Journal of Experimental Child Psychology 116 (2013) 105–119

Contents lists available at SciVerse ScienceDirect

Journal of Experimental Child Psychology

journal homepage: www.elsevier.com/locate/jecp

The cost of selective attention in category learning: Developmental differences between adults and infants

Catherine A. Best [a], Hyungwook Yim [b], Vladimir M. Sloutsky [b,*]

[a] Department of Psychology, Kutztown University, Kutztown, PA 19530, USA
[b] Department of Psychology, The Ohio State University, Columbus, OH 43210, USA

ARTICLE INFO

Article history:
Received 6 January 2013
Revised 6 May 2013

Keywords:
Selective attention
Categorization
Learning
Cognitive development
Infancy
Eye tracking

ABSTRACT

Selective attention plays an important role in category learning. However, immaturities of top-down attentional control during infancy coupled with successful category learning suggest that early category learning is achieved without attending selectively. Research presented here examines this possibility by focusing on category learning in infants (6–8 months old) and adults. Participants were trained on a novel visual category. Halfway through the experiment, unbeknownst to participants, the to-be-learned category switched to another category, where previously relevant features became irrelevant and previously irrelevant features became relevant. If participants attend selectively to the relevant features of the first category, they should incur a cost of selective attention immediately after the unknown category switch. Results revealed that adults demonstrated a cost, as evidenced by a decrease in accuracy and response time on test trials as well as a decrease in visual attention to newly relevant features. In contrast, infants did not demonstrate a similar cost of selective attention as adults despite evidence of learning both to-be-learned categories. Findings are discussed as supporting multiple systems of category learning and as suggesting that learning mechanisms engaged by adults may be different from those engaged by infants.

* Corresponding author.
E-mail addresses: sloutsky@psy.ohio-state.edu, sloutsky.1@osu.edu (V.M. Sloutsky).

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http://dx.doi.org/10.1016/j.jecp.2013.05.002

Introduction

Category learning is critically important for making sense of the world. Through categorization, individuals can organize existing knowledge and make predictions about new instances and events. For example, on observing a bouncing ball, an infant may expect a novel ball to bounce as well. Obviously, in most categorization tasks, some properties of stimuli are important for the task at hand, whereas others are not. For example, in the example above, the material of the ball (e.g., rubber vs. wooden) is predictive of whether or not it will bounce, whereas the ball's color is not. Therefore, efficient category learning may include the ability to attend selectively to what is relevant, and most theories of category learning involve a selective attention component (e.g., Kruschke, 1992; Love, Medin, & Gureckis, 2004; Medin & Schaffer, 1978; Nosofsky, 1986; see also Kruschke, 2001, for a review). Selective attention supports efficient category learning because it allows individuals to focus on category-relevant information while discarding category-irrelevant information. Selective attention is particularly advantageous when category members have few common features, with many features being irrelevant (i.e., not predictive of category membership). In this case, selective attention helps focusing on the few relevant dimensions while ignoring multiple irrelevant dimensions (e.g., when the task is to sort objects by color and ignore variance in shape, size, and texture). The advantage of selective attention is particularly noticeable when the task is to generalize—determine category membership of a novel item that has a particular value on the relevant dimension. The ability to shift attention to relevant information and inhibit attention to irrelevant has been demonstrated in both human and non-human animals (e.g., Dixon, Ruppel, Pratt, & De Rosa, 2009; Mackintosh, 1965).

Although selective attention results in multiple benefits for category learning (because some categories cannot be learned without it), it also leads to certain costs. One key consequence of attending selectively during learning is the phenomenon known as learned inattention (e.g., Kruschke, 1992), namely, a tendency to continue ignoring information that was previously irrelevant and, thus, was learned to be ignored. Furthermore, learned inattention can constitute a cost of selective attention when a learning situation requires one to shift attention back to previously ignored information.

The cost of selective attention is particularly evident in multi-phase category learning when, after learning a particular category, participants are expected to learn another category that is defined by formerly unattended dimensions (i.e., in the situation of an extra-dimensional shift between categories). For example, participants may first learn to sort by color (e.g., red objects vs. green objects), with shape varying randomly within and across colors. After learning the category-relevant dimension, they are presented with another category-learning problem in which shape becomes a relevant dimension, whereas color is not.

In contrast to the situation above, the cost of selective attention is minimized when the shift is intra-dimensional (i.e., when two categories are defined by different values of the same dimension). For example, in an intra-dimensional shift, the first to-be-learned category is defined by one color (e.g., red objects), but the second to-be-learned category is defined by a different color (e.g., green objects). During an extra-dimensional shift participants need to switch between different dimensions (e.g., from color cues to shape cues), whereas during an intra-dimensional shift participants only need to switch between values of the same dimension. Empirical evidence indicates that adults indeed exhibit learned inattention to a dimension that was irrelevant for their learning of the first category but then became relevant for their learning of the second category (e.g., Dopson, Esber, & Pearce, 2010; Hoffman & Rehder, 2010; Kruschke & Blair, 2000). These findings suggest that participants attended selectively when learning the first category, thereby incurring costs of selective attention when learning the second category.

Although selective attention plays an important role in adult category learning, less is known about the role of selective attention in early category learning. Two facts are worth considering. First, it has been demonstrated that very young infants can learn visual categories. For example, 3- and 4-month-old infants are able to form basic-level categories of natural kinds, such as dogs and cats (Quinn, Eimas, & Rosenkrantz, 1993; Quinn, Eimas, & Tarr, 2001), and artifacts, such as chairs; global-level categories, such as animals and furniture (Behl-Chadha, 1996); and categories consisting of abstract dot patterns (Bomba & Siqueland, 1983). Second, early in development, infants and young children have difficulty in selectively focusing attention on relevant information while inhibiting attention to irrelevant information (see Dempster & Corkill, 1999; Hanania & Smith, 2010, and Lane, 1982, for reviews). For example, in one task (e.g., Smith & Kemler, 1977), child participants were asked to sort cards in accordance with the target dimension while ignoring irrelevant dimensions (e.g., the task was to focus on shape, whereas color and shading could vary independently of shape). The critical finding is that interference (measured by either increase in reaction time or drop in accuracy) is still strong even for 6-year-olds and decreases only gradually with age.

