Attentional mechanisms drive systematic exploration in young children

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Abstract

Exploration is critical for discovering how the world works. Exploration should be particularly valuable for young children, who have little knowledge about the world. Theories of decision-making describe systematic exploration as being primarily sub-served by prefrontal cortex (PFC). Recent research suggests that systematic exploration predominates in young children's choices, despite immature PFC, suggesting that this systematic exploration may be driven by different mechanisms. We hypothesize that young children's tendency to distribute attention widely promotes broad information gathering, which in turn translates to exploratory choice behavior, and that interrupting distributed attention allocation through bottom up attentional capture would also disrupt systematic exploration. We test this hypothesis by manipulating saliency of the options in a simple choice task. Saliency disrupted systematic exploration, thus indicating that attentional mechanisms may drive systematic exploratory behavior. We suggest that both may be part of a larger tendency toward broad information gathering in young children.

Keywords: cognitive development; exploration; decision-making; attention

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Cognition changes dramatically in the course of cognitive development, and many of these changes stem from developmental changes in control and allocation of attention. Adults are highly adept at controlling their attention: depending on the task and the goals, they can distribute it broadly or focus selectively on a small subset of stimuli (e.g., Chong & Treisman, 2005). When only a small amount of the available information is relevant or useful, adults tend to selectively focus on that information and ignore the rest (Rehder & Hoffman, 2005; Blair, Watson & Meier, 2009).

In contrast, young children tend to distribute their attention broadly, regardless of task demands, often processing not only task-relevant information, but also information that is not relevant for their current task (Deng & Sloutsky, 2015, 2016; Plebanek & Sloutsky, 2017; Smith & Kemler, 1977). This tendency likely stems from immaturities of executive attention (Posner & Rothbart, 2007), resulting in difficulty attending selectively and filtering out irrelevant environmental stimuli.

While these immaturities may be highly limiting for learning in academic settings, it is possible that such immaturities of executive attention can be adaptive. For example, distributing attention can result in superior performance of children over adults in situations when one has to use information that was previously irrelevant (Plebanek & Sloutsky, 2017; Blanco & Sloutsky, under review).

Therefore, depending on the context, either selective or distributed attention could be advantageous. Selective attention is superior when one is confident that a small portion of the available information is sufficient to achieve their goals. Distributed attention is advantageous when there is more uncertainty about what is and is not important. This may be particularly adaptive early in development, with young children having little experience and knowledge about how the world works. Additionally, by facilitating broad information gathering, distributed attention helps to reduce that uncertainty and build up the rich general knowledge that adults rely on (which, in turn, enables effective use of selective attention). Distributed attention early in life children may be a sacrifice of immediate performance in exchange for information that can be used later. In other words, it seems that distributing attention in young children might sub-serve exploration. Recent research suggests that there is a tight link between attention allocation and decision-making behavior (Gottlieb, 2012; Konovalov & Krajbich, 2016), and perhaps distributed attention also promotes wider distribution in action selection.

There are recent reports indicating that four-year-old's choices are, indeed, highly exploratory (Blanco & Sloutsky, under review). Interestingly, children's exploration also appeared non-random. This is surprising because decision-making research critically distinguishes systematic from undirected (or random) exploration (Badre, Doll, Long, & Frank, 2012; Daw, O'Doherty, Dayan, Seymour, & Dolan, 2006; Knox, Otto, Stone, & Love, 2012; Blanco, et al., 2015; Somerville, et al., 2017), and converging evidence suggests a crucial role of prefrontal cortex in systematic exploration (Badre, Doll, Long, & Frank, 2012; Frank, Doll, Oas-Terpstra, & Moreno, 2009; Blanco et al., 2015; Otto, Knox, Markman, & Love, 2014). Because prefrontal cortex exhibits substantially protracted development (Sowell, et al., 2004; Sowell, et al., 1999), current theories predicted that young children's exploration would be largely unsystematic (Somerville et al., 2017). Due to the immaturity of PFC, young children's systematic exploration is likely driven by different mechanisms than adults'. We hypothesize that children's exploratory behavior is instead tied intricately to their immature attention allocation.

