

UC Merced

Proceedings of the Annual Meeting of the Cognitive Science Society

Title

Category Learning is Shaped by the Multifaceted Development of Selective Attention

Permalink

<https://escholarship.org/uc/item/6f41r4mj>

Journal

Proceedings of the Annual Meeting of the Cognitive Science Society, 43(43)

ISSN

1069-7977

Authors

Unger, Layla
Sloutsky, Vladimir

Publication Date

2021

Peer reviewed

Category Learning is Shaped by the Multifaceted Development of Selective Attention

Layla Unger (unger.114@osu.edu)

Department of Psychology, Ohio State University

Vladimir M Sloutsky (sloutsky@psy.ohio-state.edu)

Department of Psychology, Ohio State University

Abstract

Selective attention allows adults to preferentially exploit input relevant to their goals. One critical role of selective attention is in adult category learning: adults can simplify the entities they encounter into groups of entities that they can treat as equivalent by focusing on category-relevant attributes, while filtering out category-irrelevant attributes. However, much category learning takes place during development, when selective attention substantially matures. We designed two experiments to disentangle the contributions of the focusing and filtering aspects of selective attention to category learning over development. Experiment 1 provided evidence that learning simple categories was accompanied by selective attention in both four year-old and five year-old children and adults. Experiment 2 further provided evidence that only focusing contributed to selective attention in four year-olds, whereas both focusing and filtering contributed to selective attention in five year-olds and adults. Thus, category learning recruits different aspects of selective attention with development.

Keywords: category learning; cognitive development; selective attention; focusing; filtering

Introduction

One of the fundamental roles of cognition is to simplify and distill the barrage of input available to our senses. For example, if we encounter something that is furry, four-legged, brown with white patches, about two feet tall, and has some dead leaves caught in its fur, we can more readily determine how to interact with it if we simplify this input by categorizing it as a dog. Adults simplify entities in the world into categories by learning to selectively attend to category-relevant attributes that members of the same category share (e.g., shape), rather than irrelevant attributes that vary between them (e.g., color and pattern) (Deng & Sloutsky, 2016; Goldstone & Steyvers, 2001; Rehder & Hoffman, 2005). However, much of the categories that populate adult knowledge were originally learned during development, when selective attention undergoes substantial maturation (Plude, Enns, & Brodeur, 1994). How is category learning over the course of development shaped by the development of selective attention?

Understanding how selective attention shapes the development of category learning involves tackling the challenging question of what selective attention is. Does learning to selectively attend to relevant input consist of focusing (i.e., enhancing the processing of) relevant input, filtering out (i.e., or inhibiting/suppressing the processing of) input that is irrelevant, or does focusing on some input collaterally filter

out other input? Although researchers have grappled with these questions for decades, neuroimaging research has provided mounting evidence that focusing and filtering may be separate processes (Andersen & Müller, 2010; Bridwell & Srinivasan, 2012; Gazzaley, Cooney, McEvoy, Knight, & D'esposito, 2005; Gulbinaite, Johnson, de Jong, Morey, & van Rijn, 2014; Polk, Drake, Jonides, Smith, & Smith, 2008). Moreover, as discussed below, these processes may follow different developmental trajectories. However, little research to date has investigated the development of focusing and filtering when people must learn what to attend to, as they must during category learning. In what follows, we review this research, and present a series of studies designed to illuminate how the development of focusing and filtering shapes the development of category learning.

Selective Attention and its Development

By adulthood, a growing body of neuroimaging evidence suggests that selective attention is supported by dissociable focusing and filtering processes. For example, an fMRI study conducted by Gazzaley et al. (2005) found that relative to neutral, passive viewing, the activity evoked by a stimulus (such as a face) was both enhanced when participants were instructed to attend to the stimulus (evidence of focusing), and suppressed when participants were instructed to ignore it (evidence of filtering; see also Andersen & Müller, 2010; Bridwell & Srinivasan, 2012; Polk et al., 2008). Moreover, focusing may occur without filtering, and vice versa. For example, using an innovative EEG paradigm, Gulbinaite et al. (2014) found that responding to a target in the presence of distractors was associated with focusing on the target in individuals with low working memory, and with filtering the distractors in individuals with high working memory.