In another set of studies (Robinson & Sloutsky, 2004; Sloutsky & Napolitano, 2003), 4- and 5-year-olds were asked to make same–different judgments for two sequentially presented auditory–visual compounds. In most conditions, participants ably detected auditory change while failing to detect visual change even though they readily detected visual changes when visual stimuli were presented without sounds. Critically, when instructed to match on the basis of visual components, participants failed to ignore the salient auditory component, thereby failing the task, even though instructions were repeated on every trial (Sloutsky & Napolitano, 2003, Experiment 6).

Given that even preschoolers have difficulty in ignoring irrelevant information, it is very likely that infants have this difficulty too. And if they do, how do they optimize attention during the course of category learning? We suggest that they learn categories without selectively shifting attention to category-relevant information and away from irrelevant information. And if this is the case, then there should be little or no cost of selective attention.

To address this issue, the current set of experiments compared category learning in adults and infants by presenting participants with two sequential category-learning phases and recording their eye movements. Eye movements provide a useful way of analyzing allocation of visual attention during category learning. Thus, eye tracking is an extremely useful analytical tool for examining looking across time by providing fine-grained dynamics of visual attention. Therefore, coupled with more traditional measures of learning (e.g., accuracy in adults, novelty preference in infants), eye tracking can reveal moment-by-moment changes during category learning.

Experiment 1A

Method

Participants

A total of 32 undergraduate students (10 women and 22 men), ranging in age from 18 to 22 years (M = 19.32 years, SD = 1.27), participated in the experiment for course credit. An additional 4 participants were excluded from the sample due to accuracy below 75% during the test trials of the last two blocks of Phase 1 (n = 2) or failure to calibrate the eye-tracking equipment (n = 2). All participants provided written consent and reported normal or corrected-to-normal vision.

Apparatus

A non-invasive Tobii T60 eye tracker measured eye gaze by computing the pupil–corneal reflection at a sampling rate of 60 Hz (i.e., 60 gaze data points collected per second for each eye). The eye-tracking device, which is integrated into the base of a high-resolution 17-inch computer monitor, was located on a table inside a darkened testing booth enclosed by curtains. A trained experimenter monitored the experiment on a 19-inch Dell OptiPlex 755 computer located outside of the testing booth. A Sony Network camera was located inside the testing booth to the side of the eye tracker displaying a live feed view of participants that an experimenter monitored on a 9-inch black and white Sony SSM-930/930 CE television. Two Dell computer speakers were positioned behind a curtain and out of view on either side of the eye tracker. An Ergodex DX-1 input system was used to record keypad responses.

Stimuli

A total of 64 objects were created in Adobe Illustrator to form two pairs of contrasting categories, with 16 unique exemplars per category. Stimuli consisted of a dark gray hexagon surrounded by six colored features. Four features varied in color and shape across exemplars; whereas two features did not. Therefore, by definition, the two features where shape and color were held constant across exemplars were the category-relevant features. Examples of stimuli are presented in Fig. 1. Category-relevant features always appeared in the same spatial location. Stimuli were displayed on the computer screen, subtending approximately 11° of visual angle horizontally and approximately 11° vertically. As shown in Fig. 1B, training stimuli were presented centrally, one at a time, whereas testing stimuli were presented in pairs, side by side, each with eccentricity of approximately 7.7° of horizontal visual angle.

Procedure

Prior to the beginning of the experiment, all participants were individually calibrated to the eye tracker using a 9-point calibration sequence of shrinking red dots in various locations across the screen. After successful calibration, participants were given a practice session that procedurally resembled the experiment except that there were three blocks that had 3 learning trials and 1 test trial. The stimuli in the practice phase were natural kinds (e.g., birds, fish, butterflies) that could be categorized by color and/or shape. For the experiment proper, adults were presented with two categories in separate learning/testing phases presented without interruption. Learning of the second category involved an extra-dimensional shift from learning of the first category. The eye tracker recorded participants' eye gaze during training and testing, whereas the computer recorded participants' response time and accuracy during test trials.

The experiment was presented on the computer using E-Prime Professional 2.0 software with an approximate viewing distance of 60 cm. Participants were instructed that they would first see objects from the same category, one at a time, and then two objects side by side, where one object belongs to the studied category and the other does not. When presented with two items, participants were asked to choose the object that belonged to the studied category by pressing a corresponding left/right key on the keypad.

The experiment consisted of two phases, with participants learning one category in Phase 1 and a related, but contrasting, category in Phase 2. Between the two phases, there was an unannounced extra-dimensional shift. Each phase consisted of four blocks. As shown in Fig. 1B, each block had 4 learning trials followed by 2 test trials. On each learning trial, stimuli were presented in a random order for

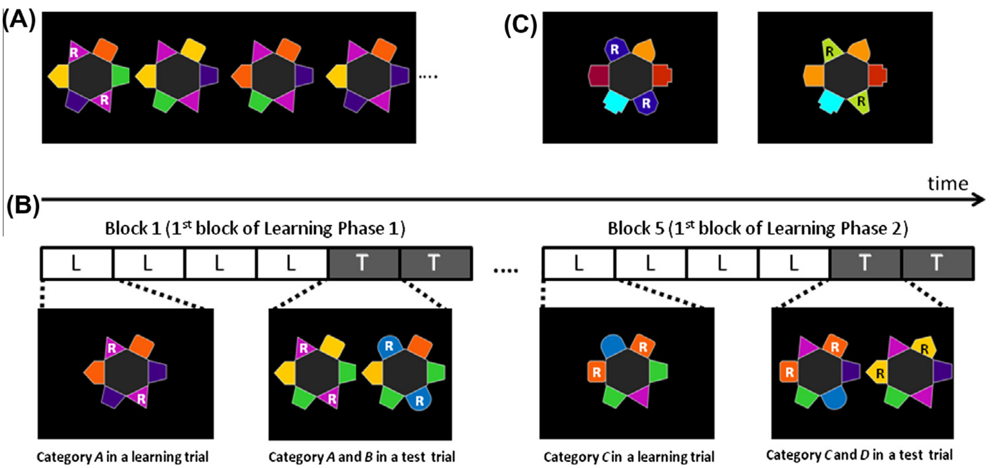

Fig. 1. (A) Example stimuli from Category A. Relevant features are marked with an "R". (B) Design of Experiment 1A with learning (L) and test (T) trial sequence for one block. (C) Additional stimuli used in Experiment 1B to examine intra-dimensional shift. Category E (left) and Category F (right) replaced Categories C and D to create an intra-dimensional shift between phases in Experiment 1B.