The Current Study

The goal of the current study is to test this idea by systematically manipulating attention allocation by manipulating salience of a cue linked to a reward. More specifically our hypothesis is that children's pattern of distributed attention promotes distributing choices in a way that enables systematic exploration. If altering the attentional pattern through bottom-up capture of attention also changes exploratory behavior, we would be able to infer that attention drives exploratory behavior early in development. In contrast, if attention is not a causal factor in exploratory behavior, manipulating attention should lead to little or no changes in exploratory behavior.

In the current study, we presented children with a simple reward learning task under three attentional conditions in order to examine the interplay of attention and systematic exploration. On each trial of the task they chose between four options that gave different amounts of reward. The conditions differed in terms of the perceptual saliency of stimuli marking the choice options. In the Baseline condition, all options were of equal salience. In the two experimental conditions, three choice options were represented by bland, invariant stimuli, while one option was represented by a highly salient stimulus that changed on every trial. In the *Congruent* condition the salient option was mapped to the highest value option. In the *Competition* condition the salient option was mapped to the lowest reward, putting reward-seeking and salience in competition.

Method

Participants

A total of 110 4-to-5-year-olds (mean age = 57 months; 58 girls) participated in the experiment: 37 in the Congruent condition, 37 in the Competition condition, and 36 in the Baseline condition. Participants were recruited from preschools and childcare centers in the Columbus, Ohio area.

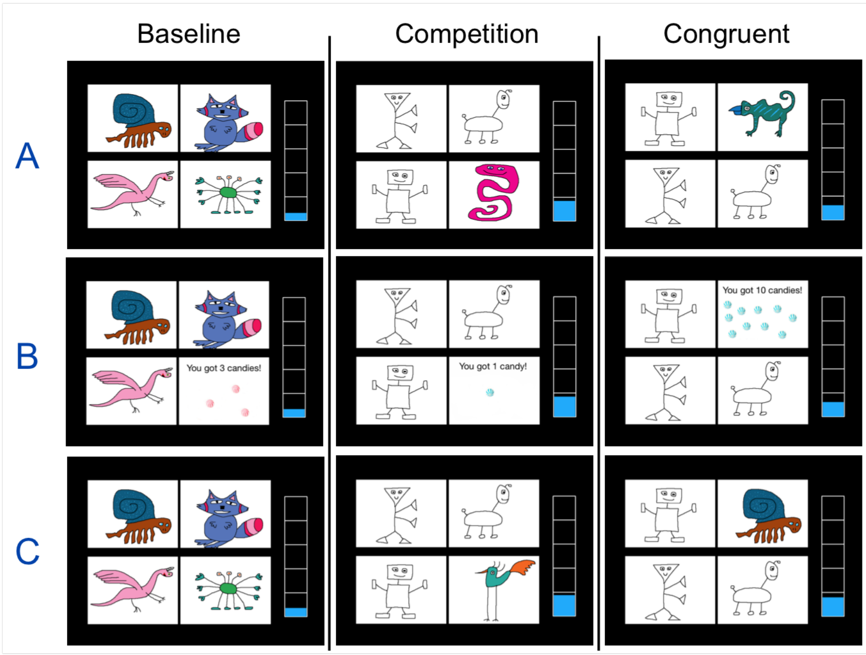

Figure 1: Trial structure. (A) After each choice, (B) the reward earned for the choice is presented for 3 s, (C) then the next trial begins. In the Congruent and Competition conditions one option is represented by a colorful image that changes on every trial, while the other three are represented by lower salience images that remain stable across trials. In the Baseline condition, all four options are represented by stable images of equal salience.

Procedure

Participants completed a decision-making task that was a simplified version of a standard *n*-armed bandit task. The task was framed as a computer game in which participants asked alien creatures for virtual candy (Figure 1). The goal was to earn as much virtual candy as possible. On each of 100 trials, participants chose one of the four creatures (using a touch screen) and received virtual candy according to their choice. The rewards received for choosing each creature were the same on every trial: One option was 10 candies, while the other three options were 3, 2, and 1 candies respectively. The locations of the reward values were stable across the experiment but were randomly determined for each participant. Following the choice, the resulting reward was displayed for 3 s (Figure 1B). Then a meter that tracked the total accumulated reward was updated. Children were given tangible rewards (stickers) for every 180 candies earned, with benchmarks on the meter indicating these goals.

Participants were assigned to one of three conditions: Congruent, Competition, and Baseline. In the Baseline condition, all creatures were approximately equally salient, whereas in the Congruent and Competition conditions, salience of the creatures was unequal. Specifically, three of the four creatures were simple black and white stick figures, whereas one was colorful and perceptually rich. In addition, on each trial the salient image was a different novel creature (Figure 1C). Fifty different images were used for the salient option, so each image appeared twice during the experiment. In the Congruent condition, the salient option was mapped to the highest reward value (10 candies), whereas in the Competition condition, the salient option was mapped to the lowest reward value (1 candy).

Results

Choice proportions

Participants' choices over the course of the experiment are presented in Figure 2. In order to assess the effect of saliency on performance, we analyzed the proportion of trials that the highest valued option was chosen across the three conditions. An ANOVA revealed a significant effect of condition, $F(2, 107) = 15.40$, $p = 0.001$, $\eta^2 = 0.22$. Pairwise comparisons showed that participants in the Congruent condition ($M = 0.53$) chose the 10-candy option significantly more often than participants in the Baseline ($M = 0.28$), $t(71) = 4.40$, $p < 0.001$, $d = 1.03$, and Competition conditions ($M = 0.30$), $t(72) = 3.93$, $p < 0.001$, $d = 0.91$. Performance in the Competition condition was not different from Baseline, $t(71) = 0.57$, $p = 0.569$, $d = 0.13$.

The proportion of trials in which the lowest valued option was chosen was also analyzed as an additional check of the effect of salience in the Competition condition. An ANOVA revealed a significant effect of condition, $F(2, 107) = 5.24$, $p = 0.006$, $\eta^2 = 0.09$. But, pairwise tests revealed only that participants in the Congruent condition ($M = 0.16$) chose the lowest option less than both the Baseline ($M = 0.23$), $t(71) = 3.22$, $p = 0.002$, $d = 0.75$, and the Competition condition ($M = 0.25$), $t(72) = 2.60$, $p = 0.011$, $d = 0.60$. The Competition and Baseline conditions did not differ significantly, $t(71) = 0.65$, $p = 0.516$, $d = 0.15$. These results suggest that saliency facilitated reward optimization in the Congruent condition, but not through simple salience-seeking since the salient option was not selected frequently in the Competition condition.

Switch proportions

We also examined the proportion of trials on which participants switched responses, choosing a different option than the previous trial, as an indicator of elevated exploration (Figure 3). In the Baseline condition, we expected participants to switch often and do so systematically. This expectation is based on a previous study (Blanco & Sloutsky, under review) using a similar task. While, because outcomes were stable and predictable, low levels of exploration would usually be expected, children tended to switch extremely often—consistent with highly elevated exploration. Systematicity in their switching was then established with subsequent computational modeling analyses. We, therefore, first analyze participants' switch responses, and we report modeling results in the next section.

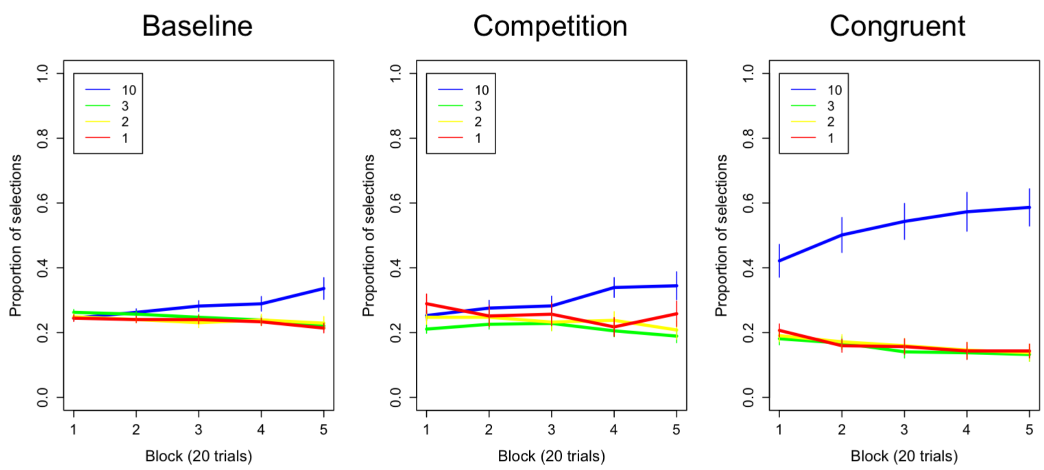

Figure 2: Choice proportions. The proportion of trials on which each option was chosen is presented for blocks of 20 trials. Children in the Congruent condition selected the highest valued option more frequently than children in both the Baseline and Competition conditions. Interestingly, children in the Competition condition did not select the lowest valued option (which was salient in that condition) more often than in the Baseline condition. This suggests that simple salience-seeking did not drive children's choices. Error bars reflect standard errors of the mean.

An ANOVA on proportion of trials that participants switched responses revealed a significant effect of condition, $F(2, 107) = 17.42$, $p < 0.001$, $\eta^2 = 0.246$. Most importantly, children in the Congruent ($M = 0.56$), $t(71) = 5.57$, $p < 0.001$, $d = 1.30$, and Competition conditions ($M = 0.77$), $t(71) = 3.22$, $p = 0.002$, $d = 0.75$, switched substantially less than Baseline ($M = 0.91$). Additionally, children in the Competition condition switched more than those in the Congruent condition, $t(72) = 3.04$, $p = 0.003$, $d = 0.71$. It is perhaps not surprising that children switched less in the Congruent condition than Baseline since they often exploit the best option, but it is surprising that switching was low in the Competition condition despite no increase in exploitation.

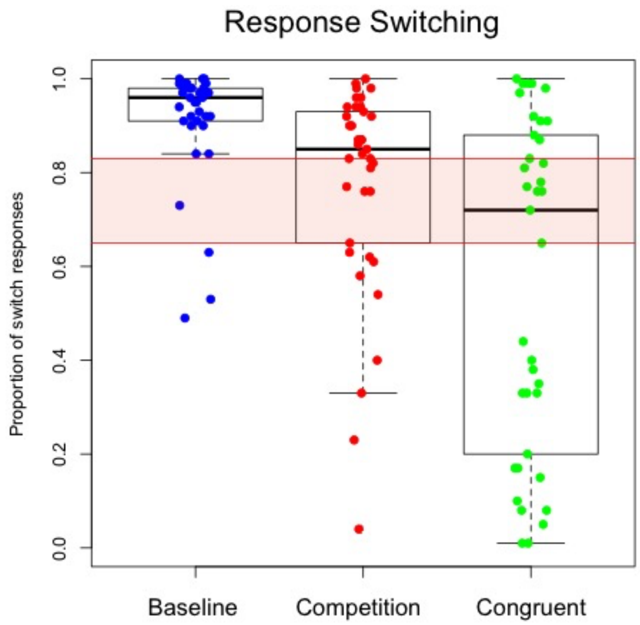

Figure 3: Response Switching. The proportion of trials on which participants made a switch response, choosing a different option than the previous trial, is presented. The pink shaded region represents 95% probability density of switch responses given random responding. Extreme switch proportions in the Baseline condition suggest elevated exploration levels. Switch proportions are less than the Baseline in both salience conditions. Dots represent individual participants.