Extensive evidence attests that selective attention in adults emerges following protracted development over infancy, childhood and adolescence (Lane & Pearson, 1982; Plude et al., 1994). However, only some of this research has attempted to disentangle focusing and filtering. First, research that has explicitly investigated the development of focusing has yielded evidence that it develops early, starting in infancy. For example, numerous findings suggest that stimulus processing is enhanced in infants both: (1) when the stimulus appears in an attentionally cued location (Johnson, 1994; Johnson, Posner, & Rothbart, 1994), and (2) when the infant

is in an attentive state (Richards, 2003).

In contrast with research on focusing, research that has explicitly investigated the development of filtering has yielded conflicting results. Conflicting findings are particularly notable in research spanning early childhood, from approximately 3 to 7 years of age. For example, equivocal results have been found from the negative priming paradigm, in which filtering is inferred when participants respond worse to targets that were recently distractors (and that could thus have been filtered) versus those that were not. This research has yielded evidence for both the early development of filtering (from at least age 3; Chevalier & Blaye, 2008; Pritchard & Neumann, 2004), and substantial increases in filtering with age (from age 7 to adulthood; Pritchard & Neumann, 2011; Tipper, Bourque, Anderson, & Brehaut, 1989). Studies of the development of filtering have also measured filtering from retrieval induced forgetting (RIF). In this paradigm, participants first study category-item pairs such as FRUIT-banana and FRUIT-apple, then retrieve memory for only a subset of pairs for a category, such that filtering is measured from worse memory for the non-retrieved pairs. Evidence from this paradigm is also equivocal: Although some RIF studies suggest that filtering changes little with development from at least age 7 to adulthood (Zellner & Bäuml, 2005), some studies have provided evidence that filtering increases across an earlier span of development, from age 4 to 7 (Aslan & Bäuml, 2010).

Taken together, research to date suggests that focusing develops early, but provides conflicting evidence for the development of filtering. Critically, much of this research does not tackle the development of selective attention when people must learn what to attend to. Illuminating this development is important because people often must learn what input is most relevant to their goals through experience, as is the case when people learn categories. In the next section, we review research that has investigated the development of selective attention in category learning, and highlight how it does not disentangle the contributions of focusing and filtering.

Role of Selective Attention in Category Learning

A handful of findings suggest that selective attention increasingly contributes to category learning over development, particularly over the course of early childhood from approximately age 4 to 7 (Best, Yim, & Sloutsky, 2013; Deng & Sloutsky, 2015, 2016). Most of these studies have used a paradigm in which children and adults learn categories with dimensions that vary in relevance to category membership, such that one dimension is deterministically associated (i.e., perfectly correlated) with category membership, multiple dimensions are probabilistically associated (i.e., imperfectly correlated) with category membership, and the remaining dimensions are irrelevant. The results of these studies suggest that attention is distributed across deterministic and probabilistic dimensions in young children (e.g., from age 4), and becomes increasingly selectively oriented to just the deterministic dimension with age (e.g., from age 6-7 to adulthood).

These findings suggest that, with age, people deploy increasingly narrow selective attention to only dimensions that they learn are most diagnostic of category membership. However, this research did not investigate attention to irrelevant dimensions, and thus leaves open the possibility that even young children may attend more to dimensions that are at least somewhat relevant (i.e., both deterministic and probabilistic) than to dimensions that are entirely irrelevant.

Critically, the research that has investigated the development of selective attention during category learning has not disentangled whether this developmental trajectory is driven by changing contributions of focusing, filtering, or both. Disentangling these contributions is challenging: When people learn a specific category structure, any difference in attention to relevant versus irrelevant dimensions can be due to focusing attention to relevant dimensions, filtering irrelevant dimensions, or both. One way to overcome this challenge is to introduce a “switch” in relevance at some point during category learning, in which a dimension that was not previously relevant becomes relevant. If category learning involves focusing, learners should always struggle to shift their focus to any newly relevant dimension after the switch. Critically, if category learning also involves filtering, learners should find it more difficult to focus on a newly relevant dimension that had been irrelevant (and thus filtered) prior to the switch, versus a newly relevant dimension that was not present (and thus could not be filtered) prior to the switch (Goldstone & Steyvers, 2001; Hoffman & Rehder, 2010). Research that has used this approach with adults has found evidence of both focusing and filtering (Goldstone & Steyvers, 2001). As described below, the present research used this approach to disentangle the contributions of focusing and filtering in the development of category learning.

