Working memory updating and the development of rule-guided behavior

CrossMark

Dima Amso *, Sara Haas, Lauren McShane, David Badre

Department of Cognitive, Linguistic, & Psychological Sciences, Brown University, United States

ARTICLE INFO

ABSTRACT

The transition from middle childhood into adolescence is marked by both increasing independence and also extensive change in the daily requirements of familial demands, social pressures, and academic achievement. To manage this increased complexity, children must develop the ability to use abstract rules that guide the choice of behavior across a range of circumstances. Here, we tested children through adults in a task that requires increasing levels of rule abstraction, while separately manipulating competition among alternatives in working memory. We found that age-related differences in rule-guided behavior can be explained in terms of improvement in rule abstraction, which we suggest involves a working memory updating mechanism. Furthermore, family socioeconomic status (SES) predicted change in rule-guided behavior, such that higher SES predicted better performance with development. We discuss these results within a working memory gating framework for abstract rule-guided behavior.

© 2014 Elsevier B.V. All rights reserved.

1. Introduction

Rules or *policies* (Badre, 2008; Botvinick, 2008; Bunge, Wendelken, Badre, & Wagner, 2004; Daw, Niv, & Dayan, 2006; Dayan, 2007; Sutton & Barto, 1998) specify the relationship between a context, an action, and an anticipated outcome. Consider the rule given to children: "When indoors, speak in a soft voice, but outside, it is okay to shout". In this example, a representation of the current context (indoor or outdoor) in working memory modulates how one should speak. Importantly, a rule can be more *abstract* to the degree that it determines a set of simpler rules. Extending our example, an older child may learn that the "indoor/outdoor voice" rule only applies when a caregiver is present. In this example, the context ("mom") does not specify the appropriate level of speech but rather which class of rules relating the context to speech is currently appropriate. Sufficiently abstract rules of this sort support adaptive and flexible behavior across a range of circumstances. Here, we focus on the development of rule abstraction from middle childhood through adulthood.

In the lab, rule abstraction can be manipulated in terms of policy order. Consider a task in which one shape indicates one response and another shape a second response (Fig. 1). Here, a single decision based on shape is required to choose a response, and so this task involves 1st order policy. Now, consider that we add a second rule set in which a blue object indicates one response and a red object indicates a second response. As the shape and color rule sets cannot govern responding simultaneously, an additional contextual cue must indicate which set is relevant. Mapping out these decisions results in a two tiered decision tree. Policy abstraction increases with the depth of this decision tree. Notably, the decisions at any level of policy are made more difficult by increasing 'competition', or the number of competing alternatives at a given branch

* Corresponding author. Address: CLPS, Metcalf Research Laboratory, 190 Thayer St., Providence, RI 02912, United States. Tel.: +1 401 863 7652.
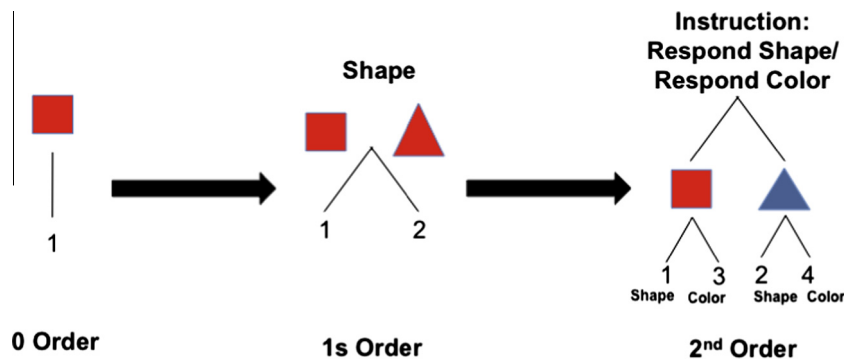*E-mail address:* Dima_Amso@Brown.edu (D. Amso).

Fig. 1. Schematic of increases in depth, and by necessity width, of decision tree when moving from 0 to 1st and 2nd order policy for action.

point (i.e., increasing the width of the tree). Badre and D'Esposito (2007) developed a set of paradigms to consider behavioral effects of competition at different levels of policy abstraction in adults. Here, we adapt these paradigms to examine the developmental course of these processes.

The developmental literature has examined rule-guided behavior largely through the lens of task switching (Crone, Bunge, Van der Molen, & Ridderinkhof, 2006; Davidson, Amso, Anderson, & Diamond, 2006; Wendelken, Munakata, Baym, Souza, & Bunge, 2012; Yerys & Munakata, 2006; Zelazo, 2006). The Dimensional Change Card Sort (DCCS) has been used to examine very young children's ability to sort cards based on rules (e.g., Zelazo, 2006). In this task, children generally succeed at sorting a red truck based on its color, for example. However, three year-olds fail to subsequently switch rules and sort based on the shape dimension, whereas four year-olds succeed. In older children, Davidson et al. (2006) required participants to switch between two rules, such that correct response was dependent on a single defining stimulus feature. These data showed that even 13 year-olds did not perform at adult levels on this task. Crone et al. (2006) also examined rule-guided behavior using a switching paradigm, but with the addition of 'bivalent' (i.e., 2nd order) relative to 'univalent' rule sets. They found that children and adolescents had greater difficulty with the bivalent rules than univalent rules, especially when switching between rules. These results provide evidence of age-related differences in the capacity to flexibly shift between rules of differing orders of policy. Here, we follow this work by separately manipulating policy level from competition.

Cognitive control depends on working memory to maintain relevant contextual information that can bias thought and action toward a desired goal. It follows that having the right rule or contextual information in working memory is crucial for adaptive responding. Both failing to update relevant information into working memory when it becomes available or failing to maintain it in working memory once it is updated could result in control failures. Thus, cognitive control requires a balance between flexibly updating relevant contextual rule information into working memory (*gating*), and maintaining it there (*maintenance*) stable against interference from irrelevant information (e.g., Chatham, Frank, & Badre, 2014;

D'Ardenne et al., 2012; Desimone & Duncan, 1995; Miller & Cohen, 2001). This flexibility/stability paradox seems a particularly difficult problem to solve for the immature developing system. Moreover, perseverative errors, the hallmark of immature cognitive control, could theoretically be attributed to both immature working memory updating or working memory maintenance.