5000 ms in the center of the screen one at a time. Eight unique exemplars from a category were randomly reserved for learning trials in each phase and were repeated twice, thereby resulting in 16 learning trials per phase (i.e., four blocks, each consisting of 4 trials). Each stimulus appeared first in the first or second block of a phase and then again in the third or fourth block of a phase. The order of presenting the exemplars in Blocks 1 and 2 and Blocks 3 and 4 was randomized.

On each test trial, a new stimulus from the learned category and a new stimulus from a new category were presented side by side. Each test stimulus was unique and was repeated only once. The stimuli were presented until participants responded by choosing one of the test items. Between trials, participants fixated for 500 ms on a red cross that appeared in random locations on a background of random dots texture.

Two contrasting categories were presented in each phase (Category A vs. Category B or Category C vs. Category D). The target category (e.g., A) was presented during learning and test trials, and the contrasting category (e.g., B) was presented only at test. The contrasting categories were related such that each category's relevant features incorporated shapes and colors that differed entirely between the two categories; however, the category-relevant dimension (i.e., spatial position) did not change. Therefore, the contrasting categories (A vs. B or C vs. D) presented during test trials within a phase differed along the same dimension, whereas the categories (e.g., A or B vs. C or D) presented between phases differed along different dimensions, thereby requiring an extra-dimensional shift (see Fig. 1B). The presentation of all four categories was counterbalanced using this structure.

Participants' categorization accuracy, response time, and eye movements were recorded in both phases of category learning. Importantly, participants were unaware that halfway through the task the target category switched (e.g., from A to C), with an extra-dimensional shift between category-relevant information. If participants optimized attention to category-relevant information before the switch, they should incur a cost of selective attention immediately after the category switch where previously relevant information becomes irrelevant (cf. Hoffman & Rehder, 2010; Kruschke & Blair, 2000).

Results

As shown in Fig. 2A, participants exhibited high overall accuracy (M = .92, SD = .22 in Phase 1 and M = .85, SD = .31 in Phase 2). Accuracy data were submitted to a 4 (Block) $\times$ 2 (Phase) within-participants analysis of variance (ANOVA). The analysis revealed a main effect of block, $F(2.49, 77.12) = 3.58$, $p < .05$, $\eta_p^2 = .103$, but no significant interaction or other main effects. The main effect of block pointed to an increase in accuracy across blocks in Phase 1 and a similar (but perhaps weaker) pattern in Phase 2. Moreover, when focusing on the exact point of the category switch, between Blocks 4 and 5 a paired t test revealed that accuracy before the switch (M = .97, SD = .12) was greater than accuracy after the switch (M = .83, SD = .35), $t(31) = 2.06$, $p < .05$, $d = 0.53$. Therefore, categorization accuracy decreased after the switch, thereby pointing to a cost of selective attention incurred by adults.

Reaction time (RT) data by block within each phase are presented in Fig. 2B. Before analyzing RT, inaccurate responses (<12% of the total data) were excluded and data points that were above or below 2 standard deviations from the mean ($\sim$3% of data) were excluded. To accommodate missing data, a linear mixed-effects model was used (Quené & van den Bergh, 2004). Phase and block were defined as repeated measures, with compound symmetry being assumed (which is similar to the sphericity assumption in a traditional within-participants ANOVA). The results revealed two significant main effects with no interaction (p = .72). The main effect of phase, $F(1, 191.95) = 5.36$, $p < .05$, indicated that participants were slower to judge category members from non-members in Phase 2 (M = 2356.34 ms, SD = 1172.87) than in Phase 1 (M = 2082.15 ms, SD = 1159.88). The main effect of block, $F(3, 190.62) = 5.20$, $p < .005$, showed a linear decrease within each phase. An additional paired t test between Blocks 4 and 5 also suggested that adults incurred a cost of selective attention, with faster RT before the switch (M = 1836.80 ms, SD = 1096.83) than after the switch (M = 2648.70 ms, SD = 1211.40), $t(24) = 3.18$, $p < .005$, $d = 0.73$.

Although adults clearly learned the categories, a cost of attention was evident from both their decreased accuracy and slower response times immediately after the unknown category switch, indicating that they attended selectively while learning the first category. To directly determine the cost of

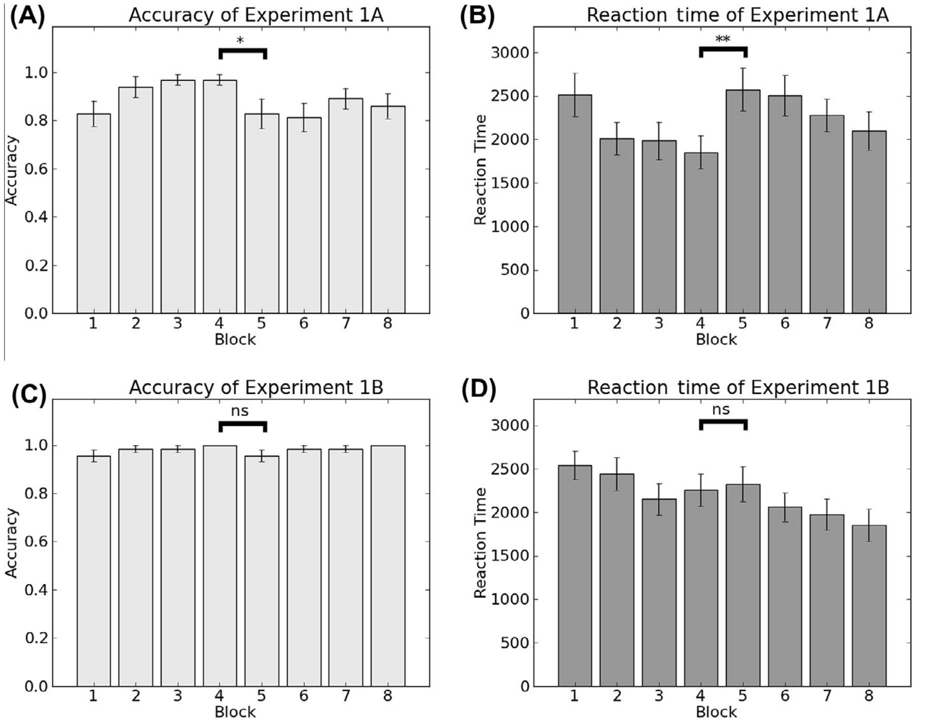

Fig. 2. Adults' accuracy and reaction time: (A) accuracy of Experiment 1A; (B) reaction time of Experiment 1A; (C) accuracy of Experiment 1B; (D) reaction time of Experiment 1B. $^{*}p < .05$; $^{**}p < .005$; ns, non-significant. Error bars represent ±1 standard error.