Computational Modeling

In order to examine the effects of the salience manipulation on systematic exploration, participants' choices were evaluated in relation to a Reinforcement Learning model (Sutton & Barto, 1998) that included the potential for both systematic and random exploration. The model used prediction errors to learn expected reward values for each option using the following equation:

$$V_{i,t+1} = V_{i,t} + \alpha\left(R_{i,t} - V_{i,t}\right)$$

where $V_{i,t}$ is the expected value of option i on trial t, $R_{i,t}$ is the reward on trial t earned for choosing option i, and α is the learning rate (a free parameter). It then made choices according to the following function:

$$P(a_{i,t}) = \frac{e^{\beta * [V_{i,t} * (1-\phi) + L_{i,t} * \phi]}}{\sum_{j=1}^{n} e^{\beta * [V_{j,t} * (1-\phi) + L_{j,t} * \phi]}}$$

where $P(a_{i,t})$ is the probability of choosing option i on trial t. $L_{i,t}$ is the lag term—a proxy for uncertainty—that simply encodes the number of trials since option i was last chosen. The weight parameter ϕ ($0 \leq \phi \leq 1$) mediates the relative extent to which the expected values and lags influence choices. Greater values of ϕ indicate greater influence of systematic exploration. When ϕ is 0, the model chooses based only on expected value; when ϕ is 1 it chooses only based on the lag. β is the inverse temperature parameter that controls random exploration. At $\beta = 0$ choice probabilities become completely random (i.e. equal between all options), and as β approaches infinity the model chooses the most favorable option (based on the weighted combination of expected value and lag described above) on every trial. Both β and ϕ were free parameters.

This model is similar to the 'exploration bonus' models used in some previous studies (Daw et al. 2006; Kakade & Dayan, 2002), but with lag as a proxy for uncertainty and with slightly different parameterization. The model was fit to each individual participant by finding the set of parameters that maximized the likelihood of producing the participant's data given the model.

The full model described above was first compared to a simplified model without systematic exploration, where ϕ was set to 0. In the simplified model choice probabilities reduce to a standard Softmax choice rule (Sutton & Barto, 1998) on expected reward value:

$$P(a_{i,t}) = \frac{e^{\beta * V_{i,t}}}{\sum_{j=1}^{n} e^{\beta * V_{j,t}}}$$

The Aikaike Information Criterion (AIC) was used to determine best-fitting model for each participant (Akaike, 1974). A large majority of children in the Baseline condition (31 out of 36) were better fit by the full model that included systematic exploration, while only about half of children were better fit by the full model in the Congruent (18 out of 37) and Competition (20 out of 37) conditions. A chi-squared test confirmed that these proportions were different, X^2 (2; N = 110) = 12.75, p = 0.002.

The best-fitting parameter values were then compared between the three different conditions (see Figure 4). Because the best-fitting parameter values were not normally distributed, we report median values (see Table 1) and compare groups using Wilcoxon rank sum tests. Best-fitting ϕ parameter (reflecting systematic exploration) was significantly lower in the Congruent, W = 1044, p < 0.001, and Competition conditions, W = 886, p = 0.015, than in the Baseline condition. The Congruent and Competition conditions did not differ in best-fitting ϕ value, W = 606, p = 0.401. The β parameter (reflecting random exploration) was lower in the Competition condition compared to both the Baseline, W = 935, p = 0.002, and Congruent conditions, W = 906, p = 0.016, suggesting somewhat higher random exploration in the Competition condition. The Baseline and Congruent conditions were not different, W = 743, p = 0.400.

The high values of ϕ in the Baseline condition and substantially lower values in both the Congruent and Competition conditions suggest that the salience manipulation dramatically decreased systematic exploration in the salience conditions compared to the Baseline, although this reduction was achieved by different mechanism – through increased exploitation in the Congruent condition and through increased random exploration in the Competition condition (as indicated by the low value of β). These results suggest a direct link between attention and exploratory behavior early in development.

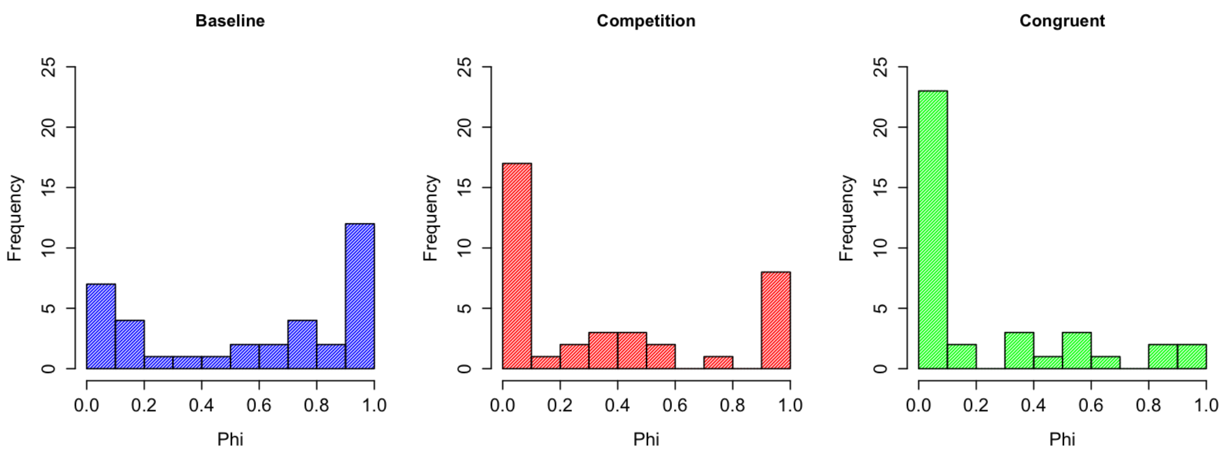

Figure 4: Best-fitting ϕ parameter. Histograms of the best-fitting ϕ parameter for each group are presented. Both salience conditions have a large proportion of participants with very low values of ϕ, indicating little systematic exploration, while the Baseline condition has a larger proportion of participants with high values of ϕ, indicating higher levels of systematic exploration.

Table 1: Median best-fitting parameter values (with standard deviations in parentheses)

	Baseline	Competition	Congruent
ϕ	0.701	0.213 (0.40)	0.045 (0.31)
β	1.348 (6.1)	0.367 (12)	0.680 (876)*

*Note: While the medians suggest most values were small, β has no upper limit, and infrequent large outliers (which are consistent with reward maximization) result in large standard deviations. This large value is mainly due to two such outliers, without which the standard deviation of the remaining sample is 12.

Discussion

The goal of the current study was to examine the link between systematic exploration and attention by manipulating attention and observing effects of such manipulation on systematic exploration. The reported results suggest that attentional manipulation (i.e., exogenously capturing attention through large differences in salience) decreased the level of systematic exploration in young children (compared to a Baseline condition).

In addition, children's choices were not simply salience-driven; instead the effect of saliency was dependent on whether or not it was congruent with or in competition with reward maximization. When the salient option was also highly valuable, children chose it more often than in the other conditions. But, when the salient option was low in value, it was not chosen more often than in the other conditions. This interaction suggests a complex role of attention in determining young children's choices.

Together these results suggest that attentional mechanisms are a major determinant of exploratory behavior in young children. When salience is otherwise equal, systematic exploration dominates choices (as in the Baseline condition), with less recently sampled options more likely to be selected. Manipulating bottom-up attention disrupts this process, leading to a reduction in systematic exploration. Once disrupted, if the salient stimulus signals a rewarding option, it can act as a cue that facilitates reward learning.

These results point to an integral role of attentional mechanisms in systematic exploratory behavior in young children, in contrast to the top-down PFC mediated processes involved in systematic exploration in adults. Despite PFC being immature, young children's tendency to distribute attention seems to support systematic exploration. Attentional mechanisms and exploratory decision-making may be part of a larger general pattern in which young children's cognition and behavior are specifically tuned to facilitate broad information gathering—which is particularly critical early in life.

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