Several models of working memory indicate a solution to these incompatible flexibility and stability demands, where the mechanisms underlying working memory updating or gating are separate from working memory maintenance (Braver & Cohen, 2000; O'Reilly & Frank, 2006). As such, this framework may provide an opportunity for specificity with respect to the precise mechanisms supporting age-related differences in rule-guided behavior in the transition from childhood into adolescence. Indeed, one complication of previous designs that manipulate rule complexity in the developmental literature is that they simultaneously increase overall demands incurred by increased rule complexity (i.e., more abstract policy) *and* maintenance demands among the fan of alternatives (Fig. 1). As such, the developmental course of higher order rule-guided behavior could be a function of updating or gating information into working memory at the level of policy abstraction, at the level of resolving the competition among the increasing fan of options, or some combination. Our work sought to address this question using the paradigms established in Badre and D'Esposito (2007). The potential for specificity and mechanistic insight has broad implications for informing basic science on the topic of the development of rule-guided behavior in this age range, but also fills an important gap with respect to the mechanisms underlying perseverative behavior in a host of developmental disorders, both marked by inefficient cognitive control of thought and action.

Finally, formation of stable rule representations for action is thought to arise through learning mechanisms over childhood (Snyder & Munakata, 2010), and models of the formation of these representations have emphasized the variability of experience as key determining factors (Rougier, Noelle, Braver, Cohen, and O'Reilly (2005). Therefore, we were secondarily interested in the impact of environmental experience in moderating the developmental profile of rule-guided behavior. Socioeconomic status

(SES) has been repeatedly used in the developmental literature as a proxy for both stressful and enriching life experiences, and shown to relate to cognitive control development (Noble, McCandliss, & Farah, 2007; Noble, Norman, & Farah, 2005; Noble, Wolmetz, Ochs, Farah, & McCandliss, 2006) as well as to electrophysiological and structural changes in brain development (Kishiyama, Boyce, Jimenez, Perry, & Knight, 2009; Noble, Houston, Kan, Bookheimer, & Sowell, 2012; Sheridan, Sarsour, Jutte, D'Esposito, & Boyce, 2012; Stevens, Lauinger, & Neville, 2009). Therefore, we explored the hypothesis that variability in environmental experiences, such as is affected by SES, may affect the formation of stable rule representations in working memory gating and maintenance.

2. Method

2.1. Participants

A total of 106 participants completed the session. The final sample ($N = 102$) consisted of 34 children (7–10 years, $M = 9.49$ years, $SD = 1.07$ years, 19 females), 34 adolescents (12–15 years, $M = 13.63$, $SD = 1.08$, 18 females), and 34 adults (19–30 years, $M = 22.28$ years, $SD = 2.66$ years, 18 females). An additional 4 subjects were excluded from the final sample for inattention or failure to understand the task (1 child, 1 adolescent, 2 adults) as evidenced by error rates higher than twice the standard deviation of their respective age group mean. Normal color vision was verified by the Ishihara test for color deficiency. Families were recruited using brochures and flyers in the community. Families were compensated for participation. Participants were consented consistent with the University IRB rules and guidelines. All children signed an assent. Each participant completed the Wechsler Abbreviated Scale of Intelligence (WASI) (Wechsler, 1999). All IQ scores were in the normal range and hence no IQ-based exclusions were necessary (children $M = 127.74$, $SD = 11.23$; adolescents $M = 118$, $SD = 13.5$; adults $M = 124.1$, $SD = 12.02$).

2.2. Materials

2.2.1. SES measures and calculation

All parents were asked to complete a questionnaire asking about both parents' current education, current occupation, and household income (McLoyd, 1998). Adult participants reported the data on behalf of their parents. Of these $N = 34$ adults, $N = 31$ were either college students or graduate students and had not yet established their own education, occupation, or income. Seven families declined to provide demographic information.

Parental reports of education were often given in milestones achieved, rather than years. As such, we coded parental education on a scale of 1–5 (1 = high school, 2 = some college, 3 = bachelors, 4 = masters, 5 = PhD or equivalent). We coded occupation on a scale of 1–5 using the O*Net rankings. O*Net, developed by the US Department of Labor/Employment and Training Administration, is a nationally recognized current database on occupational information. Job zones are groups of occupations

that share requirements of education and amount of training needed to do a job. Household income was used to generate an income-to-needs ratio (family income divided by the poverty threshold of a family of that size).

Thirty-eight additional participants declined to provide household income (10 children, 15 adolescents, 13 adults), consistent with previous literature (Bornstein & Bradley, 2003; Noble et al., 2007). We followed the example of previous literature to impute income-to-needs and a single SES factor (e.g., Noble et al., 2006, 2007). We calculated a regression equation with the parental occupation and education metrics as predictors of income-to-needs. In order to avoid skewing the regression equation in favor of extreme positive outliers, two participants with income-to-needs ratios greater than three standard deviations from the group mean were not included (resulting in $N = 93$). The regression coefficients derived from this analysis were used to impute the income-to-needs ratio of the participants who had reported education and occupation but not household income.

Parental occupation, education, and income-to-needs were all highly correlated (all $ps \leqslant .005$), raising the possibility of collinearity errors in statistical analyses. As such, we generated a single SES factor for statistical examination with our task reaction time data. We entered average parent education, occupation, and income-to-needs into a factor analysis, using the principal components method of extraction on a covariance matrix. The extracted factor was used as the SES score and explained 82.5% of the variance across the three variables. The derived SES variable correlated with all three income-to-needs, $r(95) = .99$, $p = .000$, parental education, $r(95) = .56$, $p = .000$, and parental occupation, $r(95) = .41$, $p = .000$. Preliminary analyses yielded no difference in the distribution of SES across Age Groups, $F(2,90) = .259$, $p = \text{ns}$, $\eta^2_p = .006$. Table 1 details the distributions of all three education, occupation, and income-to-needs variables for the sample of children and adolescents ($N = 61$). The data for these groups are added because they are relevant to interpreting subsequently presented SES results. An income-to-needs of 1 means living at the poverty line (McLoyd, 1998).