selective attention, looking patterns during learning trials were also analyzed. A cost of selective attention could be detected from participants' tendency to attend less to the newly relevant dimensions while maintaining attention instead to the previously relevant category features from the pre-switch category (i.e., extra-dimensional shift between Blocks 4 and 5). Areas of interest (AOIs) were defined a priori with the same 3.5 × 3.0-cm rectangle encapsulating each colored feature surrounding the central hexagon. Before the analysis, gaze points when only one eye or no eyes were tracked during learning trials were filtered out and only eye movements recording two eyes were analyzed. Based on previous findings indicating that in adults attention to category-relevant features peaks during the first second of a training trial (e.g., Rehder & Hoffman, 2005), the first 1000 ms of looking during each trial was analyzed. Using a window of 1000 ms, we calculated the average proportion of looking to category-relevant features and category-irrelevant features across blocks. Because there were more category-irrelevant features (four of six features) than category-relevant features (two of six features), the proportion of looking to category-relevant features was weighted by a multiple of two to equate the total area between relevant and irrelevant features. Furthermore, the first 250 ms of looking was cut from the analyses because it constituted the first saccade away from the randomly presented fixation points prior to the start of each trial. Overall adjusted looking data by block within a phase across different time windows are presented in Fig. 3A–C. The dashed line in each figure panel represents the adjusted chance level.

Mean proportions of looking to relevant features for the time window of 1000 ms (i.e., between 250 and 1250 ms) were submitted to a paired t test. Results revealed greater looking to category-relevant features before the switch in Block 4 ($M = .51$, $SD = .34$) than after the switch in Block 5 ($M = .30$, $SD = .34$), $t(31) = 2.55$, $p < .05$, $d = 0.64$.

To ascertain that we did not overestimate adults' cost of attention, in addition to the current analyses focusing on the first 1000 ms of looking, we also analyzed looking across learning trials for the first 500 ms and first 250 ms (see Fig. 3)A–C. Results indicated that, regardless of time window, adults' eye-tracking data consistently revealed a cost—a decrease in attention to relevant features immediately after the unknown category switch (i.e., between Blocks 4 and 5), with a significant difference for the 500-ms time window, $t(31) = 4.11$, $p < .01$, $d = 0.95$, and a marginally significant difference for the 250-ms time window, $t(31) = 1.94$, $p = .06$, $d = 0.51$.

Therefore, evidence from three different dependent variables (i.e., categorization accuracy, response time, and attention to category-relevant features) indicated a cost of selective attention precisely where an unannounced extra-dimensional shift occurred. The most direct evidence that adults used selective attention to learn the categories came from eye-tracking data, with looking perseveration to the formerly category-relevant features immediately after the unknown switch in Block 5.

However, it is also possible that the demonstrated cost of attention was due to other factors (e.g., fatigue, decreased motivation over time) rather than due to the extra-dimensional shift between phases. To eliminate these possibilities, we conducted Experiment 1B in which there was no extra-dimensional shift between phases. If the cost in Experiment 1A was due to the extra-dimensional shift (rather than fatigue), then there should be no cost once there is no longer an extra-dimensional shift. This issue was addressed in Experiment 1B.

Experiment 1B

Method

Participants

A total of 34 undergraduate adults (11 women and 23 men), ranging in age from 18 to 44 years ($M = 21.01$ years, $SD = 4.97$), participated in the experiment for course credit. An additional 7

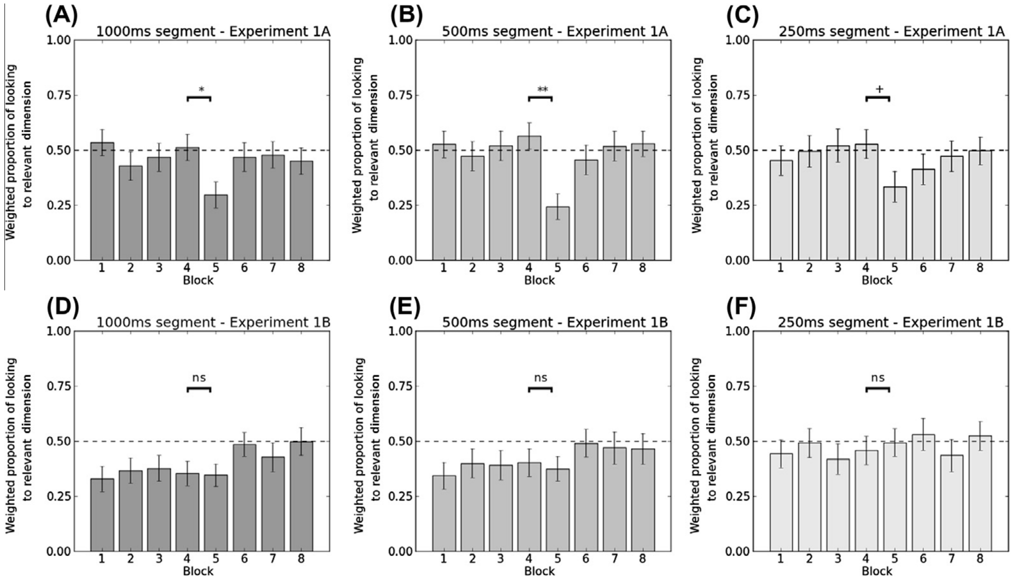

Fig. 3. Results from Experiment 1 (adults' eye tracking) during learning trials. Proportion of looking to the relevant dimension is weighted in that the chance level is .50. The top row shows Experiment 1A (extra-dimensional shift): (A) 1000-ms segments; (B) 500-ms segments; (C) 250-ms segments. The bottom row shows Experiment 1B (intra-dimensional shift): (D) 1000-ms segments; (E) 500-ms segments; (F) 250-ms segments. $^{**}p < .005$; $^{*}p < .05$; $^{+}p = .06$; ns, non-significant. Error bars represent ±1 standard error.