Present Research

The present research sought to disentangle the contributions of focusing and filtering to selective attention in the development of category learning. The research consisted of two experiments designed to accomplish this goal. To target the period of development in which the development of filtering in particular is contentious, both experiments investigated focusing and filtering in two age groups within this period (i.e., ages 4 and 5), and contrasted them with adults.

Experiment 1 investigated whether even young children deploy some degree of selective attention to relevant versus entirely irrelevant dimensions during category learning. Adults and children aged 4 and 5 learned highly simplified categories of creatures that possessed one relevant and one irrelevant dimension. To target selective attention when relevant dimensions must be learned, in contrast with some prior studies of category learning in development (Deng & Sloutsky, 2016, 2015), participants were not provided with any initial cues about the relevance of different dimensions, and thus could only learn by making categorization decisions and receiving feedback. Selective attention to the relevant dimension was measured based on better subsequent recognition

memory for familiar versus novel values of the relevant versus irrelevant dimension (Deng & Sloutsky, 2016). To anticipate the results, category learning occurred in all age groups, and was accompanied by greater attention to the relevant versus the irrelevant dimension.

Experiment 2 investigated whether the contributions of focusing versus filtering to selective attention change with age. Here, participants initially learned categories like those used in Experiment 1, but experienced a switch half-way through category learning. In this switch, the initially relevant dimension became irrelevant, and the initially irrelevant dimension became relevant. We anticipated that all participants would find it challenging to learn the new category structure following the switch. To isolate the contributions of filtering to this challenge, we assigned participants to one of two conditions. In the “Visible” condition, the initially irrelevant dimension that became relevant post-switch was visible prior to the switch, and could thus be filtered. In the “Hidden” condition, the initially irrelevant dimension was occluded prior to the switch, thus preventing it from being filtered. If selective attention involves both focusing and filtering, participants in the Visible condition should find it harder to learn the new category structure post-switch, because they have the added challenge of recovering attention to a filtered dimension. If selective attention only involves focusing, then participants should find it similarly hard to shift focus to a newly relevant dimension in both conditions. Using this approach, we investigated two alternative hypotheses: (1) Selective attention involves both focusing and filtering even early in development, and (2) Selective attention involves focusing early in development, and increasingly involves filtering with age.

Experiment 1

Methods

Participants. Participants were recruited in three age groups: Four year-olds ($N = 33$; $M = 4$ years, 5 months), five year-olds ($N = 35$; $M = 5$ years, 4 months), and adults ($N = 53$). The child age groups were selected because they capture a period of development when the contributions of filtering to selective attention are disputed (Aslan & Bäuml, 2010; Chevalier & Blaye, 2008; Pritchard & Neumann, 2004; Tipper & McLaren, 1990).

Materials. The category stimuli were created based on extensive piloting designed to identify category structures that even 4-year-old children could learn. This piloting had two key constraints. First, values on only a single dimension could be relevant to category membership, and values on all other dimensions had to be irrelevant. This constraint was necessary for testing selective attention to relevant versus irrelevant dimensions. Second, to target selective attention to dimensions that is evoked by their learned relevance, it was of critical importance to use categories that children could learn purely from categorizing exemplars and receiving feedback. This constraint contrasts with some prior studies of category learning in children (Deng & Sloutsky, 2015, 2016) that pre-

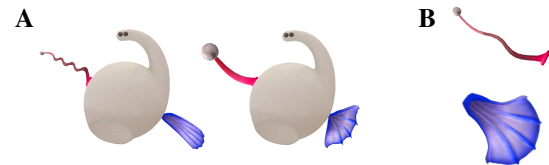


Figure 1: Panel A depicts creatures that illustrate values on the two extremes of each dimension. Panel B depicts the novel values for each dimension used in the recognition memory task.

ceded category learning with explicit cues to the dimensions relevant to category membership, which were necessary for young children to learn categories with several (e.g., seven) dimensions. The results of this piloting indicated that successful category learning only occurred in the majority of 4-year-old children with a highly simplified category structure with two dimensions: One relevant, and one irrelevant. Moreover, the values of the relevant dimension that were each associated with a different category needed to be highly visually discriminable.