2.3. General procedures

Participants completed two tasks: the Response and Feature tasks (Fig. 2).

2.3.1. Response task

On each trial, participants saw the outline of a colored square. Based on color, participants chose a key-press response. Trials were grouped into blocks. For each block, participants were given a rule set that mapped four colored boxes to be seen over the course of the upcoming block to either one (R1), two (R2), or four (R4) potential responses (Fig. 2). This provided separate manipulations of policy abstraction and competition. Specifically, during R1 blocks, there was no uncertainty about what response to make, as all colored boxes mapped to the same response. Thus, R1 provides a simple RT baseline or "0 order" policy condition. By contrast, R2 and R4 both involved selecting a response based on the colored box, and so these conditions require

Table 1
Sample SES and income-to-needs ratio statistics.

	SES Parent education (N = 61)	SES Parent occupation (N = 61)	SES Family income-to-needs ratio (N = 61)
Mean	3.19	3.62	4.87
95% Confidence interval for mean			
Lower bound	2.94	3.36	4.28
Upper bound	3.46	3.87	5.45
Median	3.00	4.00	4.53
Standard deviation	1.02	.99	2.29
Minimum	1.00	1.00	1.64
Maximum	5.00	5.00	11.85
Range	4.00	4.00	10.21
Interquartile range	1.50	1.00	2.53
Skewness	−.23	−.71	1.06

using 1st order policy. Consequently, R2/R4 vs. R1 compares different levels of policy abstraction (1st vs. 0 order). Though R2 and R4 both involve 1st order policy abstraction and both feature four different color-based rules, they differ in their degree of competition – they require a choice between 2 vs. 4 response options, respectively. Hence, R1 vs. R2 manipulates both policy and competition, while R4 vs. R2 manipulates only degree of competition during a 1st order choice.

2.3.2. Feature task

Participants saw the outline of a colored square surrounding an arrow pointing one of four directions (up, down, left, or right). The color of the square cued a particular target arrow direction. Using one of two keys, the participant indicated whether the presented arrow was pointing in the cued direction or not. Trials were grouped into blocks. For each block, participants were given a rule set that mapped four colored boxes to be seen over the course of the upcoming block to either one (F1), two (F2), or four (F4) target arrow directions. This provides separate manipulations of policy abstraction and competition. Specifically, during F1 blocks, there is no uncertainty about which arrow direction cues a target response because all the colored boxes map to the same arrow direction. Thus, F1 is at a 1st order of policy abstraction and only requires a choice between two responses. By contrast, F2 and F4 involve using the colored box to select the appropriate mappings between the orientation of the arrow and a response. Thus, these choices are at a 2nd order of policy abstraction. Consequently, F1 vs. F2 compares a 1st vs. a 2nd order of policy abstraction as well as an increase in competition among alternatives for action (policy and competition). F2 and F4 both involve a choice at a 2nd order of policy abstraction, but they differ in their degree of competition.

2.3.3. Shared procedures

Trial duration was 4 s, during which the participant may respond and terminate the trial. We jittered the intertrial interval from 0 to 2 s. For each task, participants first completed a training phase to learn the rule sets. Training time was allocated to ensure that even the youngest children explicitly and completely learned the rules and

stimulus response mappings. As such, training time varied by individual. On average, training time was 10 min per task. Following training, participants completed the tasks, 198 trials for the Response task (33 trials per block), and 192 (32 trials per block) trials for the Feature task. Task order was counterbalanced. Within task, level (1, 2, 4) order was counterbalanced across participants.

3. Results

3.1. Response task

Average error rates were low for children ($M = 4\%$, $SD = 3\%$), adolescents ($M = 2\%$, $SD = 2\%$), and adults ($M = 2\%$, $SD = 1\%$). Preliminary analyses indicated that there were mean reaction time differences across our Age Groups $F(2,99) = 64.10$, $p = .000$, with reaction times (RTs) significantly decreasing with age (all $ps = .000$). This raises the possibility that observed developmental RT effects may be more related to global mean differences in motor skill across age groups than to the Policy or Competition manipulations per se. Therefore, we used average R1 baseline RTs as covariates in all subsequent analyses labeled ANCOVA. In analyses that included R1 as a dependent variable, we applied a variance-stabilizing square root transformation per subject and Level to reaction times, such that variability on the dependent measures (reaction times on Levels R1, R2, & R4) is not directly related to their mean value.

