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Perceptual Biases During Cued Task Switching Relate to Decision Process Differences Between Children and Adults

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Previous work suggests that children engage preparatory processing differently than adults in cued task switching. One potential consequence is that they are differentially biased by visual properties of the stimuli, for example, target-choice similarity. We tested this possibility in 215 children and young adults ranging from 6 to 27 years of age. Participants played a cue-target game with varying levels of working memory and attentional demand where they matched multidimensional stimuli according to a cued dimension. Younger age, low working memory demand, and matching fine grained dimensions (i.e., pattern) increased the bias of target-choice similarity on task performance. Older age, high working memory, and matching global dimensions (i.e., shape) mitigated the bias. Developmental transitions to adult performance differed by task demands but generally occurred during adolescence. A drift diffusion analysis revealed age and task differences in decision making strategies consistent with how similarity impacted task performance, indicating that, especially with low working memory demand, children made impulsive, similarity-driven decisions. Our findings support the idea that children engage in preparation strategies that exacerbate perceptual biases on task performance; improvements are observed with age or through changes in task structure and stimuli. These results have implications for interpreting cognitive control performance in children.

Public Significance Statement

Task control allows people to flexibly respond to a changing environment, and continues to mature through adolescence. Here, we test how controlled attention to information is impacted by related yet task-irrelevant properties of visual objects. Across middle childhood to young adulthood, irrelevant information biased decision making suggestive of age-related differences in task control strategy. We probe the stability of these age effects by manipulating working memory demand through removal of visual supports, or by directing attention to aspects of a stimulus that are more global (i.e., shape) than fine-grained (i.e., pattern). These manipulations reduced similarity biases in all ages by shifting control strategy; however, developmental differences remained. Overall, children appear to not take advantage of advance information nor time to set up filters for their attention until late adolescence. This study contributes to our understanding of cognitive flexibility, a core function related to academic and life success.

Keywords: selective attention, task control, similarity, working memory, drift diffusion model

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In response to changing task demands, children have more difficulty than adults adapting their responses and engaging flexible task control (Cepeda, Kramer, & Gonzalez de Sather, 2001; Crone, Bunge, van der Molen, & Ridderinkhof, 2006; Davidson, Amso, Anderson, & Diamond, 2006; Diamond, 2013). Cognitive flexibility falls under the general executive functioning or cogni-

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tive control umbrella (Diamond, 2013; Miyake et al., 2000), and involves updating, reconfiguring, and implementing mental task sets across continually changing task demands (Kiesel et al., 2010; Logan & Gordon, 2001; Monsell, 2003).

This flexibility can be achieved in a proactive (i.e., maintaining goal-relevant information in anticipation of an event) or a reactive manner (i.e., late information processing in response to an external probe or interference) under the dual mechanisms model of cognitive control (Braver, 2012; Braver, Gray, & Burgess, 2012). Across development, it is thought that young children predominantly recruit cognitive control processes in a reactive manner and become more proactive with age (Munakata, Snyder, & Chatham, 2012). In a recent neuroimaging study of cued task switching, children had less cue-related brain activity and more target-related brain activity than adults, consistent with children recruiting later, more reactive control strategies, and adults relying more on preparatory, proactive strategies. More important, as children's preparatory and target neural activity increasingly resembled the adult pattern with age, it also tracked with improvements in task performance (Church, Bunge, Petersen, & Schlaggar, 2017). These results provide burgeoning evidence that differences in reactive or proactive stimulus processing may be a factor in explaining developmental gaps in flexible task performance. Reactive and proactive strategies can be indexed by sustained selective attention in target-distractor tasks (Doebel et al., 2017), suggesting that preparatory differences could relate to the efficacy of selective attention to multidimensional stimuli like those typically used in task-switching studies (Hanania & Smith, 2010; Kloo & Perner, 2005). The central aim of our study was to investigate how reactive and proactive preparatory strategies, working memory demand, and selective attention interact to influence flexible task performance across age using a drift diffusion model (DDM) of the decision process.

Selective Attention to Perceptual Features Across Development

Children are more likely than adults to process irrelevant information in their perceptual environment (Plude, Enns, & Brodeur, 1994; Ristic & Enns, 2015; Shepp, 1983), a signature of failed selective attention. In particular, global features capture their perception in selective attention tasks. While both adults and children *can* attend to global and local aspects of stimuli, there are many contexts where young children prioritize global features (Huizinga, Burack, & Van der Molen, 2010; Kimchi, Hadad, Behrmann, & Palmer, 2005; Krupskaya & Machinskaya, 2012; Vinter, Puspitawati, & Witt, 2010). Children can use overall similarity between multidimensional stimuli as a main categorization strategy (Smith, 1981), for example, grouping cartoon people by number of shared features, despite knowledge of the critical category feature (a symbol on their stomach; Deng & Sloutsky, 2015).

While children, compared with adults, demonstrate difficulty filtering irrelevant information,[1] this global bias reduces with age (Plude et al., 1994; Ristic & Enns, 2015). Here, we focus on selective attention to one of an object's multiple dimensions as often used in task-switching studies (Church et al., 2017; Kloo & Perner, 2005). Because of the global processing tendency in children, cases where the target-choice stimulus similarity is high (i.e., the target matches the response choice on more features than just the relevant one) should be more easily and more accurately processed; the strength of this target-choice similarity bias should decrease over development.

Attentional filtering may operate in similar ways across cognitive processes (Chun, Golomb, & Turk-Browne, 2011), but the deployment of selective attention may depend on preparatory strategy and associated costs. Theory suggests that proactive control encourages advanced setting of sustained attentional templates that bias attention both toward relevant information and away from irrelevant information (Braver, 2012; Chun et al., 2011; Miller & Cohen, 2001). While direct developmental links between attention and control are currently being established (Amso & Scerif, 2015), selection among visual search distractors is linked to proactive control in tasks that force preparation for children as young as five (Doebel et al., 2017). Conversely, reactive strategies should lead to more sensitivity to exogenous stimulus cueing (e.g., similarity), and generate greater costs for implementing selective attention filters later in the decision process because of working memory gating, as discussed further in the next section.

Cognitive Flexibility and Working Memory Are Slow to Mature

Cognitive flexibility and working memory are key factors of executive functions, a set of regulatory processes that support goal directed behaviors (Diamond, 2013; Miyake et al., 2000). Given the importance of goal maintenance to cognitive control, working memory is likely intimately related to task control strategy. Difficulty representing multiple stimulus–response associations and task rules is associated with cognitive control errors, especially in childhood (Cragg & Chevalier, 2012; Crone, Donohue, et al., 2006; Karayanidis, Jamadar, & Sanday, 2013; Logan, 2004; Mayr & Kliegl, 2000; Philipp, Kalinich, Koch, & Schubotz, 2008). Rudimentary working memory capacity develops as early as infancy, while the ability to manipulate information in working memory develops in middle childhood. This ability is closely tied to cognitive flexibility (Crone, Wendelken, et al., 2006; Davidson et al., 2006; Diamond, 2013), which requires maintaining and updating task-relevant information as new tasks come into play (Amso, Haas, McShane, & Badre, 2014; D'Esposito & Postle, 2015). For example, the strength of task representation in working memory, as shown by faster retrieval of task knowledge, supports task-switching behavior in young children (Blackwell, Cepeda, & Munakata, 2009). The less one prepares for a task, the less a task set will be robustly active in working memory, although the relevant mechanism may depend on age. For instance, recent evidence in the development of rule-guided behavior has associated the use of proactive strategies in adolescents with the filtering of information into working memory (i.e., input gating), while children's use of reactive strategies related to selecting information

[1] Tasks that demonstrate when selective attention fails in children have involved attending to a target surrounded by irrelevant distractors (Booth et al., 2003; Bunge, Dudukovic, Thomason, Vaidya, & Gabrieli, 2002; Donnelly et al., 2007; Huang-Pollock, Carr, & Nigg, 2002) and attending to a single object with multiple dimensions (Hanania & Smith, 2010; Kemler, 1983; Lane & Pearson, 1982; Pomerantz, Pristach, & Carson, 1989; Shepp, 1983; Shepp & Barrett, 1991; Shepp et al., 1987; Tipper, Bourque, Anderson, & Brehaut, 1989).

out of working memory (i.e., output gating; Unger, Ackerman, Chatham, Amso, & Badre, 2016).