Stimuli consisted of novel creatures with two dimensions: Flippers and tails. Each dimension was created by morphing between two anchor images that were different in shape (e.g., two different-shaped flippers). Values of these dimensions used in the stimuli were only taken from near one of the two extremes of the morph dimension (shown in Figure 1A). 8 category exemplars were created from combinations of 4 possible values on each dimension (2 values from near one extreme of the dimension, and 2 values from near the other extreme). In the experiment (see Procedure), these stimuli were divided into two categories, such that the values of one (“relevant”) dimension perfectly predicted category membership, and the value of the other (“irrelevant”) dimension occurred equally often in both categories. When a dimension was relevant, values from near one extreme of the dimension determined that the creature belonged to one category, and values from near the other extreme determined that the creature belonged to the other category. For a recognition memory task that followed category learning (see Procedure), we additionally created eight novel creatures: Four in which the flipper was replaced with a novel value, and four in which the tail was replaced with a novel value (Figure 1B).

Design and Procedure. The experiment consisted of two phases: Category learning, and recognition memory. Participants were randomly assigned to complete one of two versions of the experiment that counterbalanced the relevance of the two dimensions to category membership. Thus, for a given participant, the values of one “Relevant” dimension perfectly predicted category membership, and the values of the “Irrelevant” dimension occurred equally often in both categories.

The procedure was similar for adults and children, with the exception that adults followed instructions presented on the

computer screen and used the keyboard to make responses, whereas an experimenter read instructions aloud and recorded children’s verbal responses. At the start of category learning, participants were instructed that they would see two kinds of creatures: Zibbies and Tomas. They were then shown two example creatures (Figure 1A). As in the creatures that participants subsequently learned to categorize, each example creature had a flipper and tail value taken from one of the extremes of the flipper and tail dimensions. While these creatures were shown, participants were told that all creatures had two body parts that come in different shapes: A flipper, and a tail. Each body part was highlighted with a yellow outline while the instructions or experimenter pointed out its two different values. Then, participants were told that the shape of one of the body parts is important for figuring out whether a creature is a Zibbie or a Toma. Participants then completed four category learning blocks that each contained one trial for each of the 8 category exemplars described above. On each trial, participants were asked to identify the creature as a Zibbie or a Toma. Following the categorization decision, participants received corrective feedback in which the creature remained on the screen, and were told “[Correct!/Oops!] It’s a [Zibbie!/Toma!]”.

After the final category learning block, participants began the recognition memory task. Participants were told that they would see some more creatures, some of which would be the same as ones they saw during the first part of the experiment, and some that would be new. They were further told that in new creatures, one of the body parts would be a new shape, and that their job was to figure out which creatures were ones they saw before, and which ones were new. Participants then completed 32 recognition memory trials in which they saw a creature, and indicated whether it was “old” or “new”. These trials consisted of: (1) 16 “Old” trials, across which each of the 8 category exemplars was presented twice, and (2) 16 “New” trials, across which each of the 8 novel stimuli was presented twice. As described under Stimuli above, half of the New trials presented a creature in which the relevant dimension was replaced with its novel value, and half presented a creature in which the irrelevant dimension was novel.

Results

All analyses were conducted using Bayesian models constructed using the rstan package (Stan Development Team, 2020) in the R environment for statistical computing (R Development Core Team, 2008).

Category Learning. Figure 2 depicts category learning in each of the three age groups. Analyses assessed whether participants in each age group learned the categories. Trial-by-trial categorization accuracy was analyzed using a Bayesian hierarchical model in which accuracies were predicted as the outcome of a logistic regression, with an intercept and slope for change in accuracy across trials for each participant. Intercepts and slopes for participants were each drawn from one of three higher-level distributions (all given the same weak

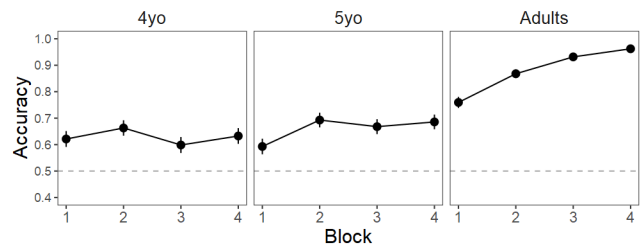


Figure 2: Categorization accuracy across blocks in each age group. The dashed line depicts chance. Error bars depict standard errors.

priors), based on the participant’s age group. We assessed whether successful category learning occurred in each age group using the predicted categorization accuracies from this model: For each posterior sample for each age group, we calculated the mean accuracy on the final two blocks of category learning predicted by the model. To capture the range of most probable values for final mean accuracy, we calculated Highest Density Intervals (HDIs) for the posterior distributions of predicted final mean accuracies. This interval is the range of a distribution that contains some specified percentage of probable values. The interpretation of such intervals is simply the probability that the “true” value falls within the range. In all age groups, categorization accuracy was predicted to be above chance (i.e., .5) in the final two blocks (Four year-olds: Median = 0.62, 90% HDI = [0.60, 0.66]; Five year-olds: Median = 0.69, 90% HDI = [0.66, 0.71]; Adults: Median = 0.96, 90% HDI = [0.94, 0.96]). Comparing the mean accuracy on the final two blocks between age groups for each posterior sample indicated that accuracy increased slightly from four to five year-olds (Median = 0.06, 90% HDI = [0.02, 0.10]), and substantially from five year-olds to adults (Median = 0.26, 90% HDI = [0.23, 0.29]).

Selective Attention. We assessed whether category learning was accompanied by selective attention to the relevant dimension based on whether participants had better recognition memory for values of the relevant versus the irrelevant dimension. We measured recognition memory for each dimension using dprime scores, calculated from hits for correctly identifying creatures with a new value on the dimension as “new”, and false alarms for incorrectly identifying old creatures as “new”. For each participant, we then calculated a “Relevant Attention” score as their dprime for the relevant dimension minus their dprime for the irrelevant dimension.

Figure 3 shows dprime and Relevant Attention scores by age, which suggest that all age groups tended to attend more to the relevant dimension. We analyzed these data to test whether Relevant Attention scores tended to be above 0 in each age group. For this analysis, we constructed a Bayesian hierarchical model in which each participant’s Relevant Attention score was drawn from a normal distribution. For each participant, the mean of this distribution was drawn from one

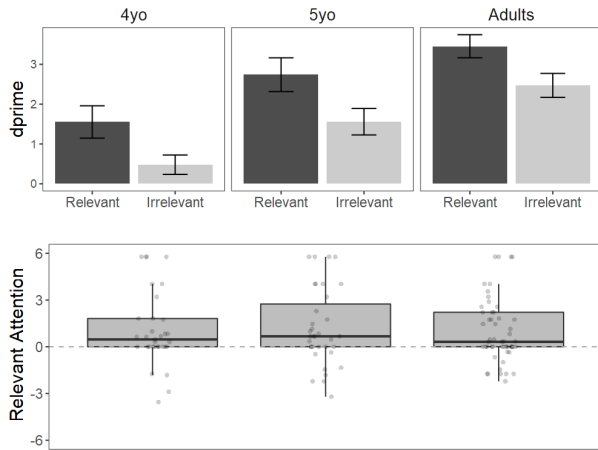


Figure 3: Top: d' values for relevant and irrelevant dimensions in each age group. Error bars depict standard errors. Bottom: Relevant Attention scores in each age group. The dashed line depicts no difference in attention to relevant versus irrelevant dimensions. Points depict participants.

of three higher-level normal distributions (all given the same weak priors), based on the participant's age. Thus, we assessed whether Relevant Attention was greater than 0 based on whether the mean of the distribution for each age group tended to be greater than 0. All age groups had a high probability that Relevant Attention scores were greater than 0: 89% for four-year-olds, 90% for five-year-olds, and 90% for adults. Thus, category learning was accompanied by similarly greater attention to relevant versus irrelevant dimensions from age four to adulthood.

Discussion

Experiment 1 revealed that successful category learning was accompanied by greater attention to a category-relevant dimension than to a category-irrelevant dimension. However, this result does not disentangle whether selective attention involves focusing on the relevant dimension, filtering the irrelevant dimension, or both. Experiment 2 was designed to disentangle these possibilities.

Experiment 2

Methods

Participants. Participants in Experiment 2 were assigned to one of two between-subjects conditions: Visible or Hidden. Participants were recruited from the same age groups as Experiment 1: Four year-olds (Visible $N = 32$, $M = 4$ years, 5 months; Hidden $N = 34$, $M = 4$ years, 5 months), five year-olds (Visible $N = 32$, $M = 5$ years, 4 months; Hidden $N = 30$, $M = 5$ years, 4 months), and adults (Visible $N = 58$; Hidden $N = 53$). An additional four four year-olds and six five year-olds were recruited but not analyzed due to poor category learning (see Results).

Materials. This experiment used the same category exemplars as Experiment 1, and a picture of bubbles.

Design and Procedure. Participants were randomly assigned to one of two between-subjects conditions: Visible or Hidden. As in Experiment 1, participants were also randomly assigned to complete one of two versions of each condition that counterbalanced the relevance of the two dimensions to category membership.

The procedure for Experiment 2 was similar to Experiment 1, except that: (1) Category learning instructions informed participants that sometimes one of the body parts might be covered by bubbles, and (2) The relevance of the two dimensions switched between blocks 2 and 3, such that the dimension that was relevant prior to the switch became irrelevant after the switch, and vice versa. In the Visible condition, both dimensions were visible throughout category learning. In the Hidden condition, prior to the switch, the initially irrelevant dimension was always occluded by bubbles.

Results

To investigate the effects of the Visible versus Hidden conditions on post-switch categorization accuracy, it was important to focus on participants who were likely to have learned the initial category structure over the pre-switch blocks. Thus, we excluded participants who achieved low ($\leq .25$) accuracy in the final pre-switch block. This criterion excluded four four year-olds, six five year-olds, and no adults. It is important to note that the sources of such low accuracy are ambiguous, and could be due to a lack of learning coupled with chance responding (i.e., $\leq .25$ accuracy in the 8 trials could occur by chance with a probability of .14), or successful learning in children who are sometimes motivated to make intentionally incorrect responses (Blanco & Sloutsky, 2021).

Figure 4 depicts category learning in three age groups. Categorization accuracy data were analyzed to compare post-switch category learning in the Visible and Hidden conditions for each age group. Accuracy data were fit using a model similar to the model used in Experiment 1, with the exception that accuracy was predicted separately for the pre-switch and post-switch phases. Using the same approach as in analyses for Experiment 1, we assessed category learning in the post-switch blocks for the Visible and Hidden conditions in each age group. 90% HDIs for post-switch accuracy were above chance for all age groups and conditions, with the exception of five year-olds in the Visible condition (Median = 0.54, 90% HDI = [0.49, 0.56]).

We used post-switch accuracy to test whether post-switch category learning was better in the Hidden than in the Visible condition in each age group. For each posterior sample, we calculated accuracy in the post-switch blocks in the Hidden condition minus the Visible condition, such that positive values indicate better category learning post-switch in the Hidden versus the Visible condition. Post-switch category learning in four year-olds was similar in the two conditions: There was only a 61% probability that accuracy was better