We began with ANOVAs examining the between subjects factor of Age Group (children, adolescents, adults) and the within subjects factor of Level (R1, R2, R4) for correct trial RTs. This resulted in main effects of Level, $F(2,198) = 662.55$, $p = .000$, and Age Group, $F(2,99) = 56.49$, $p = .000$, and an Age Group by Level interaction, $F(4,198) = 5.79$, $p = .000$, $\eta^2_p = .11$. We next addressed age-related differences in Policy and Competition. As such, we ran separate ANOVAs for each Policy + Competition (R2 vs. R1) and Competition alone (R4 vs. R2) comparisons by Age Group. We reasoned that age-related differences in the Policy + Competition comparison could reflect change in both processes, but the addition of the Competition alone comparison would reveal the extent of that change attributable to Competition effects.
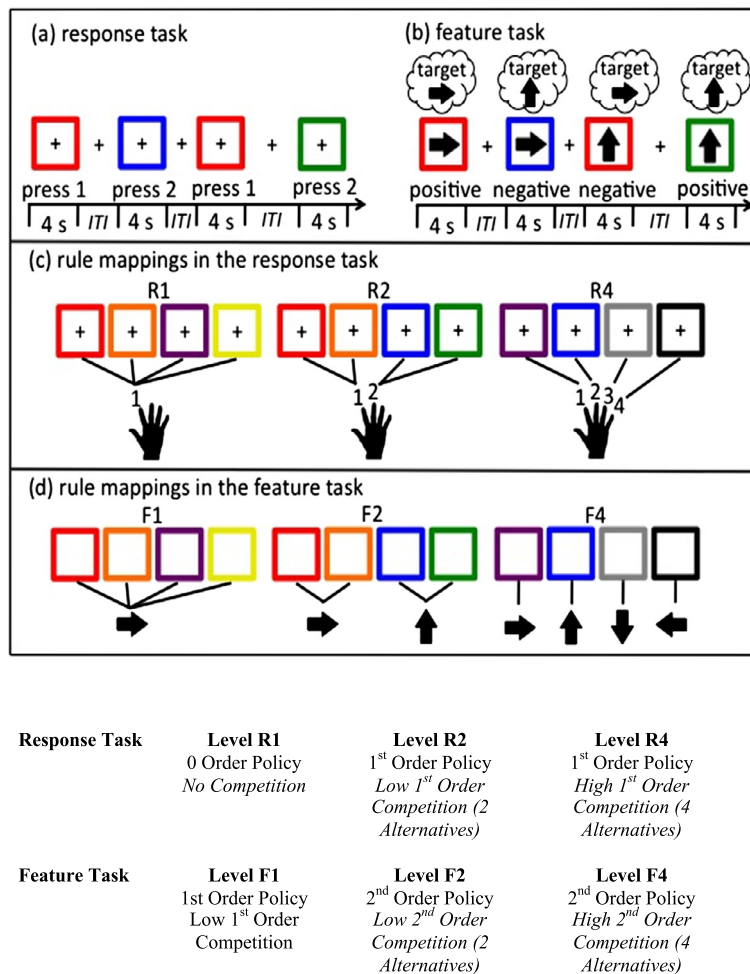
Response Task	Level R1	Level R2	Level R4
	0 Order Policy	1st Order Policy	1st Order Policy
	No Competition	*Low 1st Order Competition (2 Alternatives)*	*High 1st Order Competition (4 Alternatives)*
Feature Task	Level F1	Level F2	Level F4
	1st Order Policy Low 1st Order Competition	2nd Order Policy *Low 2nd Order Competition (2 Alternatives)*	2nd Order Policy *High 2nd Order Competition (4 Alternatives)*

Fig. 2. Depicts both Response and Feature task trial types. Participants respond by either pressing a number that maps onto the color of the box (Response) or by indicating with a "positive" or "negative" whether the color cue correctly predicts the direction of the embedded arrow (Feature).

The Policy + Competition ANOVA analysis resulted in a reliable interaction of Level with Age Group, $F(2,99) = 5.45$, $p < .01$, $\eta^2_p = .10$. Subsequent analyses comparing these effects across specific Age Group pairs showed a higher reaction time cost in R2 relative to R1 in children as compared to both adolescents, $F(1,66) = 7.88$, $p < .01$, $\eta^2_p = .11$, and adults, $F(1,66) = 8.29$, $p = .005$, $\eta^2_p = .11$. However, the R4 vs. R2 Competition ANCOVA across Age Group revealed only the expected main effect of Level, $F(1,98) = 4.66$, $p < .05$, but no interaction of this factor with Age Group, $F(2,98) = 2.26$, $p = $ ns. Taken together, these data suggest that age-related differences in the Policy + Competition comparison (R2 vs. R1) is predominantly driven by the cost of going from 0 to 1st order policy, with no additional developmental effect of adding competing choices at 1st order policy (Fig. 3, left panel).

One possibility is that the developmental policy effect is being driven by greater demand to update rule information into working memory for the R2 relative to the R1 level. If so, we would expect that the developmental effect be unique to R2 trials where the color cues change rather than repeat. We conducted a Trial Type (Cue Repeat/Response Repeat vs. Cue Change/Response Repeat) ANCOVA on R2 trials, with Age Group as the between subject variable. The analysis resulted in main effects of Trial Type, $F(1,98) = 23.14$, $p = .000$, and Age Group, $F(2,98) = 27.82$, $p = .000$. We also found an interaction of Trial Type × Age Group, $F(2,98) = 3.92$, $p < .05$, $\eta^2_p = .07$. Children had a greater cost to cue change than did adults, $F(1,65) = 6.76$, $p = .01$, $\eta^2_p = .09$, or adolescents, $F(1,65) = 3.48$, $p < .07$, $\eta^2_p = .05$ (Fig. 3, right panel). To check that this effect is specific to cue changes, we conducted the same analysis on R2 response repeat vs. change trials (holding cue type constant) and found no interaction with Age Group, $F(2,98) = 2.19$, $p = $ ns. These data suggest that the effect of policy is being driven by costs in updating rule information into working memory, above and beyond a general cost to changing response.

3.2. Feature task

We next asked whether competition is likely to exact a greater developmental cost while following a 2nd order policy. Again, average error rates were low across children
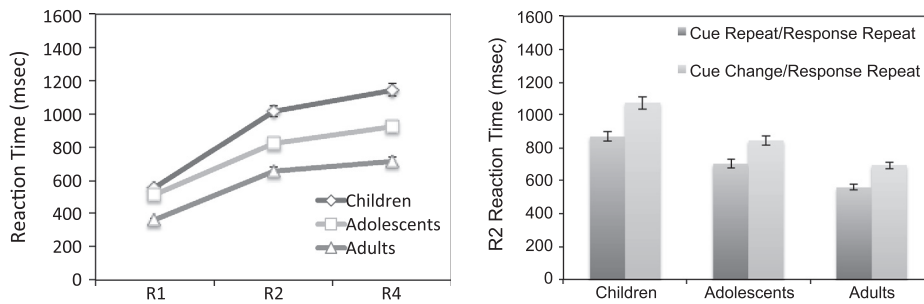
Fig. 3. Left panel illustrates mean RTs (ms) per Age Group on the Response Task across levels 1, 2, and 4. Right panel reflects Level 2 trial Change and Repeat RTs by Age Group for the Response task.