Preparation strategies also likely shift according to the availability of task-relevant information. Strategy use may be linked to management of relative cognitive costs, as selective output gating can be more resource intensive than nonselective output gating and selective input gating. Therefore, when working memory demand is low because all task-relevant information is available, proactive strategies may be too costly for children whom have difficulties updating information into working memory (Amso et al., 2014). Some reactive strategies that require selective filtering, relative to simply using all available information, may also be costly as they require effective inhibitory neural pathways (Frank & Badre, 2012). When memory demand is high because relevant information is not available during the decision, output gating or reactive strategies would lead to worse performance. Performance would therefore rely on late processing of incomplete information, pushing all ages toward more proactive, input gating, strategies. However, because of differing ability to update working memory over age, the use of a proactive strategy may still show developmental differences in performance (Unger et al., 2016).

Selective Attention, Working Memory, and Cognitive Flexibility May Interact to Impact Task Performance

Only recently has the field examined the interplay between selective attention and cognitive flexibility (e.g., Hanania & Smith, 2010; Meiran, Dimov, & Ganel, 2013). There are reasons to believe that these two processes mutually develop with age, and are more interrelated in childhood (Amso & Scerif, 2015). For example, failure to switch predominately occurs with multidimensional stimuli (Cragg & Chevalier, 2012). While young children can switch to a new rule when selective attention is not required (e.g., when stimulus information is held constant or when dimensions are spatially separated; Kloo & Perner, 2005), they often fail to switch when they must ignore irrelevant dimensions (Brooks, Hanauer, Padowska, & Rosman, 2003). Further, the nature of dimensions themselves may play a role. Eye-tracking data suggest that switch costs may be driven by preferential attention to shape over color (Chevalier, Blaye, Dufau, & Lucenet, 2010), indicating that attention among asymmetrically salient dimensions plays a critical role in task-switching performance in younger ages.

Here, we link selective attention and cognitive flexibility in later childhood through the dual mechanisms model by hypothesizing that improper task preparation should lead to a greater reliance on late reactive control, resulting in poorer selective attention and, thus, target-choice similarity bias in cued task switching, that is, the interference of irrelevant matching features on task performance. As task preparation improves over age, increasing proactive engagement with the cue should result in less target-choice similarity bias. Moreover, similarity bias may be determined by the cued dimension itself (e.g., shape), and interact with working memory demand, such that different memory demands change the type of task control used (Doebel et al., 2017).

DDMs Analyze Components of a Decision

To assess preparation strategies used by adults and children under varied cognitive load, we used a prominent computational model of perceptual decision making, the DDM (see Method for implementation details; Ratcliff, 1978; Ratcliff & McKoon, 2008). The DDM operationalizes perceptual decisions as a noisy accumulation of evidence toward response thresholds and accounts for response probabilities and reaction time (RT) distributions based on a core set of parameters (Voss, Rothermund, & Voss, 2004). Referring to Figure 1, after a stimulus is perceptually encoded, evidence stochastically accumulates over time toward the correct or incorrect response boundary separated by threshold distance (a), representing how much evidence is needed before a response is activated and a measure of response conservatism. The random walk of the evidence accumulation is summarized by a directional vector called the drift rate (v; the arrow in Figure 1), also interpreted as a measure of task difficulty or person ability. The positive or negative sign of a drift rate indicates evidence toward the top or bottom thresholds, respectively, and the magnitude indicates how quickly it reaches that boundary. Once the evidence reaches a boundary, the motor response is activated. The time it takes for motor responses and perceptual encoding make up the nondecision time (T_{er}).

DDMs have previously been used to study decisional components in task switching across development (Ratcliff, Love, Thompson, & Opfer, 2012; Weeda, Van der Molen, Barceló, & Huizinga, 2014). Here, we used a DDM to quantify how decision parameters change on a trial-by-trial basis because of stimulus similarity and across between-subjects variables like age group and memory demand. By doing so, we not only isolate the factors that influence task performance, but also link their influence to specific mechanisms of the decision-making process. For example, the relation between target-choice similarity and the drift rate may help index attention mechanisms. Because drift rate is affected by the quality of evidence available to attention, a greater match would lead to better signal-to-noise ratio. If selective attention fails, the drift rate should increase with similarity and if selective attention is successful, the drift rate's relation to similarity should be minimized. In contrast, threshold distance would not vary with similarity because threshold distances are generally driven by

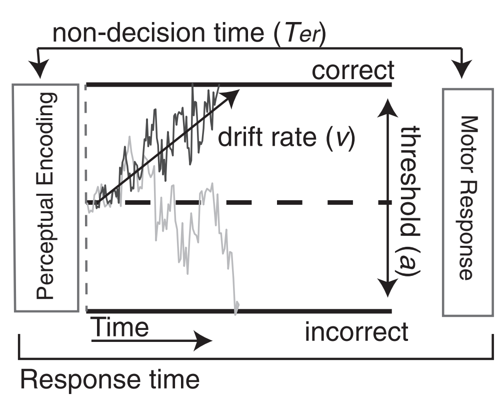

Figure 1. Diagram of hypothetical correct and incorrect response times decomposed into the drift diffusion model components. The top (dark gray) random-walk line represents hypothetical evidence accumulation toward a correct response in a single decision trial. Once the top line touches the "correct" threshold, a motor response is initiated. Likewise, the bottom line (light gray) represents hypothetical evidence accumulation toward an incorrect response.

changes in response style because of the task structure (Ratcliff et al., 2012). Shorter impulsive distances produce quicker and less accurate responses while larger distances produce slower and accurate responses. More important, the combination of the drift rate and threshold distances provide an avenue for assessing task strategy across changing task demands and age groups. Based on the literature we have just summarized, we expect a similarity effect on the drift rate along with shorter threshold distances in children and those with more reactive strategies. The latter is because of a higher level of impulsivity needed to respond quickly when the bulk of control and stimulus processing happens after the target appears. In proactive strategies, we expect little to no similarity effect on the drift rate and larger threshold distances.

While the T_{er} parameter does not necessarily factor into our hypotheses, similarity could also facilitate perceptual encoding of the stimulus or motor response, as evidenced by a reduced estimate of nondecision time. For example, masked priming, in which stimulus information is briefly previewed, provides quicker encoding of a target and manifests as a shorter T_{er} parameter (Gomez, Perea, & Ratcliff, 2013). Similarity in multiple domains, including semantic (Xiong, Franks, & Logan, 2003) and task (Arrington, Altmann, & Carr, 2003) similarity, also prime performance across trial repetitions suggesting similarity may also affect T_{er}.

Current Study

Although it has been shown that selective attention improves with age (Plude et al., 1994; Ristic & Enns, 2015), its relation to preparatory processing, working memory demand, and stimulus dimensions throughout development remains unknown. The central analysis examined the conditions under which selective attention is effectively used or hindered over age, and linked these effects to task control strategy by modeling the corresponding decision components using DDM.

We developed a nonlexical cued feature-matching game that allowed us to examine the interference of task-irrelevant features on response selection across cognitive load and development. We indirectly measured the efficacy of selective attention as a function of performance across target-choice similarity. We predicted that if a participant failed to selectively attend, possibly as a consequence of suboptimal preparation during the cue period and reactive stimulus processing, they would process the stimuli more globally and rely more on matching by overall similarity. In contrast, if a participant selectively attended to the cued feature, likely due proactively loading task parameters in advance, their performance would be less affected by target-choice similarity.

Moreover, having all relevant task information on screen when the target appears (i.e., low working memory demand) would provide the opportunity for children and adults to use either strategy, which can be indexed by the existence or absence of a similarity effect. Conversely, removing the cue and response choices when the target appears (i.e., high working memory demand) limits task control for successful performance to a proactive strategy and should theoretically show no effect of target-choice similarity for both age groups, if both are able to use proactive control successfully. Continued similarity effects with high working memory demand; thus, indicate less ideal proactive updating of working memory.

Lastly, the hypothesized attentional consequences of different preparatory strategies may be exacerbated or alleviated by properties of the stimulus. Matching on a global feature like shape may not be as impacted by a failure of selective attention as matching on a more fine-grained feature that requires careful attention to isolate.