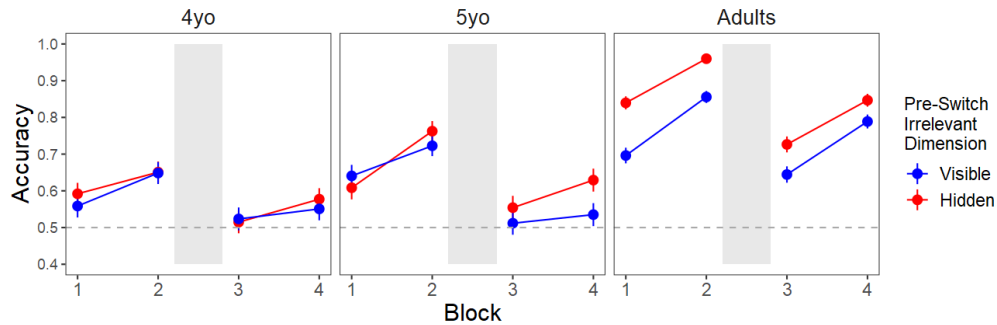


Figure 4: Categorization accuracy across blocks in each age group and condition, with the switch depicted as a gray bar. The dashed line depicts chance. Error bars depict standard errors.

in the Hidden condition. In contrast, in both five year-olds and adults, there was a $> 99\%$ probability that post-switch category learning was better in the Hidden condition.

General Discussion

Four year-olds, five year-olds, and adults learned simple categories with one relevant dimension that perfectly predicted category membership, and one entirely irrelevant dimension. Experiment 1 demonstrated that learning these categories was accompanied by selective attention across age. To disentangle the contributions of focusing and filtering, Experiment 2 introduced a switch in dimension relevance part-way through category learning designed to cause all learners to struggle to shift their focus to the newly relevant dimension. Critically, we manipulated whether learners had the opportunity to filter the dimension that became relevant after the switch. If filtering is present in an age group, then learners should have more trouble switching to the newly relevant dimension when learners had the opportunity to filter it. Four year-olds only showed evidence of focusing and not filtering, whereas five year-olds showed evidence of both. Thus, these experiments provide evidence for developmental changes in the processes that underpin selective attention in category learning.

Developmental Trajectory of Focusing and Filtering

In the present study, four year-olds showed evidence of focusing, but only five year-olds and adults also showed evidence of filtering. These findings are consistent with prior evidence that filtering emerges from pre-school to school age (e.g., Aslan & Bäuml, 2010), but inconsistent with evidence that filtering is present even early in development (e.g., Pritchard & Neumann, 2004), or only emerges even later in development (e.g., Deng & Sloutsky, 2016). This variability highlights an important possibility that the development of filtering (and of selective attention generally) does not involve a qualitative shift from absent to present. Instead, even immature selective attention may involve filtering in favorable situations (e.g., when there is a small amount of distracting input that is consistent over time). With development, filtering may become a more robust and widespread aspect of selective attention.

This possibility raises testable predictions, such as that the role of filtering in learning more complex category structures will emerge later in development than observed in this study.

Learning Relevance

Humans navigating real-world environments are often faced with the challenge of learning what is relevant to their goals. In contrast, in much of the prior research that has investigated the development of selective attention, relevance is explicitly specified for participants. For example, participants may be instructed to respond stimuli in a specific location (McDermott, Perez-Edgar, & Fox, 2007; Pritchard & Neumann, 2004), or respond to the location of specific stimuli (Tipper & McLaren, 1990). The present experiments move beyond this prior research by investigating the development of focusing and filtering processes when relevance must be learned. Thus, the present findings suggest that learning what is relevant is increasingly accompanied by filtering out input that is learned to be irrelevant with age.

References

- Andersen, S., & Müller, M. (2010). Behavioral performance follows the time course of neural facilitation and suppression during cued shifts of feature-selective attention. *Proceedings of the National Academy of Sciences*, *107*(31), 13878–13882.
- Aslan, A., & Bäuml, K.-H. T. (2010). Retrieval-induced forgetting in young children. *Psychonomic Bulletin & Review*, *17*(5), 704–709.
- Best, C. A., Yim, H., & Sloutsky, V. M. (2013). The cost of selective attention in category learning: Developmental differences between adults and infants. *Journal of Experimental Child Psychology*, *116*(2), 105–119.
- Blanco, N. J., & Sloutsky, V. M. (2021). Systematic exploration and uncertainty dominate young children's choices. *Developmental Science*, *24*(2), e13026.
- Bridwell, D. A., & Srinivasan, R. (2012). Distinct attention networks for feature enhancement and suppression in vision. *Psychological Science*, *23*(10), 1151–1158.