participants were excluded from the sample due to accuracy below 75% during the test trials of the last two blocks of Phase 1 ($n = 2$), misunderstanding the instructions ($n = 1$), or failure to calibrate eye-tracking equipment ($n = 4$). All participants provided written consent and reported normal or corrected-to-normal vision, and none of them participated in Experiment 1A.

Stimuli

A total of 32 additional stimuli were created to form two new categories, Categories E and F, and were used in place of Categories C and D. The two new contrasting categories incorporated shapes and colors that differed entirely from Categories A and B; however, the category-relevant dimension (i.e., spatial position) did not change. Therefore, learning of categories within a phase and between the two phases involved an intra-dimensional shift (see Fig. 1C).

Apparatus and procedure

The apparatus and procedure were identical to those in Experiment 1A.

Results

Experiment 1B was identical to Experiment 1A with one exception: The learning between phases involved an intra-dimensional shift rather than an extra-dimensional shift. Because no shift of attention is required in the intra-dimensional shift, no cost of selective attention (i.e., no learned inattention) was expected after the unknown switch in target categories. Therefore, if the pattern of costs observed in Experiment 1A was due to fatigue or decreased participant motivation, then comparable costs should be observed in Experiment 1B when the category-relevant dimensions do not change between the unknown category switch. This, however, should not be the case if the observed costs in Experiment 1A were in fact due to learned inattention from selective attention to category-relevant features prior to the extra-dimensional shift.

Accuracy and RT data by block within a phase are presented in Fig. 2C and D, respectively. Similar to Experiment 1A, overall accuracy was high ($M = .98$, $SD = .09$ in Phase 1 and $M = .98$, $SD = .09$ in Phase 2). The same set of analyses as in Experiment 1A was conducted in Experiment 1B. An ANOVA on accuracy revealed no significant main effects or interactions. Moreover, there was no difference in accuracy between Block 4 ($M = 1.00$, $SD = 0.00$) and Block 5 ($M = .96$, $SD = .14$), $p = .083$.

As in Experiment 1A, approximately 5% of RT data points that were above or below 2 standard deviations from the mean and 2% of RT data points where participants gave inaccurate responses were excluded from the analysis. The mean RT was 2348.46 ms ($SD = 1036.23$) in Phase 1 and 2046.79 ms ($SD = 1042.32$) in Phase 2 (see Fig. 2D). Results from the linear mixed-effects model showed a main effect of phase, $F(1, 219.84) = 10.33$, $p < .005$, and block, $F(3, 219.80) = 3.97$, $p < .001$, but no interaction ($p = .92$). In contrast to Experiment 1A, the main effect of phase shows a decrease in RT from Phase 1 to Phase 2. Moreover, comparisons between Block 4 ($M = 2252.45$ ms, $SD = 1068.44$) and Block 5 ($M = 2338.07$ ms, $SD = 1120.03$) did not show a significant difference in RT before and after the intra-dimensional shift ($p = .708$). Therefore, accuracy and RT did not reveal any cost of selective attention by adults.

As in Experiment 1A, eye movements recorded during learning trials were analyzed by selecting the first 1000 ms of looking during each trial after the first saccade away from the fixation point (see Fig. 3D). Mean proportions of looking to relevant features between Blocks 4 and 5 were submitted to a paired t test. Results showed that there was no significant difference between the proportion of looking to relevant features in Block 4 ($M = .35$, $SD = .33$) and Block 5 ($M = .35$, $SD = .30$), $p = .92$, indicating no cost of selective attention.

Similar to Experiment 1A, we also analyzed proportions of looking to relevant dimensions across learning trials for the 500- and 250-ms time windows (these time windows are presented in Fig. 3E and F). The analyses indicated that, regardless of time window, participants did not demonstrate a significant decrease in attention to relevant features between Blocks 4 and 5, thereby suggesting that there was no cost of selective attention during the intra-dimensional shift ($p = .74$ for the 500-ms time window and $p = .70$ for the 250-ms time window).

Unlike Experiment 1A, where adults demonstrated a cost of selective attention during an extra-dimensional shift, none of the same dependent variables (i.e., categorization accuracy, RT, and attention to category-relevant features) revealed any cost of selective attention during the intra-dimensional shift in Experiment 1B. In fact, in contrast to Experiment 1A, adults were faster to judge category members from non-members in Phase 2 than in Phase 1, further implying the absence of any cost in Experiment 1B. Based on the lack of any cost of selective attention in Experiment 1B, we can conclude that the cost demonstrated in Experiment 1A was in fact not due to fatigue or decreased motivation but rather stemmed from learned inattention—the very consequence of attending selectively to category-relevant information.

Experiment 2

Recall that in Experiment 1A adults exhibited evidence of attending selectively when learning categories and incurred the costs indicated by reduced categorization accuracy, increased RT, and attenuated attention to relevant features in Phase 2 of the experiment. The goal of Experiment 2 was to examine the role of selective attention in infant category learning. Accordingly, the procedure reported in Experiment 1 was changed into an infant paradigm. We were particularly interested in answering the following questions. When infants are presented with the categories used in Experiment 1, do they learn these categories the same way as adults do? In particular, do infants attend selectively during the course of category learning, and do they exhibit evidence of learned inattention? If the mechanism of category learning is the same across development, then infants should demonstrate costs of selective attention, similar to adults.

Method

Participants

A total of 22 6- to 8-month-old infants (11 girls and 11 boys, mean age = 215 days, *SD* = 34) participated in the experiment. An additional 10 infants were excluded due to fussiness. Parents provided written consent on arrival to the laboratory. All parents reported their infants to be developing typically and in good health.

Stimuli and apparatus

Infants were presented with the same stimuli as used in Experiment 1A, and the apparatus was identical to that used in Experiments 1A and 1B (except that no response pad was used with infants).

Procedure

The adult procedure was appropriately adapted to be feasibly conducted with infants but addressing the same theoretical questions. Infants were calibrated to the eye tracker twice, once before each phase to maintain tracking accuracy. Each calibration sequence lasted less than 1 min and consisted of a 5-point dynamic kitten image appearing on the screen with a corresponding "bounce" sound. Similar to Experiment 1A, learning the second category required an extra-dimensional shift. Infants sat on their parents' laps centered in front of the eye tracker within an approximate viewing distance of 60 cm, and parents were asked not to interfere with their children's performance. There were two learning/testing phases with a short break in between to recalibrate because infants were more likely than adults to change position during the course of the experiment. Like Experiment 1A, each phase consisted of four blocks. One block had 4 learning trials followed by 2 test trials. During each learning trial, two different exemplars from the same category were presented side by side until the infant accumulated 3000 ms of stimulus looking. A dynamic attention-grabbing video was presented between trials and whenever infants looked away from the screen before reaching the criterion of 3000 ms of accumulated looking. Stimulus pairs were randomly selected and shown twice, with the left–right position counterbalanced in the succeeding trial. Therefore, during the learning trials in each block, four exemplars were shown in pairs (e.g., A_1 and A_2, A_2 and A_1, A_3 and A_4, A_4 and A_3). An additional four exemplars of each category were randomly chosen and reserved for testing. These items were unique and did not repeat. On the first test trial of each block a new category member was paired with a member of a novel category (e.g., A vs. B, as shown in Fig. 1B test trial), and on the succeeding trial the position of the two stimuli was switched. Each test trial remained visible for a fixed duration of 6000 ms.

Results

An analysis of infants' eye movements during test trials was conducted to determine whether infants learned the target categories in both phases as evidenced by a preference for novelty. As with adults, data were filtered for tracking of two eyes, excluding gaze points of one eye or no eyes. In general, infant data are noisier than adult data; therefore, unlike analyses with adult eye gaze, filtered infant eye tracking data were transformed into fixations, where a fixation was defined as 100 ms of continuous looking (i.e., dwell duration) to a single AOI (i.e., 60 possible looks over 6000 ms). Moreover, because infants did not look at the stimulus during the entire test trial (i.e., 6000 ms) and looked away before the test trial terminated, a subset of each infant's looking time in a trial was used for analysis. The subset was defined for every block and included the time window from the start of the trial until when more than 25% of the infants looked away. The average length of this window was the first 24 fixations or 2400 ms of dwell time. Only the fixations in this window were submitted for analysis. One-sample t tests using Bonferroni adjustments revealed that the mean proportion of infants' looks to the novel category member were greater than the mean proportion of infants' looks to the familiar category member in Blocks 3 and 4 of Phase 1, $t(16) = 5.49$, $p < .001$, $d = 2.75$ and $t(15) = 4.72$, $p < .001$, $d = 2.44$, respectively, and in Blocks 2 and 4 of Phase 2, $t(11) = 10.36$, $p < .001$, $d = 6.25$ and $t(4) = 4.12$, $p < .05$, $d = 4.12$, respectively (see Table 1).

In addition, to gain greater power, novelty preference was analyzed in terms of number of fixations to the novel category member versus the familiar category member across infant participants. The fixations during test were detected by using a dispersion threshold identification (I-DT) algorithm (Salvucci & Goldberg, 2000) with a minimum duration threshold of 66.67 ms and a maximum dispersion threshold of 1.5° of visual angle. A Bonferroni-adjusted chi-square test was conducted by comparing the number of fixations to novel stimuli versus familiar stimuli in the first half (i.e., Blocks 1 and 2) and second half (i.e., Blocks 3 and 4) of each phase (see Table 2). Results indicated that there were more fixations to novel items than to familiar items in the second half of Phase 1, $\chi^2(1, N = 1496) = 15.44$, $p < .005$, and in the first and second halves of Phase 2, $\chi^2(1, N = 1558) = 8.05$, $p < .01$ and $\chi^2(1, N = 1250) = 11.14$, $p < .005$, respectively. However, in the first half of Phase 1, there were equivalent numbers of fixations to novel and familiar items ($p > .05$). Therefore, participants exhibited faster and more robust learning in Phase 2 than in Phase 1.

These results provide converging evidence that infants learned the target categories in both phases because they reliably discriminated category members from non-members. Moreover, in contrast to adults, who exhibited attenuated learning in Phase 2 (suggesting a cost of selective attention), infants exhibited faster and more robust learning in Phase 2 (suggesting no cost).

Using the same AOIs and calculations as in the previous experiments with adults, infant′ eye movements collected during learning trials were analyzed by calculating the average amount of accumulated looking to relevant features versus irrelevant features, with the number of relevant features multiplied by 2 to equate the total area between relevant and irrelevant features. The mean proportions of looking to relevant features compared with the total looking to relevant and irrelevant features was calculated across blocks for the first 1000, 500, and 250 ms of accumulated looking (i.e.,

Table 1
Infants' proportions of looking to a novel item by block and phase in Experiment 2.

	Block 1 test	Block 2 test	Block 3 test	Block 4 test
Phase 1	.46	.52	.56**	.54**
Phase 2	.47	.63**	.48	.63*

* $p < .05$.
** $p < .001$.

Table 2
Numbers of fixations on novel and familiar items in Phase 1 and Phase 2 of Experiment 2.

	Phase 1		Phase 2	
	First half	Second half**	First half*	Second half**
Number of fixations to novel item	849	824	835	684
Number of fixations to familiar item	862	672	723	566

* $p < .01$.
** $p < .005$.

to parallel previous analyses with adults). Overall adjusted looking data by block within a phase across different time windows are presented in Fig. 4A–C. The dashed line in each figure panel represents the adjusted chance level.

The mean adjusted proportions of looking to relevant dimensions between Blocks 4 and 5 (i.e., the point of the extra-dimensional shift) were then submitted to a paired-samples *t* test. Results revealed that looking to relevant features in Block 5 (1000 ms: $M = .39$, $SD = .21$) did not differ significantly from that in Block 4 (1000 ms: $M = .34$, $SD = .29$) in all three time windows (*t*s < .83, *p*s > .42). This attention pattern was different from that in adults; whereas looking to relevant features was lower in Block 5 than in Block 4 in adults, looking to relevant features was numerically higher in Block 5 than in Block 4 in infants. Therefore, in contrast to adults, infants did not exhibit cost of attention in Phase 2, suggesting that infants did not attend selectively to category-relevant features in Phase 1.

Eye-tracking data also revealed an important aspect of infants' looking—their tendency to look more at irrelevant features than at relevant ones. Note that category-relevant features did not change from trial to trial, whereas irrelevant features did. Therefore, learning of a category could result in either shifting attention to relevant features (which was done by adults) or shifting attention to irrelevant yet novel features (which was done by infants). Furthermore, given infants' tendency to look at a particular subset of features, their pattern of looking does not appear to be random.

In sum, Experiment 2 found novelty preference at test in both phases of the experiment. At the same time, infants did not demonstrate a cost of selective attention. Rather, in contrast to adults, they did not decrease attention to category-relevant information in Phase 2 compared with Phase 1. Taken together, these results indicate that, similar to adults in Experiment 1, infants learned both categories but that, in contrast to adults,[1] infants did so without attending selectivity to category-relevant information.

Given that there was clear evidence of category learning in infants, we deemed it necessary to examine whether infants discriminated individual exemplars within each category. The ability to discriminate would further strengthen the case that infants learned a category as an equivalence class. To address this issue, we conducted an additional experiment with a new sample of 19 6- to 8-month-old infants (an additional 4 infants were tested but were excluded due to fussiness). Because 3 of the participants included in the analysis completed only the first phase, only the first phase was used for these participants. Similar to Experiment 2 with infants, this experiment consisted of two phases separated by a short break for recalibration, but in contrast to Experiment 2, there was no shift between the phases. Each phase consisted of four blocks, with each block examining discrimination of one category (i.e., A, B, C, or D). The four categories were randomly assigned to one of the blocks. A block consisted of 4 familiarization trials and 2 test trials. During the familiarization trials, a randomly selected category exemplar was presented until infants reached 3000 ms of accumulated looking, as in Experiment 2. Therefore, each infant accumulated 12 s of looking to the same exemplar within each block. After the familiarization, participants were presented with 2 test trials. Each test trial had a familiarized exemplar and a novel exemplar from the same category presented side by side for 6000 ms.

[1] An additional sample of adults ($N = 32$) were tested using the same procedure as Experiment 1A with one exception: These adults were given a break between learning phases just as infants were in Experiment 2. However, even with an approximate break of 1 to 2 min for recalibration, adults still demonstrated a cost of selective attention between Blocks 4 and 5, as evidenced by reduced accuracy ($p < .05$), increased reaction time ($p < .001$), and attenuated eye tracking (1000-ms window: $p < .05$, $d = 0.578$).

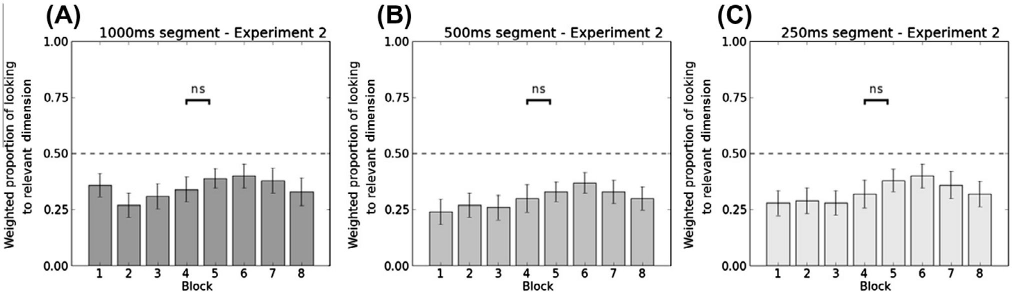

Fig. 4. Results from Experiment 2 (infants' eye tracking) during learning trials. The proportion of looking to the relevant dimension is weighted in that the chance level is .50: (A) 1000-ms segments; (B) 500-ms segments; (C) 250-ms segments. ns, non-significant. Error bars represent ±1 standard error.

Test data were analyzed by comparing fixation patterns. The fixations during test were detected by using the same I-DT algorithm as in Experiment 2. Most important, there were significantly more fixations to the novel exemplar than to the old familiarized exemplar for Category B, $\chi^2(1, N = 1132) = 14.93$, $p < .0001$, for Category C, $\chi^2(1, N = 1011) = 24.38$, $p < .0001$, and for Category D, $\chi^2(1, N = 1097) = 17.61$, $p < .0001$. These results indicate that at least exemplars in Categories B, C, and D were highly discriminable to the infants.

General discussion

The current set of experiments examined the role of selective attention during category learning by presenting participants with related novel categories where, unbeknownst to participants, the relevant and irrelevant information was switched between phases of category learning. It has been argued and demonstrated empirically that selectively attending to certain dimensions should result in learned inattention to unattended dimensions (Hoffman & Rehder, 2010), representing a cost of selective attention. The current study focused on this cost in infants and adults who were presented with similar category learning tasks. The results indicated that adults, but not infants, demonstrated costs of selective attention when learning novel categories in a multiphase learning task with an extra-dimensional shift.

Summary of findings

As discussed earlier, selective attention often results in learned inattention to previously irrelevant features that are currently relevant, representing a cost of selectivity. In Experiment 1A, adults demonstrated such a cost of selective attention as evidenced by multiple measures: a drop in accuracy immediately after the extra-dimensional shift between categories (Block 4 vs. Block 5), an increase in RT between phases (most notably between Blocks 4 and 5), and decreased looking to the category-relevant features between Blocks 4 and 5. In contrast, these same variables (i.e., accuracy, RT, and eye gaze) revealed no cost of adults' selective attention in Experiment 1B when there was an intra-dimensional shift; category-relevant information remained within the same dimension across phases. These findings are consistent with previous research demonstrating that learning is easier after an intra-dimensional shift than after an extra-dimensional shift (e.g., Kruschke, 1996; Shepp & Eimas, 1964), particularly when participants are not aware of relevant dimensional changes across multiple learning phases. More important, the current experiments demonstrate that adults deploy selective attention to learn novel categories. In contrast to adults, when infants were presented with an extra-dimensional shift (Experiment 2), they learned both categories without exhibiting costs of selective attention. Recall that infants did not exhibit a decrease in looking to relevant dimensions between the end of Phase 1 and the beginning of Phase 2 (if anything, they demonstrated an increase). These are novel findings and may point to important developmental differences in category learning.

Adults and infants: Differences in category learning

Whereas selective attention is an efficient means for learning categories, the current study presents evidence that early in development categories could be learned without attending selectively. As demonstrated in Experiment 2, infants incurred no cost of selective attention, implying that they learned the category without attending selectivity. How, then, do infants learn multiple related categories? One possible explanation is that infants learned statistics of feature co-occurrences within categories while maintaining diffused attention during learning. Previous research demonstrates that infants are skilled at extracting statistical regularities from the input (e.g., Saffran, Aslin, & Newport, 1996; Saffran, Pollak, Seibel, & Shkolnik, 2007).

The observed difference between infant and adult category learning can be readily accounted for by proposals involving multiple systems of category learning (e.g., Ashby, Alfonso-Reese, Turken, & Waldron, 1998; Cincotta & Seger, 2007; Kloos & Sloutsky, 2008; Love & Gureckis, 2007; Seger, 2008; Sloutsky, 2010), with one system involving selective attention and another system learning by exploiting redundancy in the input. It has been argued that learning within the former (selection-based) system is achieved by shifting attention to category-relevant dimensions; whereas the latter (compression-based) system learning is achieved by compressing redundancy (e.g., data reduction). Research indicates that top-down selective attention is likely to require the involvement of brain structures associated with so-called "executive functions," such as the prefrontal cortex (PFC), and that more primitive brain regions, such as the inferotemporal cortex and basal ganglia, are engaged in the compression-based learning (e.g., Ashby et al., 1998).

Moreover, the system involving selective attention (i.e., the selection-based system) depends critically on the late maturing brain structures, such as the PFC, and it is likely that it comes online later than the system exploiting redundancy (i.e., the compression-based system) (cf. Sloutsky, 2010). If these systems come online asynchronously during the course of development, with the compression-based system coming online earlier than the selection-based system, then infants and adults should learn categories differently. Given that (a) infants can learn perceptual categories during the first few months of life (e.g., Quinn et al., 1993) and (b) the circuits sub-serving selective attention come online substantially later (see Sloutsky, 2010, for a review), it is reasonable to posit that the compression-based system of learning is a developmental default. Research reported here provides support for this possibility; the current results point to different mechanisms of category learning across development—early learning that does not engage selective attention versus mature category learning that does. Furthermore, because the reported findings are the first to suggest such differences, additional research is needed to further examine potential developmental changes in mechanisms of category learning.

Although there are costs associated with selective attention, there are also benefits of selective attention. One benefit of efficient category learning is attention optimization—a prolonged increase in attention to category-relevant information coupled with a prolonged decrease in attention to category-irrelevant information over time. Although adults demonstrated a clear cost of selective attention in Experiment 1A, the benefit of selective attention during category learning was not captured by the current tasks because there was no attention optimization within a phase. This may seem surprising given previous literature; however, it should be noted that previous research showing attention optimization during category learning tasks tends to involve multiple speeded trials with feedback (e.g., Kruschke & Blair, 2000), which was not the case for the current procedure, particularly because adults and infants needed a somewhat comparable procedure for measuring learning and costs between age groups. Therefore, not surprisingly, the current task did not capture attention optimization (i.e., shifting attention to category-relevant features) because we did not incorporate speeded trials that are necessary for capturing highly motivated attentional shifts. In fact, we have preliminary data demonstrating that when adults learned similar visual categories with exposure time limited to 1500 ms (i.e., compared with the current task with 5000 ms), adults exhibited attention optimization across training blocks (cf. results with similar categories using 1.5-s trials in Yim, Best, & Sloutsky, 2011). In addition, no trial-by-trial feedback was provided in the current task. Had adults been provided with supervision, they may have been more likely to optimize attention in order to immediately improve or maintain high accuracy (see Hoffman and Rehder, 2010). Despite finding no evidence of the *benefits* of selective attention (i.e., due to non-speeded trials without any supervision), the current task clearly captured the *costs* of selective attention as measured by multiple dependent variables (i.e., categorization accuracy, RT, and eye gaze).

Limitations and future directions

One potential limitation of the current study is that infants and adults were presented with different paradigms; adults were told what the task was, something that is not possible for infants. This problem is very difficult to address because even if adults were not told what the task was, there is no guarantee that they would not come up with their own hypotheses. Furthermore, this problem is not unique to the current study; it pertains to other studies attempting to compare non-verbal and verbal populations (e.g., infants vs. non-infants, adult humans vs. non-human animals).

However, although caution in interpreting the differences is needed, the comparisons are capable of providing important information. For example, suppose that one succeeded in presenting adults with a truly implicit task and they exhibited the same pattern as infants in the current study. In this case, it should be concluded that the current study revealed a difference in explicit and implicit learning and that infants learn implicitly. It could also be concluded that adults share with infants a mechanism of implicit category learning while also having an attention-based mechanism of explicit category learning. Unfortunately, if adults exhibit costs under implicit learning conditions, these findings would be inconclusive because it would be possible that adults generate hypotheses about the goals and structure of the task. These are important questions that will require future research.

Conclusion

The current results suggest that early in development categories are learned without attending selectively to category-relevant information, and hence learned inattention is unlikely to occur. In contrast, mature category learning exhibited evidence of selective attention by exhibiting a cost of selectivity. Therefore, patterns of attention change during the course of development—from distributed attention in infants to more focused selective attention in adults. Although more research is needed, current results suggest that the mechanism of category learning may be undergoing development from learning by exploring statistics to focusing on category-relevant dimensions for more efficient category learning.

Acknoledgment

This research is supported by the NSF grant BCS-0720135 and by NIH grant R01HD056105 to Vladimir Sloutsky.

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