Method

Participants

A total of 132 adults and 127 children enrolled in the study. Participants were screened and disqualified from participating for color blindness, psychoactive medications, psychological disorders, native foreign language, and impaired vision. Adults and parents of minors provided informed consent, while minors provided informed assent. Undergraduate students were compensated with course participation credit, while other adults and children received $10 for completing the game. There were 12 adults (9 female, mean age = 19.7) and 13 children (7 female, mean age = 9.8) who were excluded from the low memory demand condition because of computer errors or failure to meet eligibility requirements. An additional five participants were excluded from this condition for having accuracy or response times (RTs) greater than 2.5 *SD* from the mean in at least 4 out of 10 levels of the game. These exclusion criteria were consistent with another analysis of this dataset (Bauer, Martinez, Roe, & Church, 2017) and meant to provide an outlier threshold that retained child data indicative of good faith performance, even if up to three levels were aberrant relative to their peers. We also excluded 12 adults (5 female, mean age = 19.38) and 7 children (5 female, mean age = 8.86) from the high memory demand for the same reasons, which included four performance outliers. The final sample included 108 young adults from the University of Texas at Austin (*M* = 20.24, *SD* = 1.94, range = 18–27; 56 female) and 107 children recruited from the city of Austin (*M* = 11.29, *SD* = 2.39, range = 6–16, 51 female) who participated in the experiment in accordance with The University of Texas Institutional Review Board (protocol #2012–09-0095). Participants were randomly assigned to the different experimental conditions. We report data from 60 young adults (30 females, mean age 20.33 years, *SD* = 2.10) and 60 children (30 females, mean age 11.36 years, *SD* = 2.62) for the low working memory demand version of the experiment and 48 adults (22 females, mean age 20.14 years, *SD* = 1.74) and 47 children (26 females, mean age 11.21 years, *SD* = 2.09) for the high working memory demand version. Sample size estimation from post hoc power analyses given our results can be seen in the online supplementary material E. We control for the between subject manipulation of the frequency of trials in which the target was an identical match to one of the response choices (0, 20, and 40%).

Task

The task was the same as reported in (Bauer et al., 2017). Participants completed a computer-based game that progressively increased in difficulty over multiple levels. Participants were asked to sort a target picture based on one of four different visual features: Shape, Inner color, Outer color, and Pattern (see Figure 2).

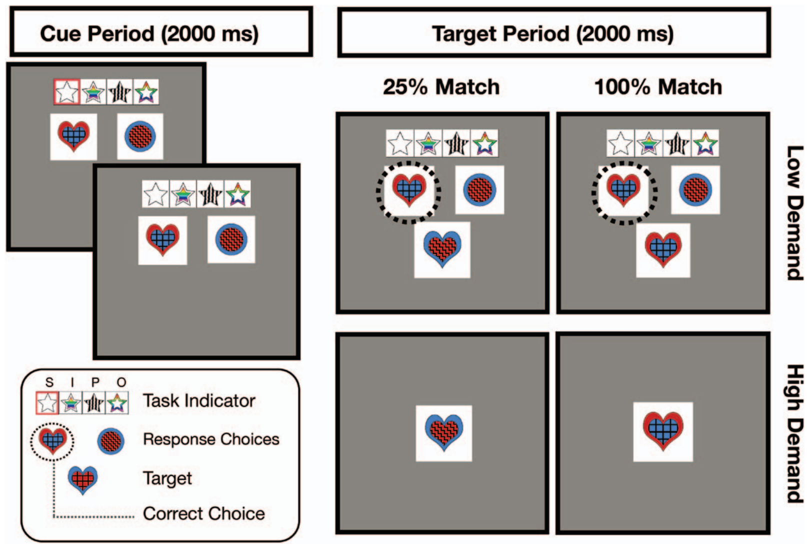

Figure 2. Task diagram. Each trial had a duration of 4,000 ms. During the cue period, the response choices, task indicator bar, and red task cue were displayed for the first 1,500 ms. The tasks in order: Shape (S), Inner color (I), Pattern (P), Outer color (O; this example is a "Shape" trial). The red task cue then disappeared for 500 ms. In the low working memory demand version, the target then appeared for 2,000 ms below the response choices while the response choices stayed on screen. The dashed circles indicating the correct choice in this figure were not present in the experiment. In the high working memory demand version, the bar and response choices disappeared when the target appeared for 2,000 ms. Depicted are examples of 25 and 100% match trials across the two working memory conditions. (The task also contained 50 and 75% match trials.) The figure only shows two choice trials; however, some levels had four choice trials with four options in the second row.

The task screen consisted of three primary elements: a task indicator bar, the response options, and a target stimulus (Figure 2, inset). The task indicator bar displayed four task cues (star icons that each represented one of the features), and a transient red box that cued each trial's relevant feature by outlining the appropriate star cue. The task order was unpredictable. Each feature had one of four options: Shape - heart, diamond, square, or circle; Inner or outer colors - red, blue, orange, or green; Pattern - dot, zigzag, grid, or X's. The response choices for each trial were displayed below the task indicator bar and contained as many features as were being cued on that level (2 or 4). The task feature was cued in the task indicator bar with a red outline for 1,500 ms, which then disappeared for 500 ms. Then the target stimulus appeared for 2,000 ms and participants were instructed to respond by indicating which response choice matched the target stimulus on the cued feature. Participants made response choices by pressing one of four buttons on a USB game controller made by Delcom Products. The number of displayed response choices (2 or 4) mapped directly to the number of buttons in the respective level. The target stimulus picture matched one of the response choices on the cued feature, such that there was always only one correct choice, but it could also match the response choice on any of the uncued features as well (see below). Target and response choice stimuli were displayed as 4.5 × 4.5 cm during the game.

Within each trial, the correct response matched the target on zero to three task-irrelevant features beyond the cued feature leading to a 25 (cued feature only), 50, 75, or 100% similarity in each trial, while the incorrect response choice(s) provided varying amounts of false-lure similarity (0–75%). The similarity was unpredictable on any given trial. Participants were randomly assigned to a 0, 20, or 40% congruency condition. The condition label indicates the overall percentage of trials across the whole experiment with a 100% target-correct response similarity. We predicted 0% should be the hardest condition because none of the trials depicted an exact match. This manipulation was a focus of a larger study (Bauer et al., 2017); here we statistically control for it. For details on the distribution of target-choice similarity trials (25–100%) in each of the three congruency conditions, see the online supplementary material B.

The experiment was implemented using PsychoPy (Peirce, 2007, 2009) on Apple 13 in. Macbook Pro laptops with USB 4-button boxes and lasted approximately 45 min. Participants completed either a low or high working memory demand version of the game (see Figure 2). In the *low demand condition*, the response choices and task indicator bar remained on the screen, and the target appeared below, requiring the participant to remember only which task feature was cued. In the *high demand condition*, the response cues and task indicator bar disappeared after 2,000 ms and the target appeared alone on screen, requiring the participants to remember not just the cued feature, but also the response choices. The first 2,000 ms of each trial (the cue period) was identical across both versions.

For both demand versions, the game contained 10 levels that had the following manipulations: *number of response choices* (two or four), *number of cued task features* (two, three, or four), and stimulus-response (S-R) *mappings* (consistent—same response choices every trial, inconsistent—different response choices every trial, mixed—alternating blocks of consistent and inconsistent trials; Table 1). Level 10 was identical to the structure of Level 1 with different stimuli. Levels 1, 2, and 10 contained 25 trials, Level 3 contained 31 trials, and the rest of the levels contained 53 trials for a total of 424 trials per person in a full data set. Participants also completed a practice level that consisted of 25 self-timed trials with two choices and two cued features. For this analysis, we excluded data from Level 3 (the only level with 3 cued features, resulting in low power for studying 33 and 66% match stimuli), and Level 10 (the repeated Level 1). While the behavioral analysis included all remaining levels to maximize statistical power and because it can accommodate levels with more than two response choices, the DDM included only Levels 4, 5, and 6 because they had a binary choice (see details in Hierarchical DDM).

Within the levels, the following variables were manipulated: *cued dimensions* (one of the four dimensions), *similarity* (the proportion of dimensions that matched between the correct answer and the target), *task switch* (whether the cued dimension repeated from the previous trial or switched), and *response switch* (whether the correct answer remained in the same location or switched). All manipulations were counterbalanced across participants. This analysis uses part of a larger study examining general development of cued task switching (Bauer et al., 2017); therefore, we limit the scope here to an analysis of the perceptual stimulus effects and group-level manipulations. For data exclusions, see the online supplementary material A.

Analysis

Mixed effect multiple regression models. RT and accuracy data were analyzed with mixed effect linear and logistic regression models on the raw data using lme4 Version 1.1.12 and lmerTest Version 2.0.33 (Bates, Maechler, Bolker, & Walker, 2014; R Core Team, 2015). We used a top-down modeling approach (West, Welch, & Galecki, 2015). First, we included all fixed effects of interest, then removed nonsignificant predictors, and finally specified the maximal random effects structure (Barr, 2013; Barr, Levy, Scheepers, & Tily, 2013). All models were fit using Maximum Likelihood estimation. The main focus of the analysis was target-choice similarity with age group and working memory demand as between-subjects moderators and cued feature and task switch as within-subject moderators. Initial models included 6 three-way interactions of interest (Similarity × Age × Memory Demand; Similarity × Age × Task Switch; Similarity × Age × Feature; Similarity × Memory Demand × Task Switch; Similarity × Memory Demand × Feature; Similarity × Task Switch × Feature) and control variables consisting of the remaining game manipulations (Response Mapping, Number of Features and Choices, Frequency Proportion, and Response Switch). Predictor significance was assessed using Type II Wald χ^2 tests from the Companion to Applied Regression (CAR) package Version 2.0.26 (Fox & Weisberg, 2011). Models included varying intercepts and slopes for participants and varying intercepts for target stimuli as crossed random effects, which were allowed to correlate. If the model did not converge, we removed higher-level interactions from the random effects first. If models continued to fail, we removed lower level interactions with the lowest variance from the random effects. For regression coefficient tables of main effects and interactions, see Table 1 and Table 2 in supplementary material C.

Estimated slopes, confidence intervals, and comparisons were computed at the reference levels of the control variables (consistent mapping, task repeat, 2 cued features, 2 response choices, and response repeat) using the Least-Squares Means (lsmeans) package Version 2.25 (Lenth & Hervé, 2015). Similarity was centered on 25% and scaled by .25 to provide meaningful intercepts and interpretable slope estimates, where each unit represented a 25% change in similarity. Condition comparisons are reported using Wald z tests (Luke, 2016).

To simplify the analysis, we dichotomized the participants as adults or children. However, we also examined age as a continuous variable as well as smaller age bins in secondary analyses (see supplementary material Figure D2 and Figure D3). For the smaller bin analyses, we grouped the children into 2-year age bins and included all adults in one bin to achieve a finer-grained analysis of potential developmental transitions in our measures. All attempts to fit a model using a continuous age variable failed to converge; therefore, we only report the bin analyses. Data and analysis scripts can be found at the Open Science Framework archive (Martinez, Mack, Bauer, Roe, & Church, 2018).

Hierarchical DDM. We modeled drift diffusion parameters (drift rate, threshold, and nondecision time, respectively, v, a, and T_{er}) for each group (adult high working memory demand [AH], adult low working memory demand [AL], and child high and low working memory demand [CH and CL], respectively), separately to provide a decisional mechanism to explain the interactive effects of age, memory demand, and similarity on task performance. Because a DDM is a model for binary choices and we wanted to examine the full range of similarity, we restricted subject data to Levels 4–6, which contained two choices and all four cued features for a total of 156 trials per participant. Similarity was centered at 25%, but not scaled, for this analysis.

Hierarchical Bayesian estimation with Markov-chain Monte-Carlo sampling using the HDDM python package (Version 0.5.3) was used to estimate posterior distributions for the DDM parameters (Wiecki, Sofer, & Frank, 2013). Similarity could affect the drift rate as facilitated evidence accumulation or nondecision time as priming, or both. Using a model comparison approach, we manipulated which parameters were estimated as static over all

Table 1
Description of Level Characteristics

	Within-subject manipulations		
Level	Number of cued features	Number of response choices	Mapping consistency
1	2	2	Consistent
2	2	2	Mixed
3	*3*	*2*	*Consistent*
4	**4**	**2**	**Consistent**
5	**4**	**2**	**Mixed**
6	**4**	**2**	**Inconsistent**
7	4	4	Consistent
8	4	4	Mixed
9	4	4	Inconsistent
10	*2*	*2*	*Consistent*

Note. DDM = drift diffusion model. Levels not used in this set of analyses are italicized. The bolded levels were used for the DDM analysis.

trials or allowed to covary with similarity on a trial-by-trial basis across three models for each group. The *v-only* model regressed similarity information on the drift rate only while estimating a static T_{er} and threshold distance. The T_{er} *-only* model regressed similarity on T_{er} while estimating a static (v) and (a). The vT_{er} model regressed similarity on drift rate and T_{er} while keeping the threshold static. The starting point (z) was fixed halfway between the boundaries for all models. All three models were compared within each group type for the lowest deviance information criterion (DIC) value, which penalizes complexity to assess best fit for hierarchical models (Spiegelhalter, Best, Carlin, & Van Der Linde, 2002).

Behavior from the CH and AL groups were best accounted for by the *v-only* model (online supplementary material Table 3). For the AH and CL groups, the DIC differences between the vT_{er} and *v-only* models were marginal and the effects of similarity on T_{er} were also minimal (βs $= -.0001$), suggesting the *v-only* model was most parsimonious for all groups. We examined group-level differences in nondecision time, relative thresholds, and how average drift rate shifted dynamically on a trial-by-trial basis with target-choice similarity. By using Bayesian parameter estimation, we were able to directly compare posterior distributions (Wiecki et al., 2013); thus, the p values ("P") indicate the proportion that a posterior distribution is overlapping with another. We regarded a "P" of 0.05 or less as indicating a significant difference between two posterior distributions. We generated 10,000 bootstrapped samples while discarding the first 5,000 to allow the chain to stabilize before recording samples. Chain convergence was assessed using the Gelman-Rubin (^R) statistic that compares within-chain to between-chain variance of iterations of the same model. The models were run three times and none of the estimates had a ^R statistic of more than 1.01, indicating a lack of convergence problems. We also visually inspected each parameter's trace for a lack of pattern and marginal posteriors for a uniform distribution. Models assumed that 0.5% of the trials were outliers to mitigate the effect of outliers on parameter estimates (Wiecki et al., 2013).

Results

We first report a manipulation check to see if there exists an effect of target-choice similarity on general task performance, then test the impact of age group (adult vs. child) and working memory load on similarity bias, and finally the report corresponding DDM indices. These factors provide an insight into preparatory processing, target similarity, and effects on task execution. Then we report the stimulus-level moderators to highlight additional effects of the cued features of the stimuli on similarity bias.

As secondary exploratory analyses, we tested smaller age bins within the child group to examine developmental transitions, and also tested how similarity bias was related to switch costs (i.e., comparing trials that switched to a different cued feature, vs. trials that repeated the same cued feature as the previous trial), an index of cognitive flexibility. Readers are directed to online supplementary material D for the results of the age binned developmental transitions and stimulus similarity effects on switch costs (see online supplemental material Figure D1, Figure D2, and Figure D3).

General Performance

Does target-choice similarity affect task performance? To examine more complex moderators of similarity effects, we first need to assess whether the data show any indication that manipulating target-response similarity influenced performance. If so, we expect that accuracy will increase and RT will decrease with increasing similarity.

Descriptive statistics.

Accuracy. Overall, the accuracy in the 25% similarity condition ranged from 57 to 86% while accuracy in the 100% match ranged from 79 to 98% (Figure 3A). These results suggest that while the groups all performed above chance, the more similar the target was to the correct response, the more likely it was that the participant got it correct.

Response times. RTs ranged from 701 to 942 ms in the 25% similarity trials and from 591 to 842 ms in the 100% similarity trials, suggesting there was a quickening in response as similarity increased (Figure 3B).

Regression estimates.

Accuracy. There was a simple effect of similarity on accuracy (Wald's $\chi^2(1) = 734.45$, $p < .0001$), where the odds of answering correctly increased with similarity between the target and response ($b = 1.57$, 95% confidence interval, CI [1.41, 1.74]).

Response times. There was also a simple effect of similarity on RT (Wald's $\chi^2(1) = 464.5$, $p < .0001$). RTs generally decreased across similarity ($b = -1.3$, 95% CI [-18, -4]). These general effects verified our manipulation check that selective attention was needed, and more challenged, at lower similarities.

Group and Task Moderators and DDM Components

Are similarity effects moderated by age group and working memory demand? This section assesses the evidence for our main hypotheses: that differences in preparatory processing drive age gaps in task switching through selective attention and this is moderated by the presence or absence of task-relevant information during the decision phase. Specifically, if participants use a reactive strategy, this will be indexed by a large similarity effect on performance and drift rates because of reliance on global stimulus processing and small thresholds. However, a proactive strategy will be shown by a smaller or nonexistent similarity effect on performance and drift rates and larger thresholds. Children and adults may use either strategy when all information is available during the decision (low working memory demand; LWMD). This is also the case when relevant information is removed during the decision phase (high working memory demand; HWMD), but participants may be pushed toward proactive strategies because reactive processing would depend on incomplete information. Therefore, we expect smaller similarity effects in the HWMD condition than LWMD for either group. However, we may expect that children still exhibit significant similarity effects in both conditions because of dominant reliance on reactive strategies that would increase global similarity matching.

Descriptive statistics. The descriptive statistics provide the range of performance from the lowest and highest similarity trials (Table 2; Figure 3A and 3B). For the full table of descriptive statistics and 95% CIs, see online data archive (Martinez et al., 2018).

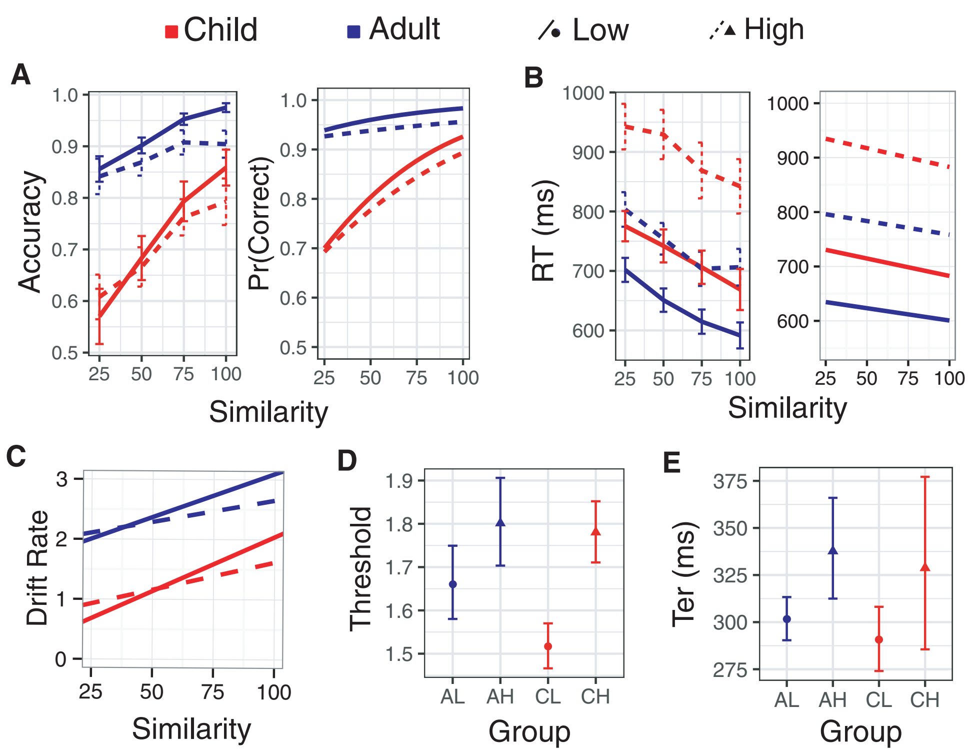

Figure 3. Performance averages and regression estimates of the impact of similarity on task performance and drift diffusion model (DDM) parameter results. Across the plots, adult data are in blue (darker) and children in red (lighter) while the low demand condition data are in solid lines or dots and high demand in dashed or triangles. The *x*-axis reflects a 25% (cued-feature match only) to 100% (full match) similarity range between the target and the correct response. (A left panel) Average accuracy performance. (A right panel) The probability of choosing the correct answer from the logistic regression. (B left panel) Average response times (RTs). (B right panel) Predicted RTs from the linear regression. For smaller age-bin analyses, see online supplementary material Figure D2. (C) Drift rate estimates across similarity. (D) Threshold distance estimates. (E) T_{er} estimates. Error bars in A and B represent 95% confidence intervals while error bars in D and E represent 95% credibility intervals. See the online article for the color version of this figure.

Accuracy. Average performance increased with similarity in each age group; however, the magnitude is greater for children, by 18 to 29%, and the lowest for adults in the HWMD condition with an improvement of 6%.

Response time. Greater similarity decreased RT across groups by 97 to 110 ms.

Regression estimates.

Accuracy. We tested the interaction between age group, similarity, and working memory demand to determine whether accuracy or RT slopes across similarity varied with age and memory demand. There was a significant three-way interaction for accuracy performance (Wald's $\chi^2(1) = 5.91$, $p = .015$; Figure 3A). Child and adult performance in both memory conditions worsened with decreasing similarity. The interaction showed that the difference between children and adult slopes in the HWMD condition was greater than the same difference in the LWMD condition ($OR_{\text{(interaction)}} = 1.15$, 95% CI [1.03, 1.30], $z = 2.43$, $p = .015$). With LWMD, the odds of adult accuracy

Table 2
Average Accuracy and Response Time per Group and Working Memory Condition

	Groups							
	Adult LWMD		Adult HWMD		Child LWMD		Child HWMD	
Similarity	ACC	RT	ACC	RT	ACC	RT	ACC	RT
25%	86%	701 ms	84%	803 ms	57%	775 ms	61%	943 ms
100%	97%	591 ms	90%	706 ms	86%	668 ms	79%	842 ms

Note. ACC = accuracy; RT = response time; LWMD = low working memory demand; HWMD = high working memory demand.

only qualitatively increased with similarity at a slightly lower rate than children ($b_{(\text{Adult})}$ = 1.57, 95% CI [1.41, 1.74]; $b_{(\text{Child})}$ = 1.75, 95% CI [1.61, 1.90]; $OR_{(\text{Adult-Child})}$ = .89, 95% CI [.79, 1.01], $z = -1.88$, $p = .06$). However, with HWMD, the odds of being correct across similarity increased significantly more for children than adults ($b_{(\text{Adult})}$ = 1.20, 95% CI [1.08, 1.37]; $b_{(\text{Child})}$ = 1.55, 95% CI [1.42, 1.69]; $OR_{(\text{Adult-Child})}$ = .77, 95% CI [.69, .87], $z = -4.29$, $p < .0001$). The odds of being accurate in the LWMD condition were more affected by similarity relative to HWMD for adults ($OR_{(\text{Low-High})}$ = 1.30, 95% CI [1.15, 1.47], $z = 4.35$, $p < .0001$) and children ($OR_{(\text{Low-High})}$ = 1.12, 95% CI [1.02, 1.26], $z = -2.23$, $p = .026$).

Overall, similarity highly influenced adults and child accuracy in the LWMD condition, where the response choices remained on the screen. Further, while the effect of similarity was mitigated for both age groups in the HWMD condition, children were still more impacted by similarity compared with adults.

Response time. There was not a significant interaction of similarity with age group and working memory demand (Wald's $\chi^2(1) = 3.82$, $p = .051$; Figure 3B). This interaction did not pass the significance threshold to be included in the final model so we report main effects. RT decreased with similarity more for children than adults ($b_{(\text{Adult})} = -11.3$, 95% CI [−18, −4]; $b_{(\text{Child})} = -16$, 95% CI [−23, −9]; $b_{(\text{Adult-Child})}$ = 4.7, 95% CI [0.4, 9.0], z = 2.15, $p = .031$). There was no difference in similarity effects between LWMD and HWMD ($b_{(\text{High})} = -11.3$, 95% CI [−18, −4]; $b_{(\text{Low})} = -12.6$, 95% CI [−20, −5]; $b_{(\text{Low-High})}$ = 1.3, 95% CI [−7.1, 9.7], $z = .295$, $p = .768$).

Drift diffusion model.

Drift rate (v). The drift rate was regressed on similarity (Figure 3C). The intercept reflected the "starting" drift rate on the 25% match trials, and the slope represented the change in drift rate as similarity increases. The base drift rates, at 25% similarity, were overall greater for the adults (AH: $v = 2.1$, 95% CI [1.92, 2.29]; AL: $v = 2$, 95% CI [1.8, 2.21]) than the children (CH: $v = .92$, 95% CI [.73, 1.13]; $P_{(\text{CH} > \text{AH})} < .0001$; CL: $v = .68$, 95% CI [.48, .89]; $P_{(\text{CL} > \text{AL})} < .0001$), reflecting greater ability to accumulate information to perform the 25% match trials faster and more accurately. There was no working memory demand difference for the adults ($P_{(\text{AL} > \text{AH})} = .236$), whereas children in HWMD had a greater drift rate than LWMD ($P_{(\text{CL} > \text{CH})} = .049$). For the lowest similarity trials, adults in both working memory conditions had comparable drift rates, while children in LWMD had the lowest drift rate.

Children's drift rate increased with similarity more than adults in both HWMD (CH: β = .009, 95% CI = [.008, .01]; AH: .007, 95% CI [.006, .009]; $P_{(\text{AH} > \text{CH})} = .032$) and LWMD (CL: β = .018, 95% CI [.017, .019]; AL: β = .015, 95% CI [.013, .016]; $P_{(\text{AL} > \text{CL})} = .027$). Within each age group, LWMD led to greater increases in drift rate across similarity compared with HWMD ($P_{(\text{AH} > \text{AL})} < .0001$; $P_{(\text{CH} > \text{CL})} < .0001$).

Threshold distance (a). There was not a significant interaction between age and working memory demand with threshold distance ($p = .062$; Figure 3D). However, further comparisons revealed small distances in the LWMD condition for adults (AL: $a = 1.66$, 95% CI [1.58, 1.75]) that were even smaller for children (CL: a = 1.52, 95% CI [1.46, 1.57]; $P_{(\text{CL} > \text{AL})} = .01$). These distances were smaller for LWMD relative to the HWMD participants (AH: a = 1.79, 95% CI [1.70, 1.90]; $P_{(\text{AL} > \text{AH})} = .02$; CH: $a = 1.78$, 95% CI [1.71, 1.85]; $P_{(\text{CL} > \text{CH})} < .0001$), but there were no age differences in the HWMD threshold distances ($P_{(\text{CH} > \text{AH})} = .37$), reflecting similar response conservatism across age when working memory demand was high.

Nondecision time (T_{er}). Adults and children in the LWMD version of the task spent less time on nondecision components (e.g., perceptual encoding or executing the motor response; AL: T_{er} = 301 ms, 95% CI [290, 313]; CL: T_{er} = 290 ms, 95% CI [272, 284]) than in HWMD (Figure 3E; AH: T_{er} = 338 ms, 95% CI [312, 367]; CH: T_{er} = 329, 95% CI [286, 379]). For adults, this difference was significant ($P_{(\text{AL} > \text{AH})} = .01$), whereas for children it was not ($P_{(\text{CL} > \text{CH})} = .06$). There were no age differences for T_{er} within each working memory demand condition ($P_{(\text{CL} > \text{AL})} = .15$; $P_{(\text{CH} > \text{AH})} = .38$).

Stimulus Moderators

Are similarity effects moderated by stimulus features? This section investigates questions regarding the role of stimulus feature type in moderating the attentional consequences of preparatory strategies. Particularly, if reactive strategies induce global stimulus processing, tasks that demand attention to more global features (e.g., shape) may show less performance costs at lower similarities than more fine-grained features (e.g., pattern). This may be more so the case for children who predominantly focus on global features.

Descriptive statistics. These averages represent the lowest and highest similarity trials (Table 3; Figure 4A). For the full summary table, see the data archive (Martinez et al., 2018).

Accuracy. At the highest similarities, performance across features was comparable. At the lowest similarity, feature performance was stratified differently per age group. In children, shape showed the best performance compared to the other features whereas in adults, pattern showed the worst performance compared to the other features.

Response time. General patterns are difficult to discern from the table; however, greater similarity did quicken RTs for every feature by 59 to 148 ms.

Regression coefficients.

Accuracy. We examined how each cued task feature (Shape, Inner color, Pattern, and Outer color) interacted with target-choice similarity across age group and memory demand. There were interactions between cued feature, similarity, and age group (Wald's $\chi^2(3) = 31.76$, $p < .0001$) and between cued feature, similarity, and working memory demand (Wald's $\chi^2(3) = 12.82$, $p = .005$). To examine all of the factors combined, we compared age group and feature performance within and across memory conditions.

In the LWMD condition, similarity contributed to a diverging pattern of results in adult and child task performance (Figure 4B). For adults, accuracy on Pattern trials was the most affected by similarity relative to Shape ($b_{(\text{Pattern})}$ = 2.39, 95% CI [2.14, 2.67]; $b_{(\text{Shape})}$ = 1.69, 95% CI [1.52, 1.89]; $OR_{(\text{Pattern-Shape})}$ = 1.41, 95% CI [1.23, 1.62], $z = 4.97$, $p < .0001$), Inner Color ($b_{(\text{Incolor})}$ = 1.56, 95% CI [1.41, 1.74]; $OR_{(\text{Incolor-Pattern})}$ = .65, 95% CI [.57, .75], $z = -6.22$, $p < .0001$), and Outer Color ($b_{(\text{Outcolor})}$ = 1.47, 95% CI [1.31, 1.63]; $OR_{(\text{Outcolor-Pattern})}$ = .61, 95% CI [.53, .70], $z = -7.03$, $p < .0001$).

Table 3
Average Accuracy and Response Time per Cued Feature

	Features							
	Shape		Inner Color		Outer Color		Pattern	
Groups similarity	ACC	RT	ACC	RT	ACC	RT	ACC	RT
Adult LWMD								
25%	90%	643 ms	87%	708 ms	88%	710 ms	78%	763 ms
100%	99%	560 ms	97%	588 ms	96%	611 ms	98%	617 ms
Adult HWMD								
25%	91%	737 ms	83%	870 ms	83%	841 ms	79%	816 ms
100%	94%	671 ms	90%	738 ms	87%	741 ms	91%	689 ms
Child LWMD								
25%	69%	730 ms	53%	785 ms	54%	790 ms	48%	803 ms
100%	89%	646 ms	84%	674 ms	85%	680 ms	85%	683 ms
Child HWMD								
25%	76%	872 ms	53%	976 ms	52%	990 ms	59%	976 ms
100%	83%	813 ms	80%	888 ms	74%	868 ms	78%	828 ms

Note. ACC = accuracy; RT = response time; LWMD = low working memory demand; HWMD = high working memory demand.

For children, Shape trial accuracy was most resilient to target-choice similarity influence relative to Inner color ($b_{(\text{Incolor})}$ = 1.74, 95% CI [1.61, 1.90]; $b_{(\text{Shape})}$ = 1.53, 95% CI [1.42, 1.65]; $OR_{(\text{Incolor-Shape})}$ = 1.14, 95% CI [1.03, 1.26], z = 2.53, p = .012), Outer color ($b_{(\text{Outcolor})}$ = 1.76, 95% CI [1.62, 1.90]; $OR_{(\text{Outcolor-Shape})}$ = 1.14, 95% CI [1.03, 1.27], z = 2.55, p = .011), and Pattern ($b_{(\text{Pattern})}$ = 2.06 95% CI [1.89, 2.25]; $OR_{(\text{Pattern-Shape})}$ = 1.34, 95% CI [1.21, 1.49], z = 5.63, $p < .0001$).

Results from the HWMD task were consistent with the LWMD results (Figure 4B). Again, adult accuracy was most influenced by similarity effects on the Pattern trials relative to Inner color ($b_{(\text{Incolor})}$ = 1.19, 95% CI [1.08, 1.33]; $b_{(\text{Pattern})}$ = 1.48, 95% CI [1.33 1.63]; $OR_{(\text{Incolor-Pattern})}$ = .81, 95% CI [.72, .92], $z = -3.24$, p = .001), Outer color ($b_{(\text{Outcolor})}$ = 1.09, 95% CI [.99, 1.2]; $OR_{(\text{Outcolor-Pattern})}$ = .74, 95% CI [.65, .84], $z = -4.74$, $p <$ .0001), and Shape ($b_{(\text{Shape})}$ = 1.18, 95% CI [1.06, 1.30]; $OR_{(\text{Pattern-Shape})}$ = 1.26, 95% CI [1.10, 1.43], z = 3.44, p = .0006).

For children, again accuracy on Shape trials was the least affected by similarity relative to Inner color ($b_{(\text{Incolor})}$ = 1.55, 95% CI [1.42, 1.69]; $b_{(\text{Shape})}$ = 1.22, 95% CI [1.13 1.33]; $OR_{(\text{Incolor-Shape})}$ = 1.26, 95% CI [1.13, 1.40], z = 4.29, $p <$ .0001), Outer color ($b_{(\text{Outcolor})}$ = 1.51, 95% CI [1.39, 1.64]; $OR_{(\text{Outcolor-Shape})}$ = 1.22, 95% CI [1.10, 1.37], z = 3.81, p = .0001), and Pattern ($b_{(\text{Pattern})}$ = 1.48, 95% CI [1.33, 1.64]; $OR_{(\text{Pattern-Shape})}$ = 1.19, 95% CI [1.07, 1.33], z = 3.27, p = .0011).

Across memory conditions, the Inner and Outer color task slopes were not different from each other ($ps > .12$) and the slopes

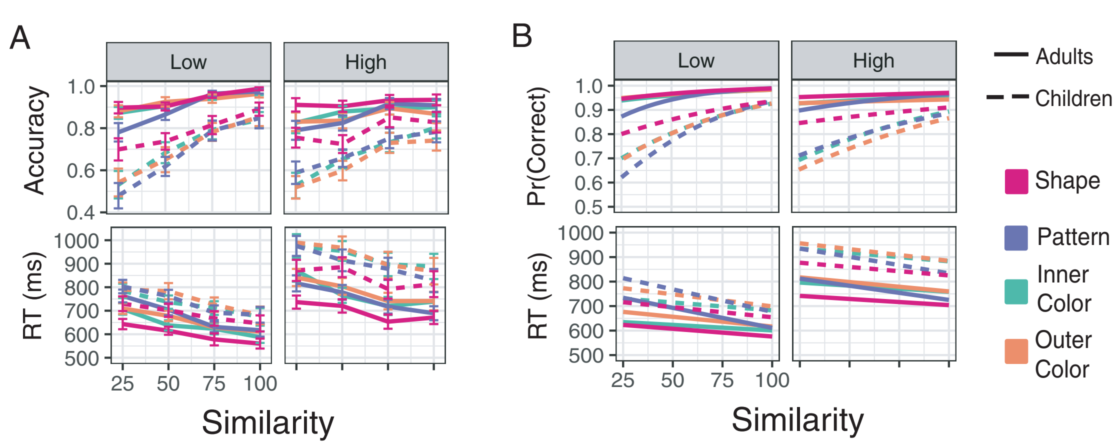

Figure 4. Average performance and regression estimates of feature effects across similarity. Across both plots, adult data are in solid lines and child data in dashed lines while the cued feature conditions are color coded (Shape—pink), Pattern—purple, Inner color—green, Outer color—orange). The x-axis represents target-response similarity. The columns separate the low and high demand conditions. (A) Average accuracy and response times (RTs) across similarity. Error bars represent 95% confidence intervals. (B) Regression estimates showing the probability (Pr) of choosing the correct answer and predicted RTs across similarity. For smaller age-bin analyses, see online supplementary material Figure D3.

for the Shape condition were not very different between adults and children ($ps > .08$).

Response time. There was an interaction between features and similarity (Wald's $\chi^2(3) = 81.9$, $p < .0001$), where Pattern trials exhibited faster RTs with increasing similarity relative to Shape ($b_{(\text{Shape})} = -15.7$, 95% CI [−21.6, −9.2]; $b_{(\text{Pattern})} = -47.5$, 95% CI [−34.5, −12.3]; $b_{(\text{Shape-Pattern})} = 25.2$, 95% CI [17, 33], $z = 6.24$, $p < .0001$), Inner Color ($b_{(\text{Incolor})} = -11.3$, 95% CI [−18.3, −4.3]; $b_{(\text{Incolor-Pattern})} = 29.7$, 95% CI [21, 38], $z = 6.72$, $p < .0001$), and Outer Color tasks ($b_{(\text{Outcolor})} = -19.9$, 95% CI [−27, −12.9]; $b_{(\text{Outcolor-Pattern})} = 21$, 95% CI [12, 30], $z = 4.67$, $p < .0001$). However, we observed no interaction between similarity, age group, and feature (Wald's $\chi^2(3) = 3.30$, $p = .347$), nor between similarity, feature, and working memory demand (Wald's $\chi^2(3) = 7.48$, $p = .058$; Figure 4B), suggesting the features' slopes were not very different across age and working memory demand.

Discussion

We investigated how preparatory differences between middle childhood and young adulthood related to the effectiveness of selective attention during cued task-switching. Task-irrelevant information from stimulus similarity biased performance in all individuals, but especially so in children. Adult and child performance was most alike when stimulus similarity was high. Age group differences in task performance depended on working memory demand, but, overall, children were least affected by similarity on the shape feature trials. DDM results indicated that the largest difference between children and adults was in the drift rate parameter, the primary marker of attention and evidence sampling in the model, and this group difference was similar across memory demand, consistent with an age-related increase in proactive control. An interesting find was that children showed more impulsive decision thresholds relative to adults when memory demand was low, yet both groups switched to conservative thresholds when memory demand was high. Our results support the possibility that suboptimal trial preparation during the cue period in children increases the bias of irrelevant information on task performance. This bias could be mitigated with age and certain changes in cognitive and perceptual load.

The Efficacy of Selective Attention Was Impacted by Age and Task Demands

While participants were given a long cue time (2 s) to use preparation time effectively and focus on the relevant feature, both child and adult performance was influenced by target-choice similarity; performance was worse when similarity was low (greater selective attention was necessary) and better when similarity was high (less selective attention was necessary). This was particularly the case when working memory demand was low, and visual information remained available throughout the trial period. Furthermore, child accuracy and RTs were more affected by similarity. These results are consistent with children implementing reactive strategies as much as possible. Lack of preparatory processing of response choices would have left little time to apply a feature-specific filter on attention, encouraging the use of all available information when comparing with the target in the latter half of the trial. This biased their matching strategies toward general similarity (Deng & Sloutsky, 2015; Sloutsky, 2003). Adults also showed greater impact of visual similarity in the low demand condition, suggesting that even a mature attention system uses reactive processing, and can be distracted by nonrelevant features when they remain available. This work extends previous reports that children's poor ability to selectively attend leads to more holistic perception (Plude et al., 1994; Ristic & Enns, 2015; Shepp, Barrett, & Kolbet, 1987; Shepp & Swartz, 1976) by suggesting the failure of selective attention is a consequence of the preparatory strategy used in tasks that demand selective filtering.

The flattening of accuracy similarity slopes for both age groups when working memory demand was high suggests that a proactive strategy was used when selective attention was greatly needed. Advanced setting of a filter to the cued feature makes the task easier, and later, reactive processing would rely on incomplete information. The adult literature supports this possibility: Working memory guides selective attention based on representational matching to visual stimuli (Olivers, Meijer, & Theeuwes, 2006) and can encode feature-specific information from multidimensional stimuli into working memory (Olivers et al., 2006; Woodman & Vogel, 2008). For example, perceptual information held in working memory can influence an orthogonal search task if the information overlaps with the search items (Soto, Heinke, Humphreys, & Blanco, 2005; Soto, Hodsoll, Rotshtein, & Humphreys, 2008). Computational models of visual working memory also suggest that capacity (number of items) and resolution (details of item) develop with age and dynamically change with task demands (Simmering & Miller, 2016; Simmering & Perone, 2013).

Structural representations of stimuli in working memory influence how representations can guide attention in the service of a task goal (Amso & Scerif, 2015), possibly through input gating mechanisms used in conjunction with proactive control (Amso et al., 2014; Unger et al., 2016). The requirement to memorize the stimuli during the cue period could have encouraged participants to attempt to retain only the relevant dimension, improving the feature's mental representation and reducing the reliance on similarity. While both groups displayed a reduced sensitivity for similarity, children still displayed a strong similarity bias, suggesting that while working memory-guided attention does occur in childhood (Olivers et al., 2006), it is perhaps not very selective or successfully executed (Marshall & Bays, 2013; Unger et al., 2016). This notion is echoed in results showing that long cue-target intervals can suppress goal-irrelevant responses by strengthening task cue information, yet children are less effective at using this mechanism relative to adults (Lorsbach & Reimer, 2011). Correspondingly, children tend to be less engaged with task cues (Church et al., 2017).

