate) is indicated by the solid black arrow. The non-decision process includes encoding and response execution. The total RT equals the sum of the decision and non-decision processes.

children lack flexibility on the Wisconsin Card Sorting Test (e.g., Chelune & Baer, 1986; Levin et al., 1996; Welsh, Pennington, & Groisser, 1991). More recent developmental studies have applied various task-switching paradigms to provide a more detailed view on age-related changes in cognitive flexibility (for a review, see Cragg & Chevalier, 2012). These studies typically reveal an age-related decrease in switching costs (Cepeda, Kramer, & Gonzalez de Sather, 2001; Chevalier & Blaye, 2009; Cragg & Nation, 2009; Crone, Bunge, van der Molen, & Ridderinkhof, 2006; Davidson, Amso, Anderson, & Diamond, 2006; Deak, Ray, & Pick, 2004; Ellefson, Shapiro, & Chater, 2006; Gupta, Kar, & Srinivasan, 2009; Huizinga, Burack, & van der Molen, 2010; Huizinga & van der Molen, 2011; Reimers & Maylor, 2005).

A prominent interpretation of developmental change in task switching refers to carryover effects of the previous task interfering with the implementation of the current task. Several studies suggest that carryover effects are larger in children compared with adults, children have greater difficulty in inhibition of carryover effects when switching to currently intended actions, or both (Cepeda et al., 2001; Crone, Somsen, Zanolie, & Van der Molen, 2006; Gupta et al., 2009; Huizinga & van der Molen, 2011; Kray, Karbach, & Blaye, 2012). An early illustration was provided by Cepeda and colleagues (2001), who required their participants to perform two tasks; deciding whether the number 1 or 3 was present and deciding whether a single number (e.g., 1, 3) or three numbers (e.g., 111, 333) was present on the screen. Participants received a cue indicating which task needed to be performed on the next trial, and both the "response-to-cue" and "cue-to-stimulus" intervals were manipulated to examine, respectively, the decay of task-set inertia and the preparation of the task set to be performed. Cepeda and colleagues observed larger switch costs for children relative to adults, but only adults benefited from a lengthening of the response-to-cue interval. In contrast, a lengthening of the cue-to-stimulus interval reduced switching costs in both children and adults. This pattern of findings was interpreted to suggest that children benefit from increased preparation time but, in contrast to adults, show little evidence for a rapid decay of task-set inertia. The adult literature, however, indicates that task switching cannot be reduced to a single mechanism. Most likely, task switching in children involves multiple mechanisms similar to adult task switching. Unfortunately, little is known about the developmental course of these mechanisms (cf. Cragg & Chevalier, 2012). The goal of this study, therefore, was to assess the mechanisms that are involved in developmental change in task switching. To this end, we applied diffusion modeling to the data reported in Huizinga, Dolan, and van der Molen (2006).

In Huizinga and colleagues' (2006) study, participants performed a battery of experimental tasks examining developmental change in executive function. The task battery included the Dots and Triangles task adopted from Rogers and Monsell (1995). In this task, participants were presented with a 4×4 grid containing three to eight dots or triangles per half of the grid. During the "dots" task, participants needed to decide whether there were more dots on the left or right side of the grid; during the "triangles" task, they needed to decide whether there were more triangles in the upper or lower half of the grid. Within trial blocks, participants received alternating runs consisting of four dots or triangle trials. Four age groups performed the task: 7-, 11-, 15-, and 21-year-olds. The results showed that switch costs decreased with advancing age until 15 years. The current application of diffusion modeling should allow for identifying the mechanisms involved in switching between the dots and triangles tasks as well as tracking their developmental course.

Method

A brief presentation of the method can be found in the original study (Huizinga et al., 2006). The current presentation provides more detail needed to fully appreciate the results reported below.

Participants

The study included four age groups: 95 7-year-olds, 107 11-year-olds, 108 15-year-olds, and 93 21-year-olds. The descriptive characteristics of the participants are shown in Table 1.

Table 1
Participant characteristics for the initial sample (top) and final sample after outlier removal (bottom).

	n	Age			Gender (F)		Raven quartile	
		Min	Mean	Max	*n*	%	Mean	*SD*
7 years	95	6.27	7.16	7.95	50	53	3.44	0.93
11 years	107	10.47	11.19	12.47	64	60	3.18	0.93
15 years	108	14.24	15.33	16.78	57	53	3.10	1.00
21 years	93	17.52	20.81	26.51	71	76	3.77	0.53
Total	403				242	60		
7 years	63	6.27	7.16	7.89	33	52	3.63	0.84
11 years	102	10.47	11.18	12.47	61	60	3.25	0.90
15 years	107	14.24	15.32	16.78	56	52	3.10	1.00
21 years	91	17.52	20.79	26.51	70	77	3.77	0.53
Total	363				220	61		

Note. Characteristics include number of participants (*n*), age (minimum [Min], mean, and maximum [Max]), gender (number and percentage of female [F] participants), and Raven quartile (mean and standard deviation).

Apparatus and stimuli

The Dots and Triangles task was presented on a Toshiba Satellite 1600 laptop (Intel Celeron 800-MHz processor, 15-inch 60-Hz monitor, 1024×768 pixels). The task required only left hand and right hand responses. The response button for the left hand was the "z" key on the computer keyboard, and the response button for the right hand was the "/" key (responses were counterbalanced across participants). Target stimuli were red circles and green triangles. The size of the target stimuli covered 18.43° visual angle (horizontally and vertically).

Design

The task-switching paradigm required participants to respond to either dots (dots task) or triangles (triangles task) with a left or right button press, depending on the instruction of the task. The mapping of the responses onto the stimuli was counterbalanced across participants and kept fixed during the experiment—with the constraint that for each participant responding to dots (or triangles) was related to one task and responding to triangles (or dots) was related to the other task. Half of the trials required a right hand response, and half of the trials required a left hand response.

Varying numbers of either green dots or green triangles were presented in a 4×4 grid on the screen (i.e., three to eight dots or triangles per half of the grid, equally distributed) covering 78.69° visual angle. The dots (or triangles) task required participants to decide whether there were more dots (or triangles) in the left or right part of the grid (the "left–right" task). The triangles (or dots) task required participants to decide whether there were more triangles (or dots) in the top or bottom part of the grid (the "up–down" task). The number of dots (or triangles) presented on the left/right (top/bottom) side of the grid varied pseudo-randomly between three and eight. The difference in the number of stimuli on both sides of the grid was set to three. A schematic of the task is depicted in Fig. 2.

Procedure

The Dots and Triangles task is part of a battery to assess the development of executive function from childhood to young adulthood (Huizinga et al., 2006). This battery was composed of 11 tasks (three tasks to assess working memory, three tasks to assess cognitive flexibility, three tasks to assess inhibition, and two more complex executive functioning tasks). These tasks were presented in pseudo-random order.

The Dots and Triangles task required participants to perform on two "pure-task" blocks and one "task-switch" block. The pure-task blocks served to familiarize participants with the left–right and up–down tasks. The task-switch block required participants to perform a switch task consisting of series of four left–right trials and series of four up–down trials that were alternately presented to participants. A task-switch block consisted of 160 trials comprising series of four dots trials and series of four triangles

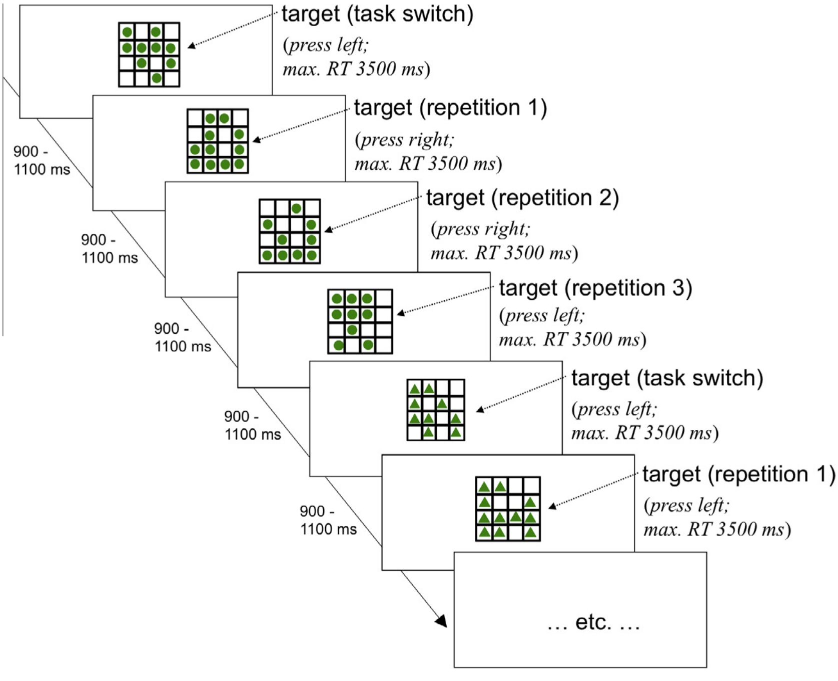

Fig. 2. A trial sequence. In the first display (from left to right), a target stimulus of the "dots" task appears and a response is required; participants need to respond by pressing the left key when there are more dots on the top half of the grid and by pressing the right key when there are more dots on the bottom half of the grid. The second and third displays show a dots task. The fourth and fifth displays show target stimuli of the "triangles" task; participants need to respond by pressing the left key when there are more dots on the left half of the grid and by pressing the right key when there are more triangles on the right half of the grid. The first, second, and third displays are task repetitions (dots), the fourth display is a task alternation (the task switches from dots to triangles), and the fifth display is a task repetition (triangles).

trials that were alternately presented to the participants. Before a switch block, participants received a practice block consisting of 60 trials.

There was a fixed delay of 1000 ms between the start of a trial block and the presentation of the stimulus. A stimulus remained on the screen until a response was given. Participants had 3500 ms to respond. The time interval between the response and the next stimulus varied pseudo-randomly between 900 and 1100 ms in steps of 10 ms.

Instructions

Prior to performing the task-switch block, participants were instructed that the left–right and up–down tasks would alternate: "Now the tasks will alternate, and the stimuli will tell you which task to perform. As before, if you see dots [triangles] in the grid, you decide on which half of the grid there are more dots [triangles] and press left if the left half of the grid contains more dots [triangles] or right when the right half of the grid contains more dots [triangles]. When you see triangles [dots] in the grid, you decide on which half of the grid there are more triangles [dots] and press left if the upper half of the grid contains more triangles [dots] or right when the lower half of the grid contains more triangles [dots]."

Data analyses

The focus of analyses was on reactions that could be preceded by a trial requiring the same task (i.e., task-repeat trials) and reactions requiring a switch to the alternative task (i.e., task-switch trials).

The difference between task-repeat trials and task-switch trials provides an estimate of the costs involved in switching between tasks. Switch costs were subjected to two sets of analyses. The first set included analyses of variance (ANOVAs) to assess the developmental trajectory of cognitive flexibility in terms of response accuracy and response latency. The second set included a diffusion model analysis to assess the developmental trajectory of the underlying components of switch costs, the relative contribution of these components to switch costs, and the effects of trial sequence. Prior to the ANOVAs, participants for whom the left–right and/or up–down tasks proved too difficult, as indicated by accuracy scores of 54% or less, were excluded. In addition, all trials with RTs shorter than 120 ms, and all error and post-error trials as well as trials on which no response was given (misses), were excluded (see also Steinhauser & Huebner, 2006). The first five responses of each block were considered warm-up trials and excluded from analysis. Finally, extreme RT outliers were removed for each participant and age group separately. An extreme RT outlier was identified as a response with a latency exceeding the individual's mean by more than 2.5 standard deviations (both sides) or a response with a latency higher than 3 times the interquartile range from the 75% percentile of all RTs within an age group or lower than 3 times the interquartile range from the 25% percentile of all RTs within an age group.

The same pre-analysis procedures were followed for the diffusion model analyses except that RTs of both correct and error responses were included. Note that post-error trials were not included in the diffusion model analyses. To obtain a detailed view on possible effects of task-set preparation and task-set inertia, trials were divided into four types: task switch, first task repetition, second task repetition, and third task repetition. The main parameters of the diffusion model, except starting point,[1] were allowed to vary freely over these conditions (i.e., all parameters were estimated separately for each condition). The starting point was fixed halfway between boundaries (Schmitz & Voss, 2012). To obtain stable parameter estimates given the relatively low number of trials available in each condition, variability parameters were fixed to zero[2] (Voss, Nagler, & Lerche, 2013). Parameters were estimated using "fast-dm" (Voss & Voss, 2007) with the Kolmogorov–Smirnov (KS) method for each condition of each individual participant separately. Fast-dm uses an efficient algorithm to reliably estimate all diffusion model parameters (Voss & Voss, 2008). The main parameters of interest were boundary separation, drift rate, and non-decision time. Developmental changes in task switching are assessed for each of the parameter values. In addition, trial repetition effects are examined across age groups. Finally, the results that emerged from the diffusion modeling analyses are used to assess the developmental time course of task-switching mechanisms (i.e., task-set inertia and task-set reconfiguration).

Results

In the analyses, age group (7-, 11-, 15-, or 21-year-olds) was included as a between-participants factor. After exclusion of the participants following the above-mentioned procedure, the final sample of the current study was composed of 63 7-year-olds, 102 11-year-olds, 107 15-year-olds, and 91 21-year-olds. Descriptive characteristics of the remaining participants are given in Table 1. The exclusion of trials in the remaining sample amounted to 23.8% in 7-year-olds, 14.5% in 11-year-olds, 11.5% in 15-year-olds, and 10.3% in 21-year-olds. The specification of outliers and the remaining number of trials in each age group are given in Table 2. The mean Raven quartile scores differed between groups, $F(3,337) = 11.81$, $p < .001$. Post hoc tests (Bonferroni corrected) indicated significant differences between the 7- and 21-year-olds compared with the 11- and 15-year-olds.

Preliminary analyses, with Raven quartile (IQ) as an additional factor, did not qualitatively change any of the main effects or interactions involving the task manipulations. The gender distribution across groups differed significantly. This was caused by a relatively larger proportion of women in the young adult group, $\chi^2(3) = 15.03$, $p = .002$. The addition of gender as a factor in the analyses reported below indicated no relationship between gender and task switching, both within groups

[1] Because the diffusion model was set up using the "correct" and "incorrect" response boundaries and correct/incorrect responses were randomly assigned to the left or right side of the grid, the starting point is assumed to be equidistant from the two response boundaries.

[2] We thank one of the reviewers for this suggestion.

Table 2
Percentage of trials removed per age group (total, percentage post-errors removed, and percentage RT outliers removed) and average number of remaining trials (mean and standard deviation).

	Outliers			Remaining trials	
	Total (%)	Post-error (%)	RT (%)	Mean	*SD*
7 years	23.8	19.5	4.3	108	22
11 years	14.5	10.6	3.8	120	17
15 years	11.5	7.7	3.8	123	17
21 years	10.3	6.2	4.0	133	13

and between groups. Therefore, Raven IQ scores and gender were not included in the analyses reported below.

Analysis of variance

The performance on trials where the current task was similar to the previous response (task repetitions) was compared with the performance on trials where the current task was different from the previous response (task switches). The square root of the proportion correct and median RTs were submitted to separate repeated measures ANOVAs with trial type (task repetition vs. task switch) and task rule (left–right vs. up–down) as within-participants factors. Descriptive statistics are shown in Table 3.

Accuracy

The ANOVA revealed a main effect of age group, indicating increased accuracy when children get older (78% [*SE* = 1.1] in 7-year-olds, 85% [*SE* = 0.9] in 11-year-olds, 88% [*SE* = 0.9] in 15-year-olds, and 90% [*SE* = 1.0] in 21-year-olds), $F(3,359) = 23.26$, $p < .001$, $\eta_p^2 = .163$; a main effect of trial type, reflecting switch costs, as indicated by a larger proportion of correct responses on task repetitions compared with task switches (91% [*SE* = 0.4] vs. 80% [*SE* = 0.7]), $F(1,359) = 314.35$, $p < .001$, $\eta_p^2 = .467$; and a main effect of task rule, indicating that the up–down task was more difficult compared with the left–right task (80% [*SE* = 0.6] in up–down task vs. 90% [*SE* = 0.6] in left–right task), $F(1,359) = 183.42$, $p < .001$, $\eta_p^2 = .338$. In addition, the interaction between age group and trial type showed a trend, indicating decreasing switch costs when children are getting older (11% in 7-year-olds, 12% in 11-year-olds, 9% in 15-year-olds, and 10% in 21-year-olds), $F(3,359) = 2.16$, $p = .092$, $\eta_p^2 = .018$ (see Fig. 3).

Follow-up analyses indicated that the effect of trial type in 7-year-olds did not differ from the effect of trial type in 11-year-olds ($p = .510$), who differed from 15-year-olds ($p = .024$), who did not differ from 21-year-olds ($p = .895$). The ANOVA also yielded a significant interaction between age group and task rule, indicating a decrease of the task rule effect when children get older (11% in 7-year-olds, 11% in 11-year-olds, 9% in 15-year-olds, and 6% in 21-year-olds), $F(3,359) = 4.81$, $p = .003$, $\eta_p^2 = .039$, Follow-up analyses indicated that the effect of task rule in 7-year-olds did not differ from the effect of task rule in 11-year-olds ($p = .750$), who differed from 15-year-olds ($p = .004$), who did not differ from 21-year-olds ($p = .213$).

Finally, the interaction between task rule and trial type reached significance, $F(1,359) = 104.49$, $p < .001$, $\eta_p^2 = .225$, suggesting that switching to the left–right task was easier (93% [*SE* = 0.5] in task-repeat trials vs. 88% [*SE* = 0.7] in task-switch trials) compared with switching to the up–down task (88% [*SE* = 0.5] in task-repeat trials vs. 73% [*SE* = 0.9] in task-switch trials). This effect was equal across age groups.

Response latencies

The ANOVA performed on median RTs yielded a significant main effect of age group, indicating shorter RTs with advancing age (1422 ms [*SE* = 26] in 7-year-olds, 939 ms [*SE* = 21] in 11-year-olds, 670 ms [*SE* = 20] in 15-year-olds, and 635 ms [*SE* = 22] in 21-year-olds), $F(3,359) = 220.09$, $p < .001$,

Table 3
Estimated marginal means (*M*) and standard errors (*SE*) for median reaction time in milliseconds (Median RT) and percentage correct responses (accuracy) across conditions (task rule and trial type) and age groups.

Median RT	Repetition						Alternation						Total					
	Left–right		Up–down		Total		Left–right		Up–down		Total		Left–right		Up–down		Total	
	M	*SE*	*M*	*SE*	*M*	*SE*	*M*	*SE*	*M*	*SE*	*M*	*SE*	*M*	*SE*	*M*	*SE*	*M*	*SE*
7 years	1058	21	1273	23	1166	21	1595	33	1760	43	1677	35	1326	25	1516	31	1422	26
11 years	693	17	834	18	764	17	1057	26	1170	34	1114	28	875	20	1002	24	939	21
15 years	538	16	622	18	580	16	716	26	804	33	760	27	627	19	713	24	670	20
21 years	513	18	578	20	545	18	686	28	764	36	725	29	600	21	671	26	635	22
Total	701	9	827	10	764	9	1013	14	1124	18	1069	15	857	11	976	13	916	11
Accuracy	%	*SE*	%	*SE*	%	*SE*	%	*SE*	%	*SE*	%	*SE*	%	*SE*	%	*SE*	%	*SE*
7 years	88	1.2	80	1.2	84	1.0	81	1.7	66	2.1	73	1.5	84	1.3	73	1.4	78	1.1
11 years	94	1.0	88	1.0	91	0.8	89	1.4	70	1.7	79	1.2	92	1.1	79	1.2	85	0.9
15 years	95	1.0	91	1.0	93	0.8	90	1.4	78	1.8	84	1.2	93	1.1	84	1.2	88	0.9
21 years	95	1.0	94	1.1	95	0.9	91	1.5	80	1.9	85	1.4	93	1.2	87	1.3	90	1.0
Total	93	0.5	88	0.5	91	0.4	88	0.7	73	0.9	80	0.7	90	0.6	80	0.6	85	0.5

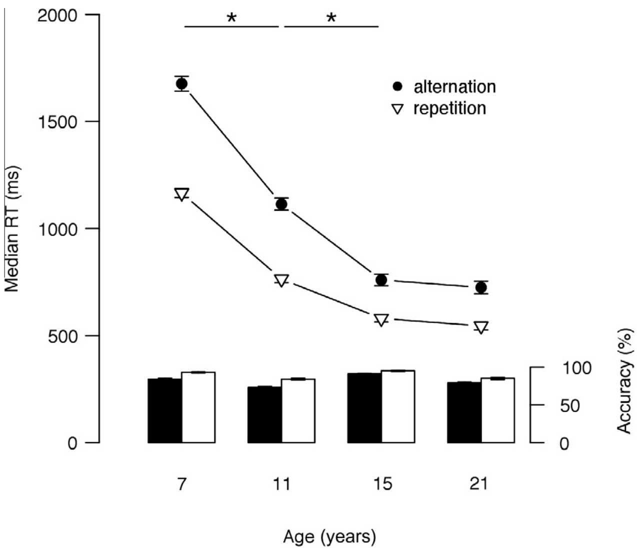

Fig. 3. Task preparation time (in milliseconds) as a function of trial type for each age group. “Repetition” refers to repeating tasks, and “alternation” refers to switching between tasks (i.e., “left–right” task and “up–down” task or vice versa). Error bars indicate 1 standard error from the mean. (*) Indicates a significant follow-up test for switch-costs (latency) at $p < .001$.

$\eta_p^2 = .648$. There was a main effect of trial type, reflecting switch costs, as indicated by shorter RTs on task-repeat trials compared with task-switch trials (764 ms [$SE = 9$] vs. 1069 ms [$SE = 15$]), $F(1,359) = 889.50$, $p < .001$, $\eta_p^2 = .712$; and a main effect of task rule, indicating faster responses to the left–right task compared with the up–down task (857 ms [$SE = 11$]) vs. 976 ms [$SE = 13$]), $F(1,359) = 209.60$, $p < .001$, $\eta_p^2 = .369$. As expected, age groups differed with respect to the effect of trial type, as indicated by a decrease of switch costs with age (511 ms in 7-year-olds, 350 ms in 11-year-olds, 180 ms in 15-year-olds, and 180 ms in 21-year-olds), $F(3,359) = 53.66$, $p < .001$, $\eta_p^2 = .310$ (see Fig. 3).

Follow-up analyses indicated that the effect of trial type in 7-year-olds differed from the effect of trial type in 11-year-olds ($p < .001$), who differed from 15-year-olds ($p < .001$), who did not differ from 21-year-olds ($p = .988$). In addition, there was a significant interaction between age group and task rule, indicating a decrease of the effect of task rule when children grow older (190 ms in 7-year-olds, 127 ms in 11-year-olds, 86 ms in 15-year-olds, and 71 ms in 21-year-olds), $F(3,359) = 9.06$, $p < .001$, $\eta_p^2 = .070$. The effect of task rule in 7-year-olds differed slightly from the effect in 11-year-olds ($p = .062$), who differed from 15-year-olds ($p = .016$), who did not differ from 21-year-olds ($p = .213$). There was no relationship between task rule and trial type, suggesting that switching between the left–right task and the up–down task takes as much time as switching between the up–down task and the left–right task. This effect was equal in all age groups.

Interim conclusion

The results indicated that performance on task-repeat trials was faster than that on task-switch trials. This is consistent with the task-switching literature (e.g., Monsell, 2003). Most important, task-switching costs decreased with advancing age in accord with the literature on developmental change in task switching (e.g., Cragg & Chevalier, 2012). Finally, switching from the left–right task to the up–down task took as long as switching from the up–down task to the left–right task. Although switching to the left–right task was easier than switching to the up–down task, the interaction between trial type and task rule was not altered by age group. Hence, the factor task rule was not included in the diffusion modeling analyses reported below.

Diffusion modeling analyses

The model fitted the data fairly well,[3] allowing for a meaningful interpretation of the parameter values (see Appendix Fig. A1 and Appendix Table A1 for model fits and model parameter estimates). The parameter values were then submitted to ANOVAs with age group as a between-participants factor and trial type as a within-participants factor. The levels of the factor trial type consisted of the average parameter value of the first, second, and third task-repeat trials versus task-switch trials. Finally, separate analyses were performed on task repetition trials.

Boundary separation

The ANOVA revealed a main effect of age group, indicating a decrease in boundary separation with advanced age (1.86 [$SE = 0.06$] in 7-year-olds, 1.64 [$SE = 0.05$] in 11-year-olds, 1.41 [$SE = 0.05$] in 15-year-olds, and 1.44 [$SE = 0.05$] in 21-year-olds), $F(3,358) = 14.64$, $p < .001$, $\eta_p^2 = .109$. Follow-up analyses showed that 7-year-olds differed from 11-year-olds ($p = .003$), who differed from 15-year-olds ($p = .001$), who did not differ from 21-year-olds ($p = .656$). A main effect of trial type was absent. The interaction between age group and trial type was also absent. See Fig. 4 (left panel).

Drift rate

The ANOVA yielded a main effect of age group showing an age-related increase in drift rate (0.81 [$SE = 0.07$] in 7-year-olds, 1.38 [$SE = 0.06$] in 11-year-olds, 1.94 [$SE = 0.06$] in 15-year-olds, and 2.16 [$SE = 0.06$] in 21-year-olds), $F(3,358) = 87.37$, $p < .001$, $\eta_p^2 = .423$. There was a significant main effect of trial type, indicating a higher drift rate on task-repeat trials (1.99 [$SE = 0.04$]) compared with task-switch trials (1.15 [$SE = 0.04$]), $F(1,358) = 515.42$, $p < .001$, $\eta_p^2 = .590$. The interaction between age group and trial type was also significant (0.48 in 7-year-olds, 0.87 in 11-year-olds, 1.03 in 15-year-olds, and 0.99 in 21-year-olds), $F(3,358) = 9.25$, $p < .001$, $\eta_p^2 = .072$. Follow-up analyses showed that the trial type effect in 7-year-olds differed from the trial type effect in 11-year-olds ($p = .001$), who marginally differed from 15-year-olds ($p = .087$), who did not differ from 21-year-olds ($p = .689$). See Fig. 4 (middle panel).

[3] For the diffusion model analyses, one additional participant was excluded because the number of trials for this participant was too low (< 10) for estimating diffusion model parameters.

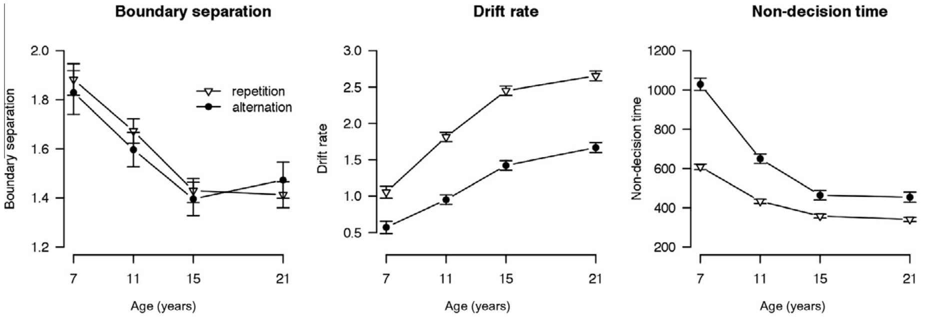

Fig. 4. Diffusion model parameter estimates as a function of trial type for each age group. The left panel shows boundary separation, the middle panel shows drift rate, and the right panel shows non-decision time (in milliseconds). Error bars indicate 1 standard error from the mean.

Non-decision time

The ANOVA revealed a main effect of age group, indicating a decrease in non-decision time when children grow older (819 ms [*SE* = 20] in 7-year-olds, 542 ms [*SE* = 15] in 11-year-olds, 411 ms [*SE* = 15] in 15-year-olds, and 397 ms [*SE* = 16] in 21-year-olds), $F(3,358) = 112.87$, $p < .001$, $\eta_p^2 = .486$. There was also a main effect of trial type, showing shorter non-decision time on task-repeat trials compared with task-switch trials (435 ms [*SE* = 6] vs. 649 ms [*SE* = 13]), $F(1,358) = 343.06$, $p < .001$, $\eta_p^2 = .489$. Finally, the effect of trial type on non-decision time decreased with age (420 ms in 7-year-olds, 217 ms in 11-year-olds, 107 ms in 15-year-olds, and 113 ms in 21-year-olds), $F(3,358) = 33.46$, $p < .001$, $\eta_p^2 = .219$. Follow-up analyses indicated that the effect of trial type on non-decision time in 7-year-olds differed from the effect of trial type in 11-year-olds ($p < .001$), who differed from 15-year-olds ($p < .001$), who did not differ from 21-year-olds, ($p = .846$). See Fig. 4 (right panel).

Interim conclusion

The current results are consistent with the findings reported previously by Schmitz and Voss (2012). Drift rate was slower on task-switch trials relative to task-repeat trials. In addition, non-decision times took longer on task-switch trials compared with task-repeat trials. In contrast with the results from Schmitz and Voss, we did not observe an increase in response caution on task-switch trials relative to task-repeat trials. The current pattern of findings suggests that switching is associated with longer durations of both response selection and non-decision processes. The developmental pattern is consistent with findings obtained by Ratcliff, Love, Thompson, and Opfer (2012) who reported age-related increases in drift rates and a reduction in non-decision time and boundary separation.

In the next section, the above results are used to assess developmental change in two major mechanisms thought to be involved in task-switching performance: task-set reconfiguration and task-set inertia.

Repetition effects

The Dots and Triangles task used an alternating runs design; that is, four dots (triangles) trials alternated systematically and predictably with four triangles (dots) trials. The previous analyses focused on performance differences between task-repeat and task-alternation trials to assess developmental change in switch costs. The current design, however, also permitted an analysis of repetition effects on the parameter values resulting from the diffusion model analyses.

Boundary separation

There was no effect on boundary separation across trial repetitions, $F(2,716) = 0.67$, $p = .510$, $\eta_p^2 = .002$.

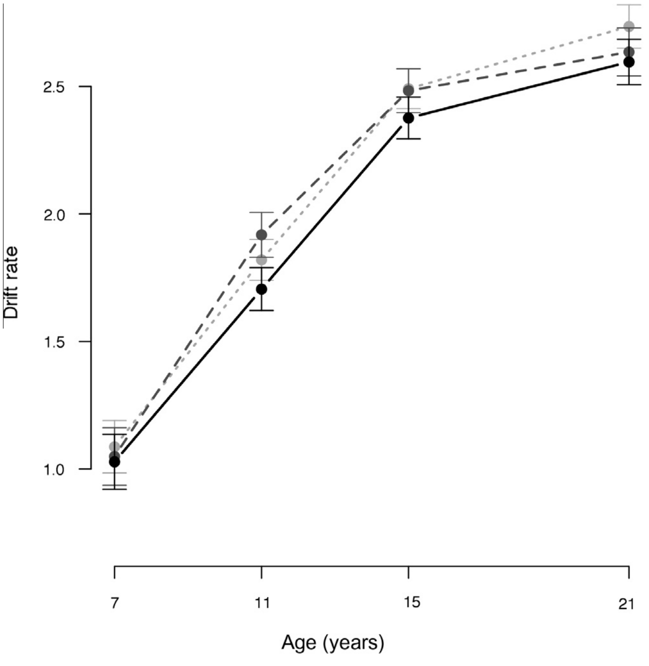

Fig. 5. Task repetition effects of drift rate as a function of age group. The solid line indicates the first repetition trial, the dashed gray line indicates the second repetition trial, and the dotted gray line indicates the third repetition trial. Error bars indicate 1 standard error from the mean.

Drift rate

Drift rate tended to increase across trial repetitions, $F(2,716) = 2.63$, $p = .073$, $\eta^2_p = .009$. There was no interaction between trial repetition and age group. Follow-up analyses revealed a significant linear increase across trial repetitions ($p = .032$) (see Fig. 5).

Non-decision time

Trial repetitions did not alter non-decision time, $F(2,716) = 0.48$, $p = .608$, $\eta^2_p = .001$. In addition, there was no interaction between trial repetition and age group.

Interim conclusion

Differences in the drift rate parameter between task repetitions indicate that on the first repetition task readiness is lower than on the second and third repetition tasks. Lower task readiness on the first repetition could be due to proactive interference from the previous task set. That is, the task set associated with the trial before the switch is still active, leading to a lower drift rate on the first repetition. Alternatively, the decrease in task readiness could be due to proactive interference from the current task set. Thus, on the second and third repetition trials, the new task set is more active than on the first repetition, leading to a higher drift rate on the second and third repetitions relative to the first repetition.

Analysis of task-switching mechanisms

Inspired by Schmitz and Voss's (2012) study, and based on the current findings, developmental change in task-set reconfiguration and task-set inertia was examined using the parameter values from the diffusion modeling analysis of the RTs that emerged from the task-switch paradigm. The primary focus of the analyses reported below is on non-decision time. Schmitz and Voss demonstrated that task-set reconfiguration is captured by non-decision time. Differences in non-decision time between alternation and repetition trials, therefore, can be interpreted in terms of the duration of task-set reconfiguration. In addition, differences in drift rate between alternation and repetition trials can be interpreted in terms of task-set inertia. It should be noted, however, that because both boundary separation and drift rate influence decision time, this measure does not provide a "pure" estimate of decision time. Therefore, we performed simulations where each individual's boundary separation parameter of the alternation trials was set to the value of this parameter in the repetition trials. Differences in response latencies of these simulations between repetition and alternation trials then provide an estimate of decision time that is driven by differences in drift rate alone (see also Wagenmakers, 2009).

Finally, differences in non-decision times and decision times were computed between task-repeat and task-alternation trials. According to Schmitz and Voss (2012), the former should provide an estimate of task-set reconfiguration, assuming that other processes (e.g., stimulus encoding, response execution) involving non-decision times do not differ between task-repeat and task-alternation trials. The latter were thought to provide an estimate of task-set inertia because the effects of boundary separation have been partialled out.

Non-decision time

The results for non-decision time have been reported above and are not presented here again for reasons of conciseness. Importantly, the results showed a developmental decrease in switch costs on non-decision times, suggesting an age-related increase in the efficiency of task-set reconfiguration processes. See Fig. 6 (left panel).

Decision time

The ANOVA performed on decision times yielded a main effect of age group, showing an age-related decrease (572 ms [*SE* = 21] in 7-year-olds, 387 ms [*SE* = 16] in 11-year-olds, 264 ms [*SE* = 16] in 15-year-olds, and 245 ms [*SE* = 17] in 21-year-olds), $F(3,358) = 60.73$, $p < .001$, $\eta_p^2 = .337$. There was also a main effect of trial type, indicating shorter decision times on task-repeat trials relative to task alternation trials (319 ms [*SE* = 7] vs. 415 ms [*SE* = 12]), $F(1,358) = 153.89$, $p < .001$, $\eta_p^2 = .301$. A marginally significant interaction between age group and trial type indicated that switch costs on decision times tended to decrease with advancing age (101 ms in 7-year-olds, 125 ms in 11-year-olds, 82 ms in 15-year-olds, and 76 ms in 21-year-olds), $F(3,358) = 2.29$, $p = .078$, $\eta_p^2 = .019$. Follow-up

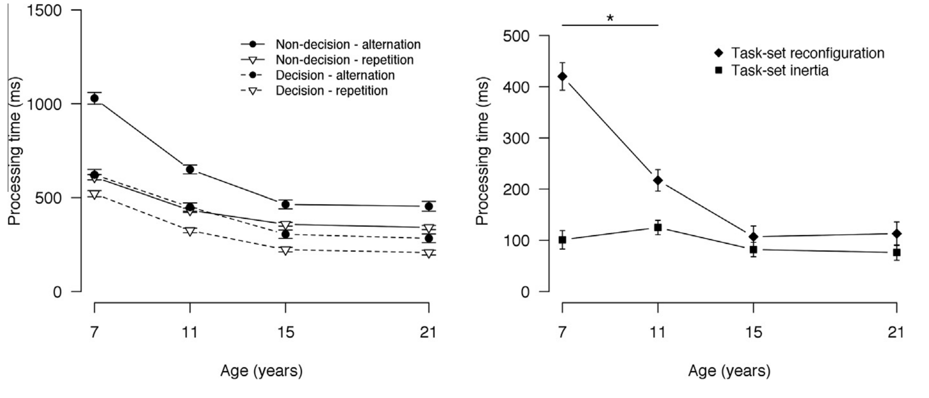

Fig. 6. Processing time of non-decision and decision-related components as a function of age group. The left panel shows non-decision time and decision time for task-repeat and task-switch trials as a function of age group. The right panel shows the developmental trajectory of task-set inertia and task-set reconfiguration effects. Error bars indicate 1 standard error from the mean. (*) Indicates a significant Time x Age group interaction ($p < .001$).

Table 4
F values obtained in three separate repeated-measures ANOVAs with age group (7-year-olds vs. 11-year-olds|11-year-olds vs. 15-year-olds|15-year-olds vs. 21-year-olds) as a between-participants variable and time (non-decision time [task-set reconfiguration] vs. decision time [task-set inertia]) as a within-participants variable.

	Comparison		
	7-year-olds vs. 11-year-olds[a]	11-year-olds vs. 15-year-olds[b]	15-year-olds vs. 21-year-olds[c]
Age group	4.76[*]	12.80[**]	.01[ns]
Time × Age group	18.03[**]	1.20[ns]	.46[ns]

Note. ns, not significant.
[a] $df = 1, 162$.
[b] $df = 1, 207$.
[c] $df = 1, 196$.
[*] $p < .05$.
[**] $p < .001$.

analyses indicated that switch costs on decision times in 7-year-olds did not differ from the effect in 11-year-olds ($p = .314$), who differed from 15-year-olds ($p = .033$), who did not differ from 21-year-olds ($p = .777$). See Fig. 6 (left panel).

Developmental trajectories

The switch costs on non-decision and decision times were transformed to *z* scores and submitted to an ANOVA to assess potential differences in developmental trajectory. The ANOVA had time (non-decision time [task-set reconfiguration] vs. decision time [task-set inertia]) as a within-participants factor in addition to the between-participants factor age group. The ANOVA yielded a significant interaction between time and age group, $F(3,358) = 17.06$, $p < .001$, $\eta_p^2 = .125$, showing that the age-related decrease in switch costs on non-decision times (task-set reconfiguration) was more pronounced compared with the decrease in decision time (task-set inertia). See Fig. 6 (right panel).

The interaction was examined further by comparing age groups using separate ANOVAs. The outcomes of these analyses are presented in Table 4. It can be seen that total switch costs decreased from 7 to 11 years of age, with a stronger decrease for non-decision time compared with decision time. Between 11 and 15 years of age, switch costs decreased, but the rates were similar for non-decision and decision times. Finally, between 15 and 21 years of age, switch costs did not change significantly.

Discussion

This study set out to examine the mechanisms underlying developmental change in cognitive flexibility by applying diffusion modeling on the data that emerged from a previous study employing a battery of executive function tasks, including a task-switch paradigm (Huizinga et al., 2006). The results are consistent with previous reports showing decreasing switch costs with advancing age (for a review, see Cragg & Chevalier, 2012). More specifically, the current results revealed that switch costs decreased from 7 to 15 years of age and then leveled off into adulthood, indicating that the ability to flexibly switch between rules is reaching mature levels during adolescence. The current developmental pattern is very similar to the one reported by Reimers and Maylor (2005), who observed that switch costs leveled off beyond 17 years of age, but differs from those reported by other studies showing that switch costs continue to decrease into young adulthood (e.g., Cepeda et al., 2001). Most likely, specific features of the task-switch paradigm contribute to the exact developmental trends reported in the literature (e.g., Cragg & Chevalier, 2012).

In the developmental literature, the ability to flexibly switch from one task set to another is typically interpreted in terms of executive control (e.g., Kray et al., 2012) or, more specifically, in terms of a reduced sensitivity to carryover effects across trials (e.g., Crone et al., 2006). The current diffusion model analysis should shed more light on the mechanisms contributing to the developmental change in task switching. Interpretations of task switching converged on the notion that multiple mechanisms must be involved during the various processing stages on a task-switch trial (e.g., Vandierendonck et al., 2010). The diffusion model seems well suited to identify some of the mechanisms that are active during these processing stages, as shown by Schmitz and Voss (2012). In the following, we discuss how parameters of the diffusion model allow for a decomposition of the mechanisms implicated in task switching.

Non-decision time (Ter)

Previous research has demonstrated that non-decision time refers to stimulus encoding and response-related processes outside the decision process proper (Ratcliff, 1978). Therefore, it seems likely that stimulus encoding and response-related processes are active on both task-repeat and task-switch trials. The current findings showed a substantial developmental trend in non-decision time, suggesting that stimulus encoding and response-related processes become more efficient when children grow older. This finding is consistent with a previous application of a diffusion model analysis to developmental change in speeded responding (e.g., Ratcliff et al., 2012). The observed developmental decrease in non-decision time is also consistent with electrophysiological studies showing age-related reductions in the latency of brain potential components related to early perceptual processes, namely N1 and P2 (for a review, see Taylor & Baldeweg, 2002). The findings are also consistent with observations showing a developmental decrease in the efficiency of response-related processes, including response preparation (e.g., Flores, Digiacomo, Meneres, Trigo, & Gomez, 2009; Killikelly & Szucs, 2013) and response activation and execution (e.g., Graziadio et al., 2010; van de Laar, van den Wildenberg, van Boxtel, Huizenga, & van der Molen, 2012).

Non-decision time was considerably prolonged on task-switch trials relative to task-repeat trials, consistent with the results reported by Schmitz and Voss (2012). In the absence of cues that signal the upcoming task set, the current lengthening of the non-decision time might be due to task reconfiguration processes and, more specifically, with the retrieval of the task set from memory (e.g., Mayr & Kliegl, 2003; for a review, see Schmitz & Voss, 2012). Importantly, the increase in non-decision time on task-switch trials decreased with advancing age, suggesting a developmental increase in the efficiency of the retrieval of task sets from memory, which would be consistent with previous studies demonstrating developmental change in active memory retrieval (e.g., Dionne & Cadoret, 2013).

Drift rate (v)

The drift rate parameter in the diffusion model reflects the speed with which information from the stimulus accumulates over time toward one of the response boundaries. Consistent with previous reports (Ratcliff et al., 2012), the current results showed an increase in drift rate with advancing age, indicating that the rate of information processing increases when children are growing older. Drift rate was more pronounced on task-repeat trials compared with task-switch trials, consistent with the findings reported previously by Schmitz and Voss (2012), who interpreted this effect to suggest that drift rate is influenced by task readiness. Importantly, the difference in drift rate between task-repeat and task-switch trials differentiated between age groups; that is, the difference in drift rate was larger in the youngest children compared with the other age groups. This finding is interpreted to suggest that the efficiency with which stimulus information is sampled reaches mature levels relatively early in development.

The analysis focusing on task-set repetitions revealed an increase in drift rate across repetitions. The observation that the information sampling rate is lower on the first task-set repetition compared with subsequent repetitions might be due to proactive interference from the previous task set, which would be more pronounced for young children compared with older children and young adults. This interpretation is consistent with the findings reported previously by, for example, Crone and colleagues (2006) (see also Gupta et al., 2009), who observed that young children suffer more than older participants from carryover effects between trials.

Boundary separation (a)

In the diffusion model, boundary separation refers to response caution. When the separation of response boundaries is large, there is more information needed from the stimulus to generate a response (Ratcliff, 1978). The current results showed a developmental decrease in boundary separation, suggesting that children respond with less caution when they are growing older. This pattern is consistent with the results observed by Ratcliff and colleagues (2012), who likewise observed that young children entertain a more conservative response style. The current findings did not reveal an effect of task switching on boundary separation. Previously, Schmitz and Voss (2012) observed larger boundary separations on task-switch trials compared with task-repeat trials, indicating that participants exercised more caution on the former relative to the latter. But this effect was observed only when participants were able to prepare for the new task set. When participants could not predict the task transition, they seemed to be cautious by default. In this regard, the current findings suggest that participants did not dynamically adjust their response boundaries based on the regularities in the trial sequences (i.e., the task set changed every 4 trials).

Additional analyses

A final set of analyses was conducted to examine the developmental trajectories of non-decision time versus decision time. Decision time was assumed to capture task-set inertia, whereas non-decision time was taken to reflect task-set reconfiguration (e.g., Schmitz & Voss, 2012). The results that emerged from these analyses showed that task-set inertia and task-set reconfiguration have different developmental trajectories. That is, task-set inertia decreased during mid-adolescence (from 11 to 15 years of age), whereas task-set reconfiguration decreased during early and mid-adolescence (from 7 to 15 years of age). This pattern of findings makes at least two important points. First, the observation of different developmental trajectories associated with task-set inertia and task-set reconfiguration contributes to the literature suggesting that multiple mechanisms are implicated in switching between tasks (e.g., Vandierendonck et al., 2010). Second, this pattern is consistent with the developmental literature suggesting that top-down mechanisms, such as task-set reconfiguration, take longer to mature than bottom-up mechanisms such as task-set inertia (e.g., Crone, Zanolie, Van Leijenhorst, Westenberg, & Rombouts, 2008).

Before closing, it should be noted that a relatively small number of trials was available for diffusion model analysis. Typically, diffusion model analysis is performed on a large number of trials per condition (e.g., Voss et al., 2013). Although the number of trials was relatively low in some conditions, the current study yielded a data pattern that is overall consistent with the findings of previous studies. Moreover, additional analyses (e.g., constraining parameters, EZ-diffusion model analysis) revealed that the current data pattern is quite robust, further heightening our confidence in the outcomes of the current study.

Conclusion

The current results are consistent with the literature showing a pronounced developmental trend in flexible rule switching (e.g., Cragg & Chevalier, 2012). The application of diffusion model analysis allowed for a decomposition of the developmental trend in task switching into a relatively early maturing mechanism, associated with task-set inertia, and a later maturing mechanism, relating to task-set reconfiguration. This pattern is consistent with neuroimaging results reported previously by, for example Crone, Donohue, Honomichl, Wendelken, and Bunge (2006), who observed two neural mechanisms involved in task switching: an early maturing mechanism, relying on the (pre-)supplementary motor area (see also Mansfield et al., 2011) and presumably related to task-set inertia, and a later maturing mechanism, implicating the ventrolateral prefrontal cortex and most likely associated with task-set reconfiguration. It would be of considerable interest to combine diffusion modeling and neuroimaging in future developmental studies investigating the mechanisms underlying flexible rule use and their developmental trajectories.

Acknowledgment

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Appendix

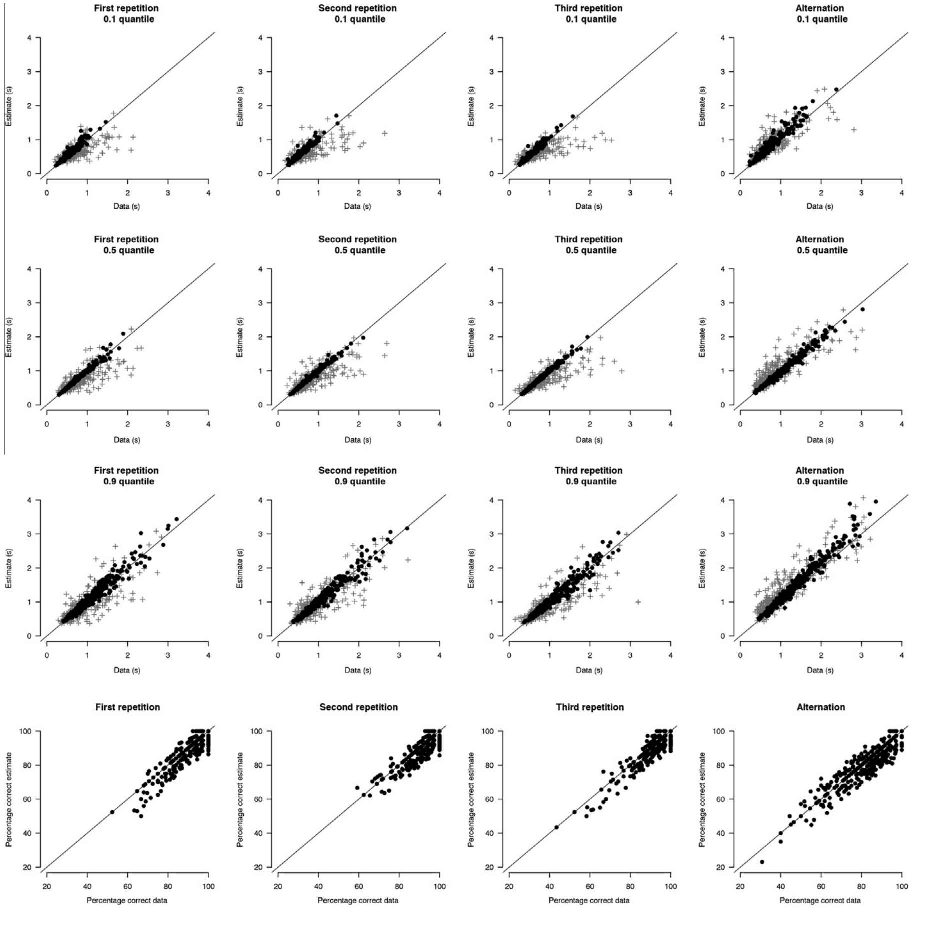

Fig. A1. Fits for the diffusion model. Observed RT (*x* axis) and estimated RT based on diffusion model parameters (*y* axis) of all participants for all trial types (first, second, and third repetitions and alternation) are shown. Solid black dots indicate correct responses, and gray crosses indicate error responses. Perfect fit would be obtained if a dot (or a cross) falls on the diagonal line. Fits are given for fast RTs (first row), median RTs (second row), and slow RTs (third row). The bottom row shows observed and estimated accuracy data (percentage correct) for all trial types.

Table A1
Diffusion model parameter estimates.

Parameter	Drift rate (v)		Boundary separation (a)		Non-decision time (Ter)	
	Mean	*SD*	Mean	*SD*	Mean	*SD*
Age 7 years						
Repetition 1	1.03	0.47	1.94	0.63	0.60	0.20
Repetition 2	1.05	0.40	1.82	0.42	0.61	0.16
Repetition 3	1.09	0.62	1.89	0.76	0.62	0.20
Alternation	0.57	0.41	1.83	0.34	1.03	0.39
Age 11 years						
Repetition 1	1.71	0.80	1.73	1.01	0.43	0.16
Repetition 2	1.92	0.87	1.72	0.97	0.43	0.14
Repetition 3	1.82	0.64	1.57	0.51	0.43	0.12
Alternation	0.95	0.48	1.60	0.46	0.65	0.25
Age 15 years						
Repetition 1	2.38	0.94	1.37	0.64	0.37	0.11
Repetition 2	2.48	0.97	1.46	0.85	0.36	0.10
Repetition 3	2.49	0.91	1.46	0.72	0.35	0.10
Alternation	1.42	0.68	1.40	0.73	0.46	0.16
Age 21 years						
Repetition 1	2.60	0.97	1.41	0.76	0.35	0.11
Repetition 2	2.63	1.06	1.48	0.86	0.33	0.09
Repetition 3	2.74	0.95	1.34	0.45	0.34	0.08
Alternation	1.67	0.94	1.47	1.01	0.45	0.19

Note. Estimates of diffusion model parameters per trial type and age group are shown. We calculated mean values by averaging parameter estimates for each trial type over all participants within an age group. The standard deviations of these values are shown in the *SD* columns. The parameters v, a, and Ter indicate drift rate, boundary separation, and non-decision time (in seconds), respectively. Note that estimates of z (starting point) are omitted because this parameter is fixed to $a/2$.

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