The Development of Learning Across Levels of Abstraction

by

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Abstract

When we learn about the world around us, we not only process what makes items unique, we also notice consistencies across items. However, it is unknown how learning at these two levels of abstraction interact. Might there be a trade-off in learning? Moreover, given children’s different cognitive abilities, do they experience a similar trade-off? Finally, are irrelevant features still processed, just in a more superficial manner? We explored these questions using a categorization task followed by a surprise recognition test in adults and children. Results suggest that adults do show a trade-off in learning. However, children’s memory scores were too low to make any definitive conclusions. Lastly, both adults and children noticed consistencies in the irrelevant features, and this knowledge also traded-off with category learning in adults and moderately in children. These data point to a fundamental cognitive process in which learning comes at a cost, at least in adults.
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1 Introduction

During the process of learning, we not only gather information about specific objects that we are exposed to, their unique features like colour and shape, we also learn about patterns that stretch across these objects, how they are similar to and different from each other. The latter is an abstraction of our knowledge, allowing us to create categorical representations with which we can group objects. However, it is not fully understood how these levels of learning interact. Do the two facilitate or impede each other? While it may seem intuitive that learning specific details of an item would improve one’s ability to categorize, it is also possible that focusing on specific items and learning them really well could actually inhibit abstraction. Likewise, while learning categories well could aid in the memory of specific items, it is also possible that focusing on abstract or categorical representations might impede the learning of details specific to individual items. In other words, might there be a trade-off between category- and item-level learning?

Moreover, it is likely that the way abstraction and item-level memory interact differs across development. In fact, some research has found that the ability to abstract seems to improve across development, with young children tending to prioritize item information over abstract information (Sloutsky, Kloos, & Fisher, 2007b). Yet, other research has found children to prioritize abstraction over item information (Gómez, 2017). This raises another question of how the learning pattern described above may differ between adult and child populations. To elucidate these and related questions further, I will review work that points to a trade-off in adults, followed by work supporting children’s focus at the level of the item, and finally contradictory work supporting children’s focus on abstraction. Diverging predictions regarding the trade-off in children will be discussed.

1.1 A trade-off in category and item-level learning

Categorization, or the ability to sort and classify items into groups, is an essential aspect of cognition. It is a form of abstraction that connects items by drawing out similarities across them, creating a gist representation (Brainerd & Reyna, 1990). It not only facilitates generalization to new items and situations, it also allows for efficient processing of these items by prioritizing diagnostic features. Unfortunately, the efficiency of abstracting to the level of the category may mean a focus on the diagnostic features at the cost of learning about the specific item. In fact,
this has been found in adults across a number of scenarios. For instance, when presented with a list of thematic words with the theme word missing, participants falsely remembered hearing the theme word (see Brainerd, Reyna, & Ceci, 2008). This is thought to have occurred because the relationship between the words was abstracted out of the list (i.e., they were categorized together), and this gist representation was remembered better than the individual words themselves. The same effect has also been found with categories of images, in which participants falsely remembered new images that shared category membership of those they had seen (Koutstaal & Schacter, 1997). These findings suggest that categorization may take precedence over item information in adults, with participants seemingly forming an abstract representation of the stimuli.

Despite a number of studies pointing to this trade-off, few have directly studied it. One example of a study that directly addressed the topic was by Sloutsky and Fisher (2004). While pursuing slightly different questions, the authors did find a trade-off. When adults were instructed to remember a set of pictures of cats, bears, and birds, they were quite successful at remembering the specific cats, bears and birds they saw in a follow-up recognition test. However, when faced with a category-based “induction” task in which they learned that only cats have “beta cells” in their bodies, their memory for the specific cats, bears, and birds dropped to chance levels. By sorting the animals into categories, they did not attend to the individual features of each animal, and thus failed to remember individual animals in a post-test. Together, these findings may suggest a decrease in memory resolution and increase in a fuzzy, generalized representation as an outcome of categorization learning.

These data not only support the notion of a trade-off across levels of abstraction, they also suggest that representations of items may become more abstract and gisted across time as the participants become experts at the categorization task. Prior categorization studies would also support this. For instance, eye-tracking studies of categorization tasks suggest that adults’ focus begins broadly across all item features, with a narrowing of focus to the diagnostic feature upon learning the category rule (Rehder & Hoffman, 2005). We know that focus of attention can reduce adults’ later memory for unattended information (Simons, 2000). As such, focusing attention on diagnostic features may reflect an increase in gist representation and loss of item details after learning to successfully categorize. Given these findings, might good category
learners have better memory for items that were presented early during category learning, that is, before successful abstraction?

Finally, while information that is outside of focused-attention may be remembered more poorly, there are data to suggest that some of this information may remain in memory to some degree. A number of studies have found priming effects from unattended information (Rock & Mack, 1998; Tipper, 1985). Furthermore, one study found that despite being unable to remember specific details about the stimuli that they did not focus on, adult participants created a statistical summary of this unattended information (Alvarez & Oliva, 2008). In other words, while they lost specific item-level information for unattended features, they created a gist representation of it. Therefore, might good category learners maintain a gist memory of orthogonal information despite a drop in specific item-level memory?

1.2 How category and item learning trade off across development

It remains unclear whether children will show a trade-off between category and item-level learning. As discussed above, adults have been shown to favour abstract information, which may lead to a drop in item memory upon abstraction. However, this picture is not so clear in children. On the one hand, some work suggests that children prioritize items over abstraction and, in fact, struggle with abstracting information (Brainerd et al., 2008; Fisher, 2011; Sloutsky et al., 2007b; Sloutsky, Kloos, & Fisher, 2007a). On the other hand, there is separate work suggesting that children prioritize abstraction over item information (Gómez, 2017; Gómez & Edgin, 2016; Gómez & Lakusta, 2004). Given that each body of work would predict a different trade-off outcome, each will be discussed as well as their implications for the current study.

1.2.1 A case against abstraction

Proponents of children’s poor abstraction abilities may point to the errors that adults fall prey to, discussed above, such as false memory. This is a rare case of performance decreasing with age, as there is quite a robust literature finding adults to have more false memories than children, as well as the number of false memories to increase across the elementary school years (Brainerd et al., 2008). It is thought that children do not fall prey to this error because of their poor abstraction. They prioritize the item-level information over the category information, so they do
not tend to fill in the missing thematic words as adults do.

Another reason why children might have difficulty abstracting for category learning is work showing that children tend to process the entirety of an item whereas adults will selectively attend to the diagnostic features. For instance, when asked to match test items with target items, 5-year-olds were found to make their decisions based on overall similarity, while older children tended to make their selections based on a characteristic from a single dimension (Smith & Kemler, 1977). If abstracting across a single dimension is required for learning, then this would leave 5-year-olds at a disadvantage. Similarly, 5- and 6-year-olds were found to treat irrelevant dimensions as relevant, specifically during a categorization task, an effect that disappeared by 9-years of age (Sheppand, Swartz, & Shepp, 1976).

Indeed, children’s tendency to observe the entirety of an item (holistic processing) is also reflected in memory. While somewhat counterintuitive, children’s holistic processing could result in superior memory for specific items because they are not attending to only the diagnostic properties. Along these lines, a memory study with 7-year olds and adults found that the adults remembered stimuli based only on the categorical properties while children remembered the specific items (Tighe, Tighe, & Schechter, 1975). Similarly, to elaborate on the Sloutsky and Fisher (2004) study discussed above, the children in that study showed a very different pattern of results than the adults. As might be expected, when simply remembering the individual animals, adults outperformed the children on a recognition task. However, once they were asked to perform a category-based “induction”, adults’ recognition of individual animals dropped to chance, while the children’s recognition scores were unaffected.

Children’s developing abilities to selectively attend to information could account for the unique learning patterns noted above. Indeed, selective attention is a top-down process in which one attends selectively to information that is relevant to a goal, while suppressing that which is irrelevant (Pashler, Johnston, & Ruthruff, 2001). Given the vast amount of information available at any moment, selective attention provides a way to optimize what information is processed. As such, and as mentioned previously, adults selectively attend to diagnostic features during categorization (Rehder & Hoffman, 2005). However, we know that children consistently perform poorly when selective attention is required, with children showing more distributed attention due to an inability to suppress irrelevant information (Rueda, Posner, & Rothbart, 2005). Adults’
focus on diagnostic features likely allows for easy extraction of meaning at the cost of item information, which also supports the trade-off prediction. However, if children’s distributed attention results in holistic processing of the items, they may categorize in a fundamentally different way than adults. Children may categorize based on perceptual similarity instead of by forming fuzzy representations. This approach to categorization would not result in a loss of item information with categorization and, as such, would not result in a trade-off. Furthermore, because they are not creating gist representations, they would likely not be sensitive to abstract information along an orthogonal dimension.

1.2.2 A case for abstraction

There is also evidence to support children’s abstraction abilities, with infants as young as 3-months old proving able to categorize (Quinn, Eimas, & Rosenkrantz, 1993). In fact, contrary to the item-level focus found above, some studies suggest that children prioritize abstract information, just like adults. For instance, when 3-year olds were provided conceptually and perceptually salient information about items, they prioritized the conceptual information when generalizing labels for these items (Booth & Waxman, 2002). Even when conceptual and perceptual information were at odds, conceptual information was given precedence.

Memories for items actually become more detailed with development, which could point to a developmental shift from abstraction towards item-level learning. This is in stark contrast with the work cited in the previous section. Children’s experiences appear to change from vague familiarity to vivid recollection (Brainerd, Holliday, & Reyna, 2004). Furthermore, details like source memory show a protracted development too, more so than less detailed memory (Cycowicz, Friedman, & Duff, 2001). These findings point to children’s memories having a lack of detail that sounds much like the fuzzy, gist representations thought to facilitate abstraction. Certainly, this would help explain children’s superior ability to pick up consistencies in language. For instance, 1-year olds are capable of extracting words from continuous speech, learning permissible orders of these words, and generalizing the structure to novel words (Gomez & Gerken, 1999; Saffran & Wilson, 2003). These can all be understood as types of abstraction, and are present at a very young age.

Taken together, these findings would suggest a different pattern of behaviour in children than what was previously discussed. They suggest that children categorize in a similar way to adults.
Following the same logic as for the adults, if they are more abstract and less item-focused, then they would likely miss out on item information as they categorize more successfully. Therefore, they would show a trade-off in learning. Moreover, their distributed attention in combination with a preference for abstraction suggests that children may be equipped to create gist representations along an orthogonal dimension outside of the diagnostic dimension.

1.3 The current study

In the current study, I aim to understand: (1) whether there is a trade-off between item-level memory and learning regularities across items in an adult population, (2) whether this trade-off exists in a child population and how these patterns of learning compare across age groups, and (3) how specific or generalized are these item representations across age groups. To address these questions, adults and children performed an A/B category learning task, followed by a surprise recognition memory test. To assess if participants were abstracting along an orthogonal dimension, half of the recognition foils were similar along an orthogonal dimension to those in the categorization task, and half were different along this orthogonal dimension. As such, if participants correctly rejected both types of lure equally, this would suggest they remembered the specific items, whereas if they rejected the different shapes more successfully, this would suggest a gist representation of the orthogonal dimension. Answers to these questions would not only help explain how and why people see the world differently across development, but would also explain an overlooked, fundamental system in cognition.
2  Experiment One

2.1  Methods

2.1.1  Participants

Sixty undergraduate students from the University of Toronto participated in exchange for course credit ($M = 19.73$ years, 76% female).

2.1.2  Category learning task

Participants completed two tests to assess their category learning and item memory, respectively. The first task was a feedback-driven categorization task consisting of 60 trial-unique trials. Participants were told they would be learning about amoebas and were instructed to press one of two buttons to sort each amoeba into one of two categories, learning from trial and error. Each stimulus was presented in a randomized order for 1.5 seconds or until the participant’s response. After each trial, feedback was given by presenting the words “Correct” or “Oops! That was wrong” for 1.5 seconds. To avoid fatigue, participants were given a break after 30 trials.

Eighty-four distinct stimuli were created to vary at the categorical and individual level. The categories were defined by distortions of two prototypical dot patterns, validated in prior categorization tasks (Fried et al., 1984; Seger et al., 2000; Figure 1a). These 84 exemplars were created by mapping each of the two prototypical patterns onto a 10 x10 grid and assigning a 7% chance of distortion to each square of the grid. This script was looped 84 times, 42 times per prototype, with no exemplar repetitions.

Stimuli also varied at the individual level, consisting of shapes and colours unique to each stimulus. Both of these features were task-irrelevant, varying orthogonally to the categories. Colour was selected using a random number-generating script to assign unique RGB values to each stimulus. Seventy-two distinct shapes were created along a shape continuum. The two shapes at the extreme ends of the continuum are depicted in Figure 1b. These two shapes were then morphed together, outputting 72 unique but related shapes. Twelve more shapes were created outside of the shape continuum (novel-space lures), based on other unrelated images of amoebas (Figure 1c). The three features were then combined with the dot patterns presented in
black, centered within the shape. All stimuli appeared on an Apple desktop computer screen, and were presented using PsychoPy (Peirce, 2008).

![Image](image_url)

Figure 1. a) Diagnostic features defining category membership: Every item had a unique exemplar dot pattern distorted from one of these two prototypes, b) Item-unique features: These two shape extremes were morphed together to create a shape space, c) Novel-space lures: These shapes were created outside of the shape space to assess gist representation.

### 2.1.3 Item memory task

Following the categorization task, participants performed an item recognition test. Participants were asked to assess whether they had seen a series of stimuli in the categorization task or if they were new. Each participant saw the same 48 stimuli presented in a different, randomized order. Of these stimuli, 24 were familiar and 24 were unfamiliar. The 24 unfamiliar stimuli included the 12 novel-space lures from a different shape space, as well as 12 same-space lures from the same shape space. Participants had unlimited time to respond.

### 2.1.4 Data analyses

To determine memory for the items, signal detection was calculated using d’ (hit rate – false alarm rate) and compared to chance with an independent-samples t-test. All basic correlations were analyzed using the general linear model. For analyses involving trial number, general linear mixed-effects models were applied using the lme4 package in R (Bates, Mächler, Bolker, &
Walker, 2015). Trial number and categorization accuracy were fixed effects, and all models contained random intercepts and slopes grouped by stimulus. All analyses were conducted using R (R Core Team, 2017).

2.2 Results

2.2.1 Category learning and item memory

Categorization accuracy increased across trials ($\beta = 0.025, z = 9.793, p < .001$; Figure 2a), indicating that participants were able to learn the categories. Participants also demonstrated memory of the items during the memory test, with $d'$ scores significantly greater than 0 ($M = 0.268, SD = 0.374$; $t(59) = 5.558, p < .001$; Figure 2b).

![Figure 2. a) Category learning across trials. This figure illustrates the average category accuracy across participants (%) and across the 60 trials of a category learning task, b) Item memory across participants. This figure illustrates individual difference scores of item memory, calculated as $d'$. The blue box represents the second and third quartile, and the median is represented by the horizontal black line. The vertical lines represent the first and fourth quartile. The dotted line is at chance at $d'=0$.]

2.2.2 A trade-off in category learning and item memory

As predicted, overall categorization accuracy was negatively related to recognition such that those with higher categorization accuracy had poorer memory for the items ($F(1,58) = 14.31, p < .001$, Figure 3a).
In addition, while memory for correctly and incorrectly categorized items did not differ overall ($t(495.18) = 0.463, p = 0.644$), categorization accuracy (correct or incorrect) interacted with time (trial number) to predict recognition ($\beta = -0.016, z = -2.062, p = 0.039$, Figure 3b), such that error trials were remembered moderately better with increasing categorization trials ($\beta = 0.001, z = 1.873, p = 0.061$), while memory for correct trials decreased moderately with increasing categorization trials ($\beta = -0.006, z = -1.648, p = 0.099$). In other words, as the task progressed (and participants learned), items for which participants received incorrect feedback were remembered better and items for which they received correct feedback were remembered worse.

Figure 3. a) Item memory (d’) by category accuracy (%). This figure illustrates that as individual difference categorization accuracy scores increased, memory for items decreased. The dark blue line indicates the slope and the light blue indicates standard error, b) Average item memory accuracy across participants (%) separated by categorization accuracy. The blue line indicates correctly categorized items and the red line indicates incorrectly categorized items. The x-axis indicates at what trial number the item was presented.

2.2.3 Gist representation

To address how specific or generalized item memory was, d’ was calculated twice to compare how well participants could correctly reject items from the same or different shape space. When calculated with only novel-space lures from outside the shape space, the average d’ score was found to be 0.727, significantly different from 0 and, thus, showing memory ($t(59) = 8.986, p < .001$). However, when calculated with only same-space lures from the same shape space, no
evidence for memory was found with a mean of -0.103 ($t(59) = -1.488, p = 0.142$). To further analyze this distinction, difference scores were calculated between correct rejection of novel-space lures and same-space lures. These scores were found to be significantly different from 0 ($t(59) = 7.761, p < .001$), suggesting that participants abstracted along the shape dimension, and this gist representation was remembered better than specific items.

To determine how the different lure types contributed to the observed trade-off between item memory and categorization, we used the $d'$ scores calculated using same-space and novel-space lures separately and related each of these to categorization performance across individuals. Using $d'$ calculated from novel-space lures, the trade-off was significant ($F(1,58) = 25.7, p < .001$, Figure 4a), while there was no significant relationship when including only the same-space lures ($F(1,58) = 0.57, p = 0.453$, Figure 4b). Correspondingly, there was a trade-off in difference scores and categorization accuracy ($F(1,58) = 8.731, p < .01$, Figure 4c), suggesting that learning to categorize well meant less sensitivity to the shape space.

![Figure 4](image-url)

*Figure 4. a) Item memory calculated with novel-space lures ($d'$) by categorization accuracy (%). $d'$ was calculated excluding the same-space lures. Individual difference $d'$ scores were related to categorization accuracy scores and found to be significantly negatively correlated. The dark blue line indicates the slope, and the light blue indicates standard error. b) Item memory calculated with same-space lures ($d'$) by categorization accuracy (%). $d'$ was calculated excluding the novel-space lures. Individual difference $d'$ scores were related to categorization accuracy scores and not found to be significant. The dark blue line indicates the slope, and the light blue indicates standard error. c) Difference scores by categorization accuracy (%). Difference scores were calculated between correct rejection of novel-space lures and same-space lures ($0 = no difference$). Individual difference scores were related to categorization accuracy scores and found to be significantly negatively correlated. The dark blue line indicates the slope, and the light blue indicates standard error.*
3 Experiment Two

3.1 Methods

In experiment two, we were interested in how children’s learning might differ from that of adults. Specifically, we were interested in whether children would show the same trade-off as adults and how their memory for the items might differ.

3.1.1 Participants

Sixty-one children ages 5 to 8 (\(M = 6.42\) years, 48% female) were recruited at the Ontario Science Centre in exchange for a toy of their choosing. One child was excluded due to lack of proficiency in English and inability to understand the instructions.

3.1.2 Category learning task

Participants completed the same two tasks as Experiment One. Participants were told that two alien families, the BlipBlop family and the ZipZop family, got mixed together and needed help getting on the right spaceships home. A cartoon spaceship was presented on either side of the screen, and participants were instructed to press one of two buttons to sort the aliens into their family spaceship. Each stimulus was presented for 3 seconds or until the participant responded. After each trial, feedback was given by presenting the words “Yay! You found my family!” below a smiley emoji or “Oh no! That’s not my family!” below a crying emoji.

3.1.3 Item memory task

Following the categorization task, participants performed the item recognition test. They were told that the aliens needed to know who had gotten on the spaceship already and to sort them into old aliens they had seen and new aliens they hadn’t yet seen. A total of 32 stimuli were presented in a randomized order, 16 familiar, 8 novel-space lures, and 8 same-space lures. Each stimulus was presented until the participant’s button response and verbal confirmation. All stimuli appeared on an Apple laptop computer screen and were presented using PsychoPy (Peirce, 2008).
3.1.4 Data analyses

The same analyses were run as Experiment One with the addition of comparisons between adults and children using independent samples t-tests.

3.2 Results

3.2.1 Category learning and item memory

Like the adults, categorization accuracy increased across trials indicating that children successfully learned to categorize the stimuli ($\beta = 0.015, z = 6.619, p < .001$). Accuracy scores were found to differ across age groups ($\beta = -0.073, t = -3.399, p < .001$), with lower overall accuracy in the child group. However, there was no significant interaction between trial number and age, suggesting a similar learning rate to adults ($\beta = -0.001, t = -1.532, p = .125$; Figure 5a). Unlike adults, children did not show memory for the items during the memory test ($M = 0.065; t(59) = 0.984, p = .329$) and were significantly worse than the adult group ($t(110) = 2.743, p = .007$; Figure 5b).

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Figure 5. a) Average category accuracy (%) by trial number. This figure illustrates the increase in average category accuracy in the adult and child groups across the 60 trials of the categorization task. The dark blue line signifies the adults and the turquoise line signifies the children, b) Item memory across age. This figure illustrates individual difference scores of item memory as d’ scores. The adults are signified by the dark blue box and children the turquoise box. The adults’ scores are significantly higher than the children’s scores. The adults show memory, as they are significantly different from 0 (illustrated by the dotted line), but children do not show memory as their scores are not significantly different from 0.
3.2.2 A trade-off in category learning and item memory

There was no relationship between children’s categorization accuracy and item memory (d’) on the memory test ($F(1,58) = 1.766, p = .1891$, Figure 6a). Unlike adults, children did not show a trade-off between categorization learning and item memory.

Children’s memory for correctly and incorrectly categorized items was moderately different ($t(690.2) = 1.950, p = .052$), with items on which children made errors being remembered slightly better (mean accuracy = 56.25%) than items that children got correct (mean accuracy = 49.68%). This differed from the adults whose item-level categorization accuracy was not at all predictive of item memory.

Using a mixed-effects model in which we included trial number as a fixed effect, we again observed an effect of categorization accuracy, with children having better memory for items that were incorrectly categorized ($\beta = -0.669, z = -2.431, p = .015$). In addition, and similar to adults, the interaction between categorization accuracy and trial number moderately predicted item memory ($\beta = 0.013, z = 1.660, p = .097$, Figure 6b). Interestingly however, children’s memory showed the opposite pattern as adults, with memory for errors improving at the beginning of the task, and memory for correct responses increasing throughout the task.

Figure 6. a) Item memory (d’) by categorization accuracy (%). Children’s individual difference item memory scores were not related to their categorization accuracy scores. The dark turquoise signifies the slope and the light turquoise signifies standard error, b) Average item memory accuracy
This figure illustrates children’s average item memory accuracy across participants (%) separated by categorization accuracy. The turquoise line indicates correctly categorized items and the red line indicates incorrectly categorized items. The x-axis indicates at what trial number the item was presented.

### 3.2.3 Gist representation

Children also successfully rejected the novel-space lures, as d’ with only these lures showed learning, with a mean of 0.27 ($t(59) = 2.547, p = 0.013$). Again, like the adults, learning disappeared when analyzing only same-space lures, with their d’ averaging at -0.092 ($t(59) = -1.361, p = .179$). Difference scores between novel-space lures and same-space lures were also significantly different from 0 ($t(59) = 3.462, p = .013$). However, while children could also differentiate the novel items, they were not nearly as successful as adults. Adults’ novel-space lure d’ scores were significantly higher than children’s ($t(110.22) = 3.43, p <.001$, Figure 7a). This suggests that children also prioritized abstract information, creating a gist representation of the shape space, but they were much less successful in their abstraction than the adults.

Interestingly, while prior analyses found that children did not show a trade-off between item memory and categorization accuracy, a moderate trade-off appeared when the novel-space lure d’ scores were used ($F(1,58) = 3.504, p = .0663$, Figure 7b). Furthermore, and analogous to the adults, the trade-off disappeared when using the same-space lure d’ scores ($F(1,58) = 0.07289, p = .788$, Figure 7c). However, there was no trade-off between difference scores and categorization accuracy ($F(1,58), 2.444, p = .1234$). This pattern of results suggests that children were able to differentiate items from a different shape space, but not nearly as well as adults. Moreover, these lures were the driving force behind a strong trade-off in adults and a moderate trade-off in children.
Figure 7. a) Item memory (d’) with same-space lures and novel-space lures across age groups. d’ scores were calculated first excluding novel-space lures and then same-space lures in the adults and children. The dark blue boxes signify the adults and the turquoise signify the children. The d’ scores with only the same-space lures were not significantly different from 0 (dotted line), suggesting no memory in either group. The d’ scores with only the novel-space lures were significantly different from the first set of scores, significantly different from 0, and the adults’ scores were significantly higher than the children’s. b) Children’s item memory (d’) with novel-space lures by category accuracy (%). d’ was calculated excluding the same-space lures. Individual difference d’ scores were related to categorization accuracy scores and were found to be significantly negatively correlated. The dark turquoise line indicates the slope, and the light turquoise indicates standard error. c) Children’s item recognition (d’) with same-space lures by category accuracy (%). d’ was calculated excluding the novel-space lures. Individual difference d’ scores were related to categorization accuracy scores and were not found to be significantly related. The dark turquoise line indicates the slope, and the light turquoise indicates standard error.
4 Discussion

In experiment one, we found that adults successfully learned to categorize and were then able to discriminate novel and familiar items in a surprise memory test. Looking at individual differences of these scores, the two were related such that individual memory scores were worse in those who performed better on the categorization task and vice versa; those with the best memory for items performed the worst on the categorization task. This trade-off was also found to change across time, with categorization accuracy interacting with time of exposure (trial number) to predict memory. Adults were less likely to remember items they correctly categorized and more likely to remember items they incorrectly categorized later in the task. Finally, adults showