Driven by Information: Children's Exploration Shapes Their Distributed Attention in Category Learning

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Abstract

Categories simplify the vast number of entities we encounter into equivalence classes, serving as a fundamental block of our cognition. This simplification of information supports our ability to reason about and interact with members of each category. In adulthood, selective attention helps us form categories efficiently by focusing on relevant attributes while filtering out irrelevant information. However, young children tend to encode more attributes than necessary, and this developmental difference is partly due to a prolonged development of selective attention. Additionally, the present study proposes that some children have an innate preference for information regardless of its value. In two category-learning experiments, children sampled more information than adults when filtering demands were low. Such exploratory behavior was not due to the motor actions associated with information sampling. The results suggest that children's tendency to explore plays a significant role in shaping their attentional processes in category learning. This work sheds light on the interplay of the developmental courses of exploration and selective attention and highlights the importance of considering children's preference for information in category learning research.

Keywords: cognitive development; category learning; selective attention; exploration; information sampling; decision making

Introduction

The ability to categorize is a fundamental cognitive process that plays a crucial role in human learning. It allows individuals to organize and simplify the vast amount of information available to their senses by grouping similar objects, events, or concepts together. This process enables individuals to interact efficiently with, recognize, and understand the world around them. During the categorization process, adults optimize their performance by learning to selectively attend to the most category-relevant attributes that members of the same category share rather than all category-relevant attributes (Deng & Sloutsky, 2016; Goldstone & Steyvers, 2001; Rehder & Hoffman, 2005)

While such selective attention mechanisms grant us the power to focus on some and filter out other aspects of information, it takes time to develop (Plude, Enns, & Brodeur, 1994). The question then arises: how do young children learn categories efficiently by focusing on a few relevant features? Studies suggest that the way children learn categories is influenced by the development of selective attention (Best & Miller, 2010; Deng & Sloutsky, 2016). Young children, whose selective attention is not fully developed, tend to encode more irrelevant information compared to adults. With age and experience, they become better at filtering out irrelevant information in category learning tasks.

In these studies, categories are structured with dimensions that vary in relevance, with one dimension perfectly predicting category membership and others probabilistically predicting it. Young children exhibited better memory after category learning for the probabilistic dimensions, which was not different from the memory for the deterministic dimension. While researchers have found that as children age, they become more selective in encoding the dimensions and have better memory for the perfectly predictive dimension, young children could be struggling to filter out less relevant dimensions when sampling information while being able to focus on the diagnostic dimension.

Recently, research on selective attention has shown that the ability to focus on relevant information and filter out irrelevant information develops asynchronously. According to Unger and Sloutsky Unger and Sloutsky (2023), filtering develops later than focus, suggesting that the two are potentially separate processes. In their study, participants were given a task where they had to switch their focus from an irrelevant to a relevant dimension. The study found that 6-year-olds and adults had more difficulties switching than the 4-year-olds when participants were given access to all dimensions before the switch. This was not the case when participants had access only to the relevant dimension, indicating immature filtering in the younger group that results in a failure to inhibit the irrelevant dimension. Other studies have also found similar evidence and estimated that filtering develops between the ages of three and seven (Chevalier & Blaye, 2008; Pritchard & Neumann, 2004), possibly continuing development into preadolescence.

Together, research to date suggests that the development of selective attention plays a role in shaping category learning. Specifically, the later onset of the filtering component might impede children's ability to optimize attention. However, children's tendency to distribute their attention may also be due to a higher level of uncertainty about the world. Distributing their attention is a simple way of broadly sampling information, with the goal of decreasing this uncertainty. While some have suggested that attention is a mechanism for active learning and uncertainty reduction (Gottlieb, 2012), the current study intends to investigate the developmental changes in attention when people sample information for category learn-

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ing. Before going into the details of the current study, we will discuss the findings describing children's information sampling.

Children tend to favor exploring new information over utilizing the information they already have, which can lead to lower rewards or less task-relevant information gain (Meder, Wu, Schulz, & Ruggeri, 2021). In a grid-based search task correlated with noisy reward, children were observed to explore uncertain options more than adults who were driven by rewards (Schulz, Wu, Ruggeri, & Meder, 2019). Additionally, children in the 20-question game often continued asking questions even after they should have known the answer, indicating a greater focus on acquiring information for general uncertainty reduction rather than optimizing for rewards (Ruggeri, Lombrozo, Griffiths, & Xu, 2016).