Secondary analyses showed that a critical transition from child-like performance to adult-like task accuracy for similarity effects occurs around 11–12 years when memory demand is low and 13–14 years when memory demand is high (online supplementary material Figure D2 and Figure D3). While our age bin sizes were small and, thus, should be interpreted with caution, these age transitions are consistent with adolescence and puberty as critical periods for cognitive growth (Aoki, Romeo, & Smith, 2017; Blakemore, Burnett, & Dahl, 2010; Juraska & Willing, 2017). By adolescence, indices of executive functions (Best & Miller, 2010; Diamond, 2013) and selective attention (Ristic & Enns, 2015) are already highly developed.

The shift from more reactive to predominately proactive control is developed by adolescence (Blackwell & Munakata, 2014; Chevalier, Martis, Curran, & Munakata, 2015), which is consistent with previous work where improved preparatory processing of the cue during a cued-probe task correlated with age (Church et al., 2017). Although children showed slightly more impulsivity, our DDM results indicate developmental changes occur mainly in the ability to efficiently execute a task-appropriate strategy rather than in qualitatively changing strategy choice.

Further Evidence for the Role of Task Control Strategy From the DDM

The DDM results revealed that target-choice similarity loaded on the drift rate itself, suggesting that similarity affected the quality of stimulus information sampled by selective attention. The drift rate was more impacted by stimulus similarity in the low working memory demand condition, as predicted if participants reactively processed the stimuli that remained on the screen during the decision phase. In particular, greater quality information was extracted from the stimuli at higher similarities that likely facilitated the comparison process (Farell, 1985). At low similarity, interference from irrelevant features reduced the quality of evidence for the correct choice. This interference was amplified for children, suggesting they were more likely to process irrelevant information as a result of failed selective attention.

Attention did not act in isolation to influence performance; differences in decision threshold across conditions provide further evidence for the use of reactive and proactive task preparation strategies that flexibly shifted to accommodate task demands. Adults used a relatively impulsive threshold when the response choices remained on screen, which became more conservative when the visual information was removed. Children also demonstrated a level of adult-like conservatism in the high memory demand condition and more impulsivity in the low memory demand condition. More important, adults' employment of strategies across tasks resulted in better performance and less similarity bias relative to children.

Children's impulsive decision making may be a product of reactively relying on the visual "cheat sheet" during the decision phase, potentially a consequence of less preparation during the cue period. This lack of preparation may have impaired the effectiveness of selective attention thereby magnifying similarity effects. This was not possible when response choices were not available, placing value on proactive preparation that readied attentional sets and reduced similarity bias. However, an alternative explanation for the reduced similarity effect in the high working memory demand condition is that working memory representations carry less information than visual stimuli (Zhang & Luck, 2008), naturally leading to less similarity effects. We cannot distinguish between these two hypotheses; however, the decision threshold differences between the two conditions point to a potential role for strategy.

The DDM results suggest that suboptimal task preparation amplified heuristic perceptual biases in decision making, especially in children. These data are consistent with divergent reactive and proactive task control strategies across memory demand (Braver, 2012; Braver et al., 2012) and build on recent accounts showing that children and adults differentially process the cue and target during the preparation phase (Church et al., 2017). Our results also further inform how reactive and proactive strategies are used across development (Munakata et al., 2012). Task structure can nudge toward either strategy (Chevalier et al., 2015; Doebel et al., 2017); however, the consequences differ based on developmental constraints (Unger et al., 2016). The biases inherent in different strategies may lead to positive outcomes, such as when bias and response are congruent, but may also subvert performance if bias and response are at odds. Therefore, final performance likely does not solely reflect the functional state of a single cognitive process across age, but also the downstream consequences of used strategies.

The Impact of Stimulus Features

Our findings also support feature-based theories of selective attention. The stimuli contained a hierarchical organization of features in order from global to local: Shape, Outer Color, Inner Color, and Pattern. This structure stratified performance. When similarity was high, all of the cued features were performed with high accuracy for both adults and children. However, when similarity was low, shape and pattern were consistently the least and most affected, respectively, across age and working memory demand. This pattern of results is congruent with a prominent finding that children and adults find it easier to attend to more global aspects of an object like shape (Chevalier et al., 2010; Huizinga et al., 2010; Kimchi et al., 2005; Vinter et al., 2010). Preschool children preferentially attend to the shape dimension (Chevalier et al., 2010), and our data indicate that this tendency continues into later childhood.

Furthermore, patterns in multidimensional stimuli might function as an inseparable object texture when selective attention is needed (Kimchi & Palmer, 1982), facilitating holistic perception of the whole object. Pattern was the only task with a negative RT slope across similarity (see Figure 4), lending evidence to its textural role. This result could mean that the global or local positioning of a feature affects relative discriminability and consequently the effectiveness of selective attention (Theeuwes, 1991, 1992). Thus, our data suggest preparatory effects on selective attention are not equal across different features: the more global the feature, the smaller the cost of suboptimal preparation. The lack of effect across age and working memory demand suggest that these visual effects are robust and are already set in childhood.

The relative performance on the color tasks to the other features and to each other may also inform interference models of working memory (Oberauer & Lin, 2017). These models assume that continuous dimensions (e.g., color) that overlap in context space will interfere with performance. In this study, one color is similar to the other color in spatial context. When selective attention demand was high in the low working memory condition, only children's performance on the color tasks was reduced. Children may not have the context separation ability to reduce dimensional interference, which can also be seen in the lack of developmental transition in the color tasks (online supplementary material Figure D3). On the other hand, there is evidence from computational models of visual working memory that capacity for common colors develops earlier than shapes in change detection tasks (Simmering, Miller, & Bohache, 2015), suggesting poor color performance in our data may simply be paradigm-specific (Simmering & Perone, 2013).

Asymmetries in spatial context like positioning within the target stimulus may have further influenced flexible task control shown by the switch cost of the inner but not outer color task at lower similarities (online supplementary material Figure D1).

Limitations

While our results demonstrate clear age differences in general performance as a function of selective attention (Figure 3A), similarity-related switch costs were comparable in adults and children and across memory demand (online supplementary material Figure D1). Study design limitations may have influenced the lack of observed switch cost differences in accuracy over the age range in this study. The cue period allowed ample time (2,000 ms) for decay of the previous task set. Larger cue-target intervals (e.g., 1,200 ms) can reduce switch costs (Rogers & Monsell, 1995). With shorter cue-interval times, age differences in selective attention could more strongly influence switch costs, as has been seen in adults (Meiran et al., 2013).

One possibility that could explain the low threshold for children is that it is a byproduct of model fitting; a lower drift rate may necessarily reduce the decision threshold to make the decision in time (Ratcliff & McKoon, 2008). However, we found the opposite pattern in which children's thresholds were low when the drift rate slope was high and vice versa, indicative of an impulsive response style. This ambiguity in interpreting strategy arises from the sole use of a computational model to indirectly assess preparatory strategy, future research should corroborate these results with a more direct measure of stimulus processing such as eye tracking.

Our working memory load manipulation was conflated with perceptual load, raising uncertainty about which load type caused a shift in preparation (Lavie, Hirst, de Fockert, & Viding, 2004). The transition analyses should be considered preliminary given the small sample sizes for the child age bins. Finally, future studies should include neuropsychological testing to account for individual differences in cognitive ability.

Conclusion

We found age effects consistent with developmental differences in task control strategy and selective attention on cued task switching performance. Target-choice similarity biased performance greatly if response options were visible, especially in children. Removing response options from the screen during the target period increased working memory demand and reduced the impact of irrelevant features across participants (although children still exhibited similarity bias). Moreover, global features led to better performance than more fine-grained features, while features that overlapped in category led to interference that was better resolved by older adolescents and adults. Lastly, using the DDM provided insight into how preparation strategies might lead to age-related biases and differences in performance. When task design allowed continued comparison of the target with possible responses, children were more impulsive decision-makers and reactively sampled less quality information from the stimuli. These findings highlight the importance of choosing stimuli thoughtfully, taking into account each possible decision-making strategy for the task at hand, as well as the selective attention ability of the study population.

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