($M = 7\%$, $SD = 6\%$), adolescents ($M = 4\%$, $SD = 2\%$) and adults ($M = 2\%$, $SD = 1\%$). We conducted an ANCOVA on the within subjects factor of Levels (F1, F2, F4) and the between subjects factor of Age Group (children, adolescents, adults) for correct trial RT, including the R1 baseline covariate. The analysis revealed a main effect of Age Group, $F(2, 98) = 34.39$, $p = .000$, Level, $F(2, 196) = 33.92$, $p = .000$, and a Level × Age Group interaction, $F(4, 196) = 5.06$, $p = .001$, $\eta^2_p = .09$. We followed this up with ANCOVAs specific to the Policy + Competition (F2 vs. F1) and Competition alone (F4 vs. F2) comparisons with the between subjects factor of Age Group. The Policy + Competition comparison showed a main effect of Level, $F(1, 98) = 38.87$, $p = .000$, Age Group, $F(2, 98) = 30.74$, $p = .000$, and an Age Group by Level interaction, $F(2, 98) = 4.33$, $p < .05$, $\eta^2_p = .08$. Children had a greater cost for going from 1st to 2nd order Policy + Competition, than did either adults, $F(1, 65) = 3.96$, $p = .05$, $\eta^2_p = .06$, or adolescents, $F(1, 65) = 6.62$, $p < .05$, $\eta^2_p = .08$ (Fig. 4, left panel). The ANCOVA comparing F4 and F2 competition values at a 2nd order of policy resulted in a trending main effect of Level, $F(1, 98) = 2.79$, $p. = 09$, a main effect of Age Group, $F(2, 98) = 30.56$, $p = .000$, but no interaction of any of these variables with Level or Age Group (all $ps = ns$). These data again further indicate that age-related differences in rule-guided behavior cannot be explained by changes in managing increasing competition.

We asked once again whether the effect of policy is being driven by having to update rule information into working memory in the F2 task. In the F2 task, both the cue and the target arrow feature can change across trials.
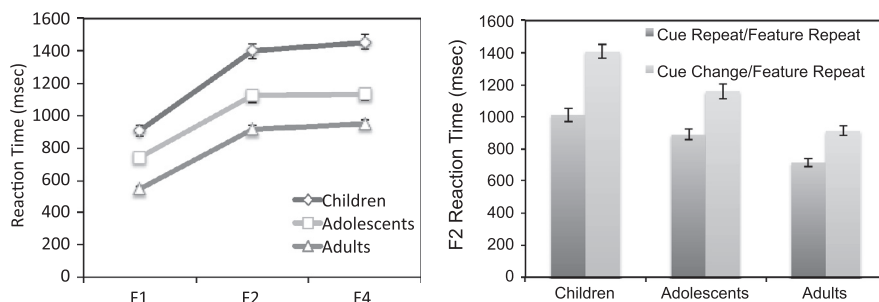
We conducted a Trial Type (Cue Repeat/Feature Repeat vs. Cue Change/Feature Repeat) ANCOVA on F2 trials, with Age Group as the between subject's variable. The analysis resulted in a main effect of Trial Type, $F(1, 98) = 16.64$, $p = .000$, Age Group, $F(2, 98) = 16.64$, $p = .000$, $\eta^2_p = .25$, and an interaction of Trial Type × Age Group, $F(2, 98) = 7.05$, $p = .001$, $\eta^2_p = .13$ (Fig. 4, right panel). As in the Response Task, children had a greater cost to cue change than did either adults, $F(1, 65) = 9.03$, $p = .004$, $\eta^2_p = .12$, or adolescents, $F(1, 65) = 5.97$, $p = .017$, $\eta^2_p = .08$. As a control for general change costs, we ran the same analysis on trials where the feature changed (Feature Repeat/Cue Change vs. Feature Change/Cue Change), and found an interaction of Age Group × Trial Type, $F(2, 98) = 5.65$, $p = .005$. However, the interaction does not mirror that shown for policy but was driven by smaller feature change cost in adolescents than both children, $F(1, 65) = 9.61$, $p < .005$, and marginally adults, $F(1, 65) = 3.11$, $p = .08$. Children and adults did not differ from each other, $F(1, 65) = 1.11$, $p = ns$. We interpret these data, along with the R2 data, to suggest age-related differences specific to updating rule information in working memory (as dictated by the cue color) as the likely mechanism underlying the effect of policy.

3.3. Cross task comparisons and SES

Our next analysis had a twofold purpose. First, we examined the explanatory power of SES on policy abstraction. We also used a cross-task comparison to address whether the Policy + Competition effects above were due

Fig. 4. Left panel illustrates mean RTs (ms) per Age Group on the Feature Task across levels 1, 2, and 4. Right panel reflects Level 2 trial Change and Repeat RTs by Age Group for the Feature task.

to an interaction of Policy and Competition or were specific to Policy. Theoretically, Level 2 in the Response task is equivalent to Level 1 in the Feature task, in that both required first order policy. Thus, any interaction of Task with Age Group could only be explained by surface differences across tasks not related to our questions (e.g., instructions, stimuli, etc.). However, there was no such interaction, $F(2,99) = .46$, $p = $ ns, justifying a cross-task comparison.

We conducted a General Linear Model with the within subjects factors of 1st and 2nd order Task Policy (Response and Feature) × Competition Level (Level 2 and Level 4). We included, as continuous variables Age, SES, IQ, R1 baseline, and an Age × SES interaction variable. Only participants who contributed SES data were included ($N = 93$ across all ages). We found the expected main effect of Policy, $F(1,87) = 3.83$, $p = .05$, $\eta^2_p = .04$, and a Policy × Age interaction, $F(1,87) = 5.93$, $p < .05$, $\eta^2_p = .06$, but no Policy × Competition interaction. We also found main effects of Age, $F(1,87) = 45.04$, $p = .000$, $\eta^2_p = .34$, and an Age × SES interaction, $F(1,87) = 4.08$, $p < .05$, $\eta^2_p = .05$. Notably, the Age × SES variable did not interact with either Policy or Competition Level across 1st and 2nd Order Policy. That is, the effect was the same across 1st vs. 2nd Order Policy and regardless of whether there were two or four competing choices for action. We next used linear regression to probe the precise nature of the Age × SES interaction on our Policy variable of interest.

We generated a single dependent Policy variable representing average RT to 1st and 2nd Order Policy as above (R2, R4, F2, F4). In order to account for any variance associated with changes in Competition across these levels, we generated an average Competition Cost predictor metric (mean of Response Task 4 minus 2 & Feature Task 4 minus 2) and a Competition Cost × Age metric for inclusion as predictors in the model. IQ, SES, and Age were also included as predictors, along with Age × SES, and Competition Cost × SES interaction variables. All values were standardized prior to analysis. A first regression using this model included all participants, including adults. A second regression verified the results using only children and adolescents ($N = 61$), thereby controlling for bias in the first analysis introduced by adults reporting on behalf of their parents. The first model ($N = 93$) explained a significant amount of the variance in Policy $R^2 = .58$, $F(8,84) = 14.31$, $p = .000$. All results are presented in Table 2A. Both Age ($p = .000$) and Age × SES ($p < .05$) were reliable predictors of Policy. The second model ($N = 61$), $R^2 = .60$, $F(8,52) = 9.85$, $p = .000$, effectively replicated these effects (Table 1B). The smaller number of subjects in the second model resulted in an Age × SES interaction that was only trend-level ($p < .09$). However, the more relevant regression metric, size of beta coefficients, indicates that the Age × SES effect is actually larger in the second model than in the first (Table 2). To illustrate this two-way regression interaction, we used the standard simple slopes method wherein a linear equation is developed describing the relation between Age and Policy for children in the lowest end of the sample SES range and another equation for those in the higher end of the sample SES range. These lines were generated using unstandardized regression coefficients

Table 2
Policy regression table.

Variable	B (SE)	β (Sig)
A. Full Sample		
Constant	.01 (.07)	
Age	−.55 (.09)	−.55 ($p = .000$)
SES	−.07 (.09)	−.06
IQ	−.05 (.08)	−.05
R1 Baseline RT	.27 (.09)	.28 ($p < .005$)
Competition Cost	.13 (.09)	.13
Age × SES	−.21 (.10)	−.17 ($p < .05$)
Competition Cost × Age	−.003 (.08)	−.003
Competition Cost × SES	−.08 (14)	−.05
R^2	0.58	
N	93	
B. Children & Adolescents (7–15 years)		
Constant	−.67 (.16)	
Age	−1.53 (.22)	−.68 ($p = .000$)
SES	−.28 (.20)	−.24
IQ	−.16 (.09)	−.18
R1 Baseline RT	.24 (.09)	.25 ($p = .01$)
Competition Cost	.16 (.16)	.18
Age × SES	−.45 (.26)	−.28 ($p < .09$)
Competition Cost × Age	.09 (.18)	.09
Competition Cost × SES	−.03 (.16)	−.02
R^2	0.60	
N	61	

for the independent variable of Age, the moderator variable SES, and the interaction term Age × SES (Dawson, 2014). Fig. 5 graphically illustrates this pattern of results in children through adolescents, where the biggest difference in policy abstraction was observed. There was less efficient age-related improvement in rule-guided behavior for children in the lower end of the sample SES range than for those at the higher end of the sample SES range. By adolescence, higher SES children outperformed lower SES children. Please see Table 1 for SES statistics.

We ran a separate regression ($N = 93$) with Competition Cost as the dependent variable. The model was not significant, $R^2 = .05$, $F(5,87) = .95$, $p = $ ns, nor were the predictors (all ps > .1). As a control, we asked whether Age, SES, or IQ predicted performance on the R1 variable, or 0 Order Policy. The regression model explained a significant amount of the variance, $R^2 = .30$, $F(4,88) = 9.40$, $p = .000$, with only Age serving as a reliable predictor of performance, $\beta = −.54$, $t = −5.94$, $p = .000$, 95% CI[−.72, −.36].
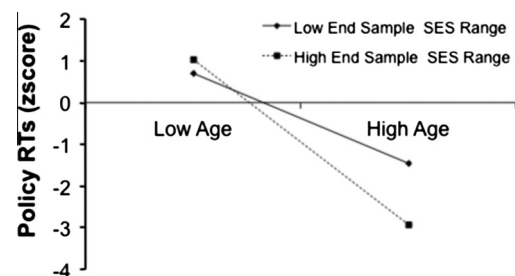

Fig. 5. Illustrates how SES moderates the relationship between policy abstraction and age. Data shown are for children through adolescents (7–15 years, $N = 61$).

4. Discussion

Here, we asked whether developing complex rule-guided behavior derives from changes in policy abstraction or in the capacity to resolve competition among choice alternatives in working memory. In the range of rule abstraction we tested, our data indicate that age-related differences in the transition from childhood to adolescence derive precisely from changes in policy abstraction. Increasing difficulty via competition did not result in developmental differences. That is, increasing the complexity of the rule, in terms of policy abstraction, showed a differential developmental time-course. By contrast, all groups showed a similar, reliable cost to the increase in competition from two to four choice alternatives. This was the case for both the first- and second-order policy tasks. This finding highlights that while the competition manipulation was effective in eliciting behavioral costs, these costs do not explain age-related differences in rule-guided behavior.

The selectivity of developmental effects to the policy cost is consistent with prior observations. Zelazo, Muller, Frye, and Marcovitch (2003) presented 3 and 4 year-old children with a version of the DCCS that varied competition demands but held policy order constant. Specifically, children sorted cards based on color (2 colors) and shape (2 shapes) but the shape and color rules did not overlap. They found that children who would otherwise fail the standard version of the task succeeded on this version, indicating that the difficulties in rule-guided behavior were unlikely to be explained by age-related differences in maintenance. In other words, once the appropriate contextual information is maintained in working memory, its impact on the adjudication among competing alternatives is comparable at all levels of competition across age groups. This working memory gating account is also consistent with explanations of perseverative behavior on the DCCS that favor learning as a stabilizing influence on conflict resolution (Ramscar, Dye, Gustafson, & Klein, 2013; Snyder & Munakata, 2010).

Further, our developmental effects were specific to trials where color cues changed in both the first and second order policy tasks. The clearest evidence for this was during the R2 and F2 conditions. In both of these conditions, two colors map to the same response or target feature. Consequently, it is possible to demand contextual updating – i.e., updating a new color into working memory – without requiring a change of the response or feature that is selected on the basis of that context. We found that the developmental effects of a policy increase were at least partly carried by demands on cue changes, independent of response or feature changes. As such, our results may be best understood within the frame of current mechanistic models of selective updating of working memory. Working memory, supported by prefrontal cortex (PFC), maintains contextual information to modulate thought and action (Miller & Cohen, 2001). This requires a mechanism whereby only useful contextual information is selectively updated into working memory; in other words, a working memory gate. Several influential models of

working memory updating assume separate *gating* and *maintenance* mechanisms (Braver & Cohen, 2000; O'Reilly & Frank, 2006). In this case, the demand to flexibly update the context, such as when the cue changed, appeared to drive developmental differences. As such, our data potentially provide evidence for a slower rate of age-related change in flexible updating or gating of working memory, specifically, in the service of rule-guided behavior.

We further showed that as policy abstraction develops beyond childhood, SES moderates the efficiency of this development such that lower SES children show less efficient age-related differences. We note that while we attempted to mathematically account for the cost of the increase in competition cost (Table 2) on the Policy dependent variable, we cannot directly speak to the specificity of the SES relationship with policy order in this investigation. Table 1 shows the education, occupation, and income-to-needs ratio statistics. The latter is provided in order to allow the reader a general sense of the spread of the demographic sample in units relevant to determining poverty and comparable to national statistics. Although we have a good range across SES, our sample has a slight positive skew, indicating that we are seeing effects of even middle to high SES on rule-guided behavior. This strengthens the argument that these effects are not specific to poverty, but are more generally the result of variable environments on rule-guided behavior. We note here that the point of this investigation is not to classify some group of children into a niche based on SES. It is rather to describe age-related changes in rule-guided behavior that are sensitive to differences in environmental experience.

Fig. 5 shows that SES did not play a role in rule-guided behavior at the younger end of our age range. With age, both children in the higher and lower end of the SES range showed faster response times, indicating better performance on these tasks. However, the children with higher SES values showed a steeper slope and ultimately have faster reaction times, and therefore better performance, with age and development. Related data from preschool age children indicate a less prominent role for family income in the slope of developmental change in executive functions (Hughes, Ensor, Wilson, & Graham, 2010), indicating that SES may influence the development of related constructs differently at alternate points in child development.

As noted, rule-guided behavior requires the ability to update relevant contextual information in working memory and to robustly maintain it in order to bias selection of appropriate responses. Formation of these stable codes is hypothesized to arise through learning mechanisms over childhood (Ramscar et al., 2013; Snyder & Munakata, 2010), and models of such learning have emphasized the variability of experience as a key determining factor (Rougier, Noelle, Braver, Cohen, & O'Reilly, 2005). Relevant to SES, cognitively stimulating materials and experiences are less common in low SES homes (Adams, 1990; Bradley, Corwyn, Burchinal, McAdoo, & Garcia Coll, 2001). Electrophysiological and neuroimaging data have also shown reductions in prefrontal cortex-mediated cognitive control behavioral performance and anatomical measurements in high relative to low SES children (Kishiyama

et al., 2009; Noble et al., 2012; Sheridan, Sarsour, Jutte, D'Esposito, & Boyce, 2012; Stevens et al., 2009). Taken together, SES may serve as a proxy for enriching experiences relevant to development at the level of rule-guided behavior. Though, other factors correlating with SES, such as exposure to stressful life events, could also impact the development of systems thought to support working memory updating. While we are pleased to have considered the role of SES in this work, we acknowledge that it is a variable of limited mechanistic potential and are currently addressing the precise variables, under the SES umbrella, that are driving age-related differences in rule-guided behavior observed here. We additionally acknowledge that directionality is difficult to establish in these investigations. Work using the logic of identical twin studies to establish heritability estimates has identified executive functions as highly heritable (Friedman et al., 2008; Miyake & Friedman, 2012). While it is possible that poor executive functions in parents contribute to poor policy abstraction and low SES, the assumptions of twin studies for deriving heritability estimates have extensively been called into question both in general and with respect to executive functions processes (e.g., Muller, Baker, & Yeung, 2013). Nonetheless, these issues are worthy of future empirical consideration.

During the transition from childhood to adolescence, the developing child is confronted with increasingly complex contexts in which to implement rule-guided behavior, as well as a larger number of competing options to choose from. Our data specify that age-related differences in flexible rule-guided behavior derives from the unique demands on working memory updating that are imposed by increases in policy abstraction. Future work will examine the limits of these selective age-related differences, with a focus on higher order levels of policy.

Acknowledgements

References

Adams, M. J. (1990). *Beginning to read: Thinking and learning about print.* Cambridge, MA: MIT Press.

Badre, D. (2008). Cognitive control, hierarchy, and the rostro-caudal axis of the prefrontal cortex. *Trends in Cognitive Science, 12*(5), 193–200.

Badre, D., & D'Esposito, M. (2007). FMRI evidence for a hierarchical organization of the prefrontal cortex. *Journal of Cognitive Neuroscience, 19*(12), 1–18.

Bornstein, M. H., & Bradley, R. H. (2003). *Socioeconomic status, parenting, and child development.* Mahwah, NJ: Lawrence Erlbaum Associates.

Botvinick, M. M. (2008). Hierarchical models of behavior and prefrontal function. *Trends in Cognitive Science, 12*, 201–208.

Bradley, R. H., Corwyn, R. F., Burchinal, M., McAdoo, H. P., & Garcia Coll, C. (2001). The home environments of children in the United States. Part II: Relations with behavioral development through age thirteen. *Child Development, 72*(6), 1868–1886.

Braver, T. S., & Cohen, J. D. (2000). On the control of control: The role of dopamine in regulating prefrontal function and working memory. In S. Monsell & J. Driver (Eds.), *Attention and performance XVIII.* London: MIT Press.

Bunge, S. A., Wendelken, C., Badre, D., & Wagner, A. (2004). Analogical reasoning and prefrontal cortex: Evidence for separable retrieval and integration mechanisms. *Cerebral Cortex, 15*(3), 239–249.