- Chevalier, N., & Blaye, A. (2008). Cognitive flexibility in preschoolers: The role of representation activation and maintenance. *Developmental Science, 11*(3), 339–353.
- Deng, W., & Sloutsky, V. M. (2015). The development of categorization: Effects of classification and inference training on category representation. *Developmental Psychology, 51*(3), 392.
- Deng, W., & Sloutsky, V. M. (2016). Selective attention, diffused attention, and the development of categorization. *Cognitive Psychology, 91*, 24–62.
- Gazzaley, A., Cooney, J. W., McEvoy, K., Knight, R. T., & D'Esposito, M. (2005). Top-down enhancement and suppression of the magnitude and speed of neural activity. *Journal of Cognitive Neuroscience, 17*(3), 507–517.
- Goldstone, R. L., & Steyvers, M. (2001). The sensitization and differentiation of dimensions during category learning. *Journal of Experimental Psychology: General, 130*(1), 116–139.
- Gulbinaite, R., Johnson, A., de Jong, R., Morey, C. C., & van Rijn, H. (2014). Dissociable mechanisms underlying individual differences in visual working memory capacity. *Neuroimage, 99*, 197–206.
- Hoffman, A. B., & Rehder, B. (2010). The costs of supervised classification: The effect of learning task on conceptual flexibility. *Journal of Experimental Psychology: General, 139*(2), 319.
- Johnson, M. H. (1994). Visual attention and the control of eye movements in early infancy. *Attention and Performance Xv: Conscious and Nonconscious Information Processing, 15*, 291–310.
- Johnson, M. H., Posner, M. I., & Rothbart, M. K. (1994). Facilitation of saccades toward a covertly attended location in early infancy. *Psychological Science, 5*(2), 90–93.
- Lane, D. M., & Pearson, D. A. (1982). The development of selective attention. *Merrill-palmer Quarterly, 31*7–337.
- McDermott, J. M., Perez-Edgar, K., & Fox, N. A. (2007). Variations of the flanker paradigm: Assessing selective attention in young children. *Behavior Research Methods, 39*(1), 62–70.
- Plude, D. J., Enns, J. T., & Brodeur, D. (1994). The development of selective attention: A life-span overview. *Acta Psychologica, 86*(2-3), 227–272.
- Polk, T. A., Drake, R. M., Jonides, J. J., Smith, M. R., & Smith, E. E. (2008). Attention enhances the neural processing of relevant features and suppresses the processing of irrelevant features in humans: a functional magnetic resonance imaging study of the stroop task. *Journal of Neuroscience, 28*(51), 13786–13792.
- Pritchard, V. E., & Neumann, E. (2004). Negative priming effects in children engaged in nonspatial tasks: Evidence for early development of an intact inhibitory mechanism. *Developmental Psychology, 40*(2), 191.
- Pritchard, V. E., & Neumann, E. (2011). Classic stroop negative priming effects for children and adults diverge with less-conflicting and nonconflicting conditions. *The American Journal of Psychology, 124*(4), 405–419.
- R Development Core Team. (2008). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing.
- Rehder, B., & Hoffman, A. B. (2005). Eyetracking and selective attention in category learning. *Cognitive Psychology, 51*(1), 1–41.
- Richards, J. E. (2003). Attention affects the recognition of briefly presented visual stimuli in infants: An erp study. *Developmental Science, 6*(3), 312–328.
- Stan Development Team. (2020). *Rstan: the r interface to stan*. Retrieved from <http://mc-stan.org/>
- Tipper, S. P., Bourque, T. A., Anderson, S. H., & Brehaut, J. C. (1989). Mechanisms of attention: A developmental study. *Journal of Experimental Child Psychology, 48*(3), 353–378.
- Tipper, S. P., & McLaren, J. (1990). Evidence for efficient visual selectivity in children. In *Advances in psychology* (Vol. 69, pp. 197–210). Elsevier.
- Zellner, M., & Bäuml, K.-H. (2005). Intact retrieval inhibition in children's episodic recall. *Memory & Cognition, 33*(3), 396–404.