Previous findings have together described children's curiosity as a developmental default mode, which could be understood as an adaptive behavior driven by the need to resolve uncertainty (Gopnik, 2020). Young children optimize their learning for the amount of information rather than efficiency. In a study where participants learned categories with an unannounced switch in the relevance of the dimensions, children were less affected due to their distributed attention (Blanco, Turner, & Sloutsky, 2023). Adults in the study quickly identified the most deterministic dimension and limited their attention to it, resulting in their inability to learn the new structure. More findings have suggested that adults' susceptibility to this kind of suboptimal learning, often known as 'learning traps,' was caused by individuals' prior beliefs, knowledge, and experiences interfering with their ability to learn from new information (Liquin & Gopnik, 2022; Rich & Gureckis, 2018). In contrast, children are less prone to learning traps and learned inattention than adults due to their broader information sampling strategy.

Given the previous findings on children's immaturity in selective attention and their tendency to explore, it is still being determined if both are contributing to their distributed attention pattern in category learning. Therefore, the present study investigates if children's innate preference for rich information will shape their attention distribution during category learning. Critically, when children are encouraged to be selective, and their filtering mechanism is facilitated, would they be more selective in attention like adults, or would their tendency to explore drive the distributed attention?

Present Study

We investigated children's tendency to explore as a potential mechanism underlying their distributed attention during category learning development. To simulate the exploration process, we employed a task in which participants revealed dimensions of stimuli sequentially and allowed children to focus their attention by hiding less relevant dimensions. Children were not required to inhibit any dimension if they chose not to explore. Our findings revealed that, as children age, they become less likely to explore more dimensions than necessary. Despite the younger children's tendency to explore, they are aware of the differential values of the dimensions by prioritizing them. These results suggest that while immaturity in selective attention plays a role in distributed attention, the tendency to explore is another significant contributor.

Experiment 1

We investigated children's tendency to explore in a category learning task where all dimensions were initially occluded in each trial. In this paradigm, participants were required to tap on each dimension to reveal its feature value. Thus, the hidden dimensions did not require active suppression from the filtering mechanism. We expected that participants who optimized their learning would only reveal dimensions with higher information value for category decisions. The paradigm allowed us to measure the contribution of the tendency to explore in distributed attention, given that their difficulty in the filtering process was addressed.

Methods

Participants Participants in Experiment 1 were recruited from four age groups: 4-year-olds (N = 18, M = 4 years, 1 month), 5-year-olds (N = 25, M = 5 years, 5 months), 6-year-olds (N = 32, M = 6 years, 5 months), and adults (N=35, M = 22 years). The child age groups were selected because they capture a period of development when selective attention is not yet fully mature (Tipper & McLaren, 1990).

Materials The stimuli category was based on the rule-plus-similarity structure (Deng & Sloutsky, 2016). Each stimulus had one feature (i.e., the rule feature) that determined category membership, and the remaining six features (i.e., the probabilistic features) determined two-thirds of the trials. The categories could be learned through multiple probabilistic features, but an optimized learner would prioritize the rule feature due to its lower sampling cost. Such a category structure was useful for detecting different learning strategies. If one sampled more features than the rule feature, they were taking a more explorative strategy during category learning.

The study used bird-like creatures with seven dimensions (i.e., horn, head, beak, body, wing, feet, and tail) created from randomly chosen color shapes. Each dimension had two values, and each stimulus had four dimensions with values congruent with the correct category and two dimensions with values from the other category. Through permutation, the researchers generated 15 different training items for each category. For each participant, the rule dimension was randomly assigned from all dimensions except the head, due to its saliency.

After the training phase, participants were tested with both training items and novel items. There were four types of novel items: all-newP, new-D, one-newP, and switch. All-newP items had the rule feature from a studied category and all new features replacing the studied probabilistic feature (labeled as AP in the results section). New-D items had all probabilistic features of a studied category and a novel feature replacing the rule feature (labeled as ND in the results section). One-newP items had all features of a studied category but a novel feature replacing one probabilistic feature (labeled as OP in the results section). Switch items had the rule feature of a studied category but most probabilistic features consistent with the opposite category (labeled as S in the results section).

The training items and one-newP items were used to examine category learning, while the other items were used to determine if participants relied on overall similarity or the rule feature when asked to generalize. Rule-based learners were expected to categorize the Switch and all-newP items based on the rule feature, whereas similarity-based learners were more likely to generalize based on the probabilistic features. Moreover, if participants encoded the probabilistic features, they were more likely to categorize the new-D items correctly compared to those who only encoded the rule feature.

Design and Procedure The experiment had two phases: category learning and categorization testing. Participants learned about two kinds of birds, Hibi and Gora, and made category responses after uncovering the bird's features. Adults and children followed the same procedure with different apparatus. While adults read the instructions and pressed keyboards themselves, children received verbal instructions from an experimenter and used a touch screen to uncover the bird to be studied and verbally respond with the category label.

Before the training, participants were introduced to the prototypes of the birds, and each feature was presented slide by slide. On each training trial, participants were free to choose any or all dimensions to uncover, taking as long as they liked. They were encouraged to uncover fewer features to win more stickers, and this dynamic was emphasized with a practice phase where participants were asked to identify whether an image behind bubbles was a dog or a car. We ensured that children understood that partial observation was sufficient for categorization (i.e., seeing a wheel suggests it is a car, not a dog). After intensive pilot testing, we decided to scaffold the category learning by providing corrective feedback, with special emphasis on the rule feature (i.e., 'Good job! This is a Hibi because it has Hibi's feet!'). While the studied item of a trial remained on the screen during feedback, participants did not see the dimensions they did not uncover. In total, there were 30 training trials.

After the training, there were 55 testing trials with both studied and novel items, as described in the Materials section. Participants needed to uncover the dimensions to respond as before, but no feedback was given.

Results

The main analyses were performed with Bayesian methods in the R environment (R Core Team, 2021), using the rstan package (Stan Development Team, 2021). Bayesian models were used to model the age-dependent bimodal distribution observed in participants' tendency to explore and to investigate the relationship between age, learning accuracy, and tendency to explore.

All model estimates were based on the posterior distribution of the best-fit Bayesian models. We reported the predictions with their Highest Density Intervals (HDIs) instead of a single estimate. HDIs represent the range of values that contain a specified percentage of probable values and indicate the probability that the true value falls within that range.

For model comparisons, such as comparing models that take age as a covariate and those that do not, we used leave-one-out cross-validation (LOO-CV) to evaluate model fitness. LOO-CV is a method that trains a model on all but one data point and evaluates it on the left-out point. The Leave-One-Out Information Criterion (LOOIC) was chosen for its ability to incorporate prior information. To compare the LOOIC of two models, we estimated the difference in their expected predictive accuracy using the Bayesian LOO estimate of the expected log pointwise predictive density (ELPD) and the 'LOO' package (Vehtari et al., 2023). The preferred model has a larger ELPD. In the report, we present the difference in ELPDs and the standard error (SE) of the prediction.

For all fitted models, we examined trace plots and autocorrelation plots for the model parameters and checked that the Gelman-Rubin diagnostic indicated convergence. Posterior predictive checks were also computed to compare the observed distribution to the distribution predicted by the model. We conducted sensitivity analysis with a range of prior distributions to ensure predictive robustness. No differences in comparison results were found due to prior distribution changes. The modeling results were reported using weak priors.

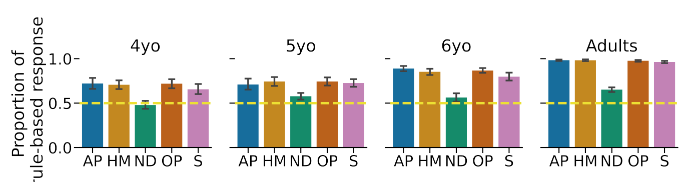

Figure 1: **Proportion of Rule-based Response during Testing.** AP: items with rule feature from a studied category and all new features replacing the studied probabilistic features. HM: studied items. ND: items with a novel feature replacing the rule feature. OP: items with all features of a studied category but a novel feature replacing one probabilistic feature. S: items with rule feature of a studied category but most probabilistic features consistent with the opposite category. Yellow dotted line stands for the chance level.

Category Learning Figure 1 shows the category learning results for each tested item type for different age groups. All age groups performed above chance in categorizing the studied items. Analyses were conducted to determine participants' category learning outcomes. The dependent variable was the mean accuracy of each item type. The mean accuracy was calculated based on the rule-based response for item types (e.g., Switch items) that could be categorized based on overall similarity or a single rule feature. Through model comparison, the best-fitted model included age as a categorical variable that combined 4- and 5-year-olds as one age group and 6-year-olds and adults as the other two groups (largest ELPD difference = 169.1, SE difference = 94.8). This suggests that 6-year-olds represent a critical transition point in category learning that matches the transition in their tendency to explore (discussed in the next result section). Table 1 reports the estimated median and 95% HDI of the rule-based response during testing from this best-fitted model.

Table 1: Model Estimated Rule-based Response by ages and item types. Median [95% HDI]

Item type	4yo & 5yo	6yo	Adults
AP	.71 [.65, .74]	.89 [.85, .93]	.98 [.97, .99]
HM	.73 [.68, .78]	.85 [.80, .90]	.98 [.96, .99]
ND	.54 [.49, .58]	.56 [.63, .50]	.65 [.61, .69]
OP	.73 [.68, .78]	.87 [.83, .91]	.98 [.96, .99]
S	.70 [.64, .75]	.80 [.73, .86]	.96 [.94, .98]

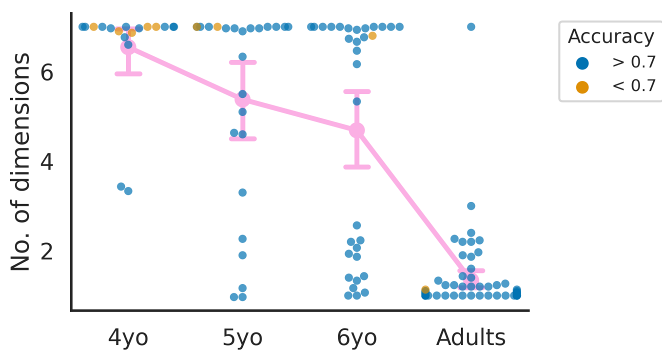

Figure 2: **Average Number of Dimensions Sampled during Training.** Error bar stands for standard error. Each dot represents a participant's average number of dimensions sampled. Yellow dots are participants with response accuracy below 70%.

Information Sampling Figure 2illustrates the relationship between age and the average number of dimensions sampled during the training phase. The results indicate a clear trend of decreasing exploratory behavior with increasing age, with 6-year-olds showing the highest tendency to exploit only a few dimensions during categorization. To further explore this relationship, a Bayesian model was fit, assuming that each participant's average number of dimensions sampled during training was generated from a mixture of two normal distributions corresponding to two behavioral types of exploration and exploitation, with mixture weights varying by age group. The model predicted that 4-year-olds had the highest mixture weights for the explorer's distribution (medium = 0.40, 95% HDI = [0.25,0.53]), while the mixture weights decreased with age. Specifically, for 5-year-olds and 6-year-olds, the model predicted the mediums of mixture weights to be 0.34, 95% HDI = [0.21,0.48], and 0.24, 95% HDI = [0.14, 0.37], respectively. For adults, the medium of mixture weights was 0.02, 95% HDI = [0.002, 0.06]. These findings suggest that children's tendency to explore plays a unique and important role in their interaction with the world and that this tendency decreases with age.

We conducted additional analyses to investigate whether categorization accuracy is related to children's tendency to explore. We considered the possibility that children who sampled all dimensions during training might have a harder time learning the categories because of the distracting information they encountered. However, a Bayesian linear regression model revealed that neither age nor the number of dimensions sampled significantly predicted training accuracy (largest ELPD difference between the full model and the one predictor model = 5.5, SE difference = 5.1). This finding could be due to the fact that almost all participants (105 out of 110) were able to learn the categories with the help of rule-based corrective feedback. On the other hand, children who sampled more information during training might benefit from it by forming more similarity-based representations of the categories. We therefore tested the hypothesis that these children might be less rule-based when generalizing to the test items with new or opposite rule features. However, another Bayesian linear regression model revealed no significant evidence that children who explored more were more similarity-based (largest ELPD difference between the full model and the one predictor model = 3.9, SE difference = 3.0). One potential explanation is that the process of uncovering dimensions of an item makes it harder to form a similarity-based representation than viewing the item as a whole.

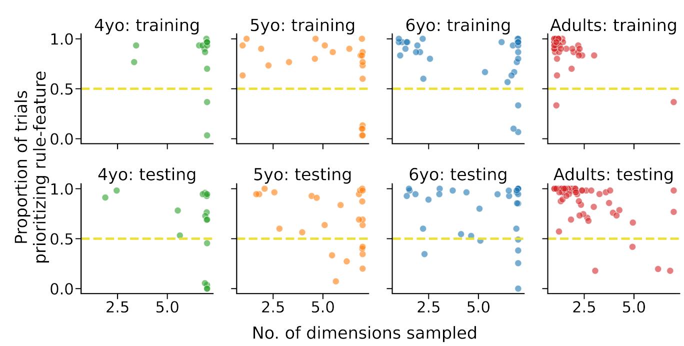

Figure 3: **Average Number of Dimensions Sampled x Proportion of trials prioritizing rule feature during training and testing.** A trial is counted as prioritizing the rule feature if the rule feature was sampled first or second. The yellow dotted line stands for half of the trials.

To gain more insights into children's categorization decision-making processes, we analyzed the proportion of trials where the rule feature was chosen among the first two dimensions explored (see Figure 3). Our findings show that, in general, children who explored more also tended to prioritize the rule feature in the same way as adults. This pattern was also evident during testing trials. However, unlike adults who explored more when encountering a novel rule feature and less when the rule dimension was familiar (as illustrated in Figure 4), children's exploration tendency was not influenced by the familiarity of the rule feature.

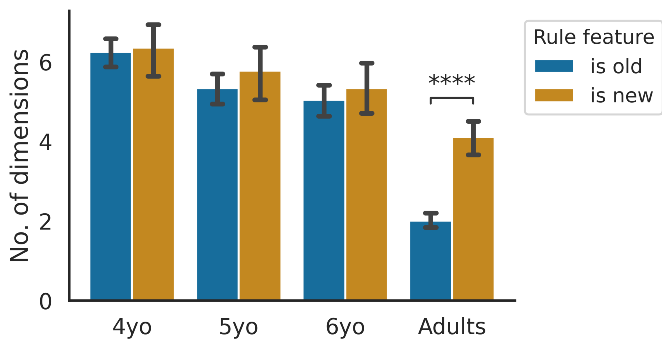

Figure 4: **Average Number of Dimensions Sampled for Test Items with Novel/familiar Rule Feature.** Mann-Whitney-Wilcoxon test was conducted between each age group. **** means p ¡ 1.00e-04.

Discussion

The results of Experiment 1 suggest that children tend to explore more than adults during information sampling, with younger children exploring more than older children. This developmental trend is consistent with previous findings indicating that young children have a bias toward exploration. Despite exploring all dimensions of an item, children were still able to categorize in a rule-based manner, as indicated by their prioritization of the rule feature in their choice patterns. This finding aligns with previous research on the unsynchronized development of focusing and filtering. Furthermore, children's exploration patterns remained stable throughout the experiment and were not influenced by the novelty or familiarity of test items, in contrast to adults who explored more when encountering novel rule features. However, children's exploration tendencies may also be motivated by the reward value of the tapping action in the experiment.

Experiment 2

While Experiment 1 examined children's tendency to explore using a category learning task that did not require the filtering mechanism from selective attention, it remained unclear whether children were driven by the desire for information or the enjoyment of tapping actions. In Experiment 2, we tested this idea using a similar occlusion paradigm as in Experiment 1, but with an additional express option of revealing everything with one tap. If children were not drawn to the tapping actions, they should prefer choosing this express option.

Methods

Participants Participants in Experiment 2 were recruited in three age groups: 4-year-olds (N = 2, M = 4 years, 5 months), 5-year-olds (N = 19, M = 5 years, 3 months), and 6-year-olds (N = 9, M = 6 years, 5 months).

Materials This experiment used photos of cats and squirrels instead of artificial stimuli.

Design and Procedure In Experiment 2, we aimed to investigate the reason for children's intense exploration in Experiment 1. We hypothesized that children might be more attracted to the tapping process than the information hidden behind the bubbles. To test this hypothesis, we presented children with the option to either 'blow away' all the bubbles at once or 'tap away' the bubbles one by one, revealing the stimulus behind the bubbles. Importantly, we made the 'blow away' option visually identical to the other bubbles. If children preferred tapping the bubbles, they would choose the latter option more often. The experiment consisted of 15 testing trials and 3 practice trials, and 5 bubbles covered each stimulus. The task was to identify whether a cat or a squirrel was hiding behind the bubbles.

Results

Most of the children (29 out of 30) showed a clear preference for the 'blow away' option over the 'tap away' option, as indicated by the binomial tests (p ¡ .001). A remarkable 23 children consistently chose the 'blow away' option. The results suggest that children were attracted to the occluded information in Experiment 1 rather than the tapping action.

General Discussion

In the present study, we aimed to investigate children's tendency to explore as one of the mechanisms shaping the development of category learning. Participants of different ages, including 4- to 6-year-old children and adults, learned categories in which one dimension perfectly predicted category membership while the other six dimensions probabilistically predicted category membership. By occluding all dimensions at the beginning of each trial to facilitate the filtering process, we measured participants' tendency to explore during information sampling.

Experiment 1 showed that children had a higher tendency to explore than adults, even when direct information on the category structure was provided as feedback. This suggests a unique contribution of exploration in children's distributed attention. We observed a developmental trend in both improved performances in category learning and a decreased tendency to explore during information sampling. Four-year-olds were more likely to explore than 5- and 6-year-olds, and at age six, children were transitioning into optimizers who only sampled the most valuable information. Across all ages in our sample, children exhibited awareness of information value by prioritizing the rule feature during information sampling. Furthermore, Experiment 3 ruled out the possibility that children did not stop sampling after the most important dimensions due to enjoyment. Overall, our findings provide novel evidence of the crucial contribution of exploration in children's distributive category learning.

The present study contributes to the existing literature on the development of category learning by highlighting the role of exploration in children's attentional processes. While selective attention has traditionally been viewed as the main contributor to category learning, this study shows that young children default to exploratory information sampling. Despite being encouraged and facilitated to be selective in filtering relevant information, children showed a strong preference for broad information sampling. Critically, the study allowed us to tease apart the independent contributions of the immature filtering component from selective attention and children's tendency to explore. Comparing the results from children aged four, five, and six, we observed a developmental trend of decreasing exploration bias. Our findings are consistent with prior research on children's exploratory behavior (Gopnik, 2020), suggesting that children engage in a more holistic and less biased approach to category learning.

Our findings also highlight the robustness of children's exploration tendency. Even when information value was provided, and they used rule-based categorization, young children still explored more than necessary, consistent with previous studies (Blanco et al., 2023; Liquin & Gopnik, 2022). Furthermore, the unchanging exploration rate of children throughout the testing phase, regardless of the novelty of the sampled information, suggests that they employ a consistent and effortless exploration strategy. In contrast, adults only continued to sample when the sampled information was unfamiliar, and their uncertainty about categorization was high. While such flexibility comes at the cost of actively balancing between efficiency and certainty, children prioritize information over efficiency, enabling them to observe the world more holistically. As seen in previous studies (Blanco et al., 2023), children perform better than adults when the task structure changes in the middle of the experiment, providing them with a strong evolutionary advantage when they have limited knowledge and experience. Taken together, our findings suggest that during the development of categorization, the critical ability to simplify and generalize knowledge and experience not only shifts from distributed to selective attention but also begins with extensive exploration and gradually narrows it down for efficiency.

Open Questions

While the present study sheds light on the contribution of exploration in children's attentional processes, further research is needed to fully understand its developmental trajectory and its relationship with the maturity of selective attention. One open question is the source of the observed variability in children's exploration. It remains unclear whether this variation is due to individual differences in personality, developmental stages, or a combination of both. Additionally, the study did not investigate the metacognitive level of exploration. It is unclear whether children explore because they enjoy exploring or because they have a sense of uncertainty about their knowledge. Future studies that address these questions can help advance our understanding of the development of category learning.

Conclusion

The present study investigated the contribution of exploration in shaping the development of category learning in children. While children's developing ability to filter out irrelevant information shapes their attentional processes in category learning, their natural tendency to gather information is also a significant contributor. The results showed that children have a preference for gathering as much information as possible, as evidenced by their tendency to explore and sample information, even when constraints on filtering were addressed and when information value was available to them. This tendency contrasts with adults, who prioritize learning efficiency over information gathering. The findings suggest that exploration plays a significant role in shaping children's attentional processes and highlight the importance of considering children's preferences for information in category learning research.

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