Chatham, C. H., Frank, M. J., & Badre, D. (2014). Corticostriatal output gating during selection from working memory. *Neuron, 81*(4), 930–942.

Crone, E. A., Bunge, S. A., Van der Molen, M. W., & Ridderinkhof, K. R. (2006). Switching between tasks and responses: A developmental study. *Developmental Science, 9*(3), 278–287.

D'Ardenne, K., Eshel, N., Luka, J., Lenartowicz, A., Nystrom, L. E., & Cohen, J. D. (2012). Role of prefrontal cortex and the midbrain dopamine system in working memory updating. *Proceedings of the National Academy of Sciences, USA, 109*(49), 19900–19909.

Davidson, M., Amso, D., Anderson, L., & Diamond, A. (2006). Development of cognitive control and executive functions from 4 to 13 years: Evidence from manipulations of memory, inhibition, and task switching. *Neuropsychologia, 44*(11), 2037–2078.

Daw, N. D., Niv, Y., & Dayan, P. (2006). Actions, policies, values, and the basal ganglia. In E. Bezard (Ed.), *Recent breakthroughs in basal ganglia research.* Nova Science Inc..

Dawson, J. F. (2014). Moderation in management research: What, why, when and how. *Journal of Business and Psychology, 29*, 1–19.

Dayan, P. (2007). Bilinearity, rules, and prefrontal cortex. *Frontiers in Computational Neuroscience, 1*.

Desimone, R., & Duncan, J. (1995). Neural mechanisms of selective attention. *Annual Review of Neuroscience, 18*, 193–222.

Friedman, N. P., Miyake, A., Young, S. E., DeFries, J. C., Corley, R. P., & Hewitt, J. K. (2008). Individual differences in executive functions are almost entirely genetic in origin. *Journal of Experimental Psychology: General, 137*, 201–225.

Hughes, C., Ensor, R., Wilson, A., & Graham, A. (2010). Tracking executive function across the transition to school: A latent variable approach. *Developmental Neuropsychology, 35*(1), 20–36.

Kishiyama, M. M., Boyce, W. T., Jimenez, A. M., Perry, L. M., & Knight, R. T. (2009). Socioeconomic disparities affect prefrontal function in children. *Journal of Cognitive Neuroscience, 21*(6), 1106–1115.

McLoyd, V. C. (1998). Socioeconomic disadvantage and child development. *American Psychologist, 53*(2), 185–204.

Miller, E. K., & Cohen, J. D. (2001). An integrative theory of prefrontal cortex function. *Annual Review of Neuroscience, 24*, 167–202.

Miyake, A., & Friedman, N. P. (2012). The nature and organization of individual differences in executive functions: Four general conclusions. *Current Directions in Psychological Science, 21*(1), 8–14.

Muller, U., Baker, L., & Yeung, E. (2013). A developmental systems approach to executive functions. *Advancements in Child Development & Behavior, 45*, 39–66.

Noble, K. G., Houston, S., Kan, E., Bookheimer, S. Y., & Sowell, E. R. (2012). Neural correlates of socioeconomic status in the developing human brain. *Developmental Science, 15*(4), 516–527.

Noble, K. G., McCandliss, B. D., & Farah, M. J. (2007). Socioeconomic gradients predict individual differences in neurocognitive abilities. *Developmental Science, 10*(4), 464–480.

Noble, K. G., Norman, M. F., & Farah, M. J. (2005). Neurocognitive correlates of socioeconomic status in kindergarten children. *Developmental Science, 8*(1), 74–87.

Noble, K. G., Wolmetz, M. E., Ochs, L. G., Farah, M. J., & McCandliss, B. D. (2006). Brain- behavior relationships in reading acquisition are modulated by socioeconomic factors. *Developmental Science, 9*, 642–654.

O'Reilly, R. C., & Frank, M. J. (2006). Making working memory work: A computational model of learning in the prefrontal cortex and basal ganglia. *Neural Computation, 18*, 283–328.

Ramscar, M., Dye, M., Gustafson, J. W., & Klein, J. (2013). Dual routes to cognitive flexibility: Learning and response–conflict resolution in the Dimensional Change Card Sort. *Child Development.* epub ahead of print.

Rougier, N. P., Noelle, D., Braver, T. S., Cohen, J. D., & O'Reilly, R. C. (2005). Prefrontal cortex and the flexibility of cognitive control: Rules without symbols. *Proceedings of the National Academy of Sciences, 102*, 7338–7343.

Sheridan, M. A., Sarsour, K., Jutte, D., D'Esposito, M., & Boyce, W. T. (2012). The impact of social disparity on prefrontal function in childhood? *PLoS One, 7*(4).

Snyder, H. R., & Munakata, Y. (2010). Becoming self-directed: Abstract representations support endogenous flexibility in children. *Cognition, 116*(2), 155–167.

Stevens, C., Lauinger, B., & Neville, H. (2009). Differences in the neural mechanisms of selective attention in children from different socioeconomic backgrounds: An event-related brain potential study. *Developmental Science, 12*(4), 634–646.

Sutton, R. S., & Barto, A. G. (1998). *Reinforcement learning: An introduction.* Cambridge, MA: MIT Press.

Wechsler, D. (1999). *Wechsler abbreviated scale of intelligence.* New York, NY: The Psychological Corporation: Harcourt Brace & Company.

Wendelken, C., Munakata, Y., Baym, C., Souza, M., & Bunge, S. A. (2012). Flexible rule-guided behavior: Common neural substrates in children and adults. *Developmental Cognitive Neuroscience, 2*, 329–339.

Yerys, B. E., & Munakata, Y. (2006). When labels hurt but novelty helps: Children's perseveration and flexibility in a card-sorting task. *Child Development, 77*, 1589–1607.

Zelazo, P. D. (2006). The Dimensional Change Card Sort (DCCS): A method of assessing executive function in children. *Nature Protocols, 1*, 297–301.

Zelazo, P. D., Muller, U., Frye, D., & Marcovitch, S. (2003). The development of executive function in early childhood. *Monographs of the Society for Research in Child Development, 68*(3). Serial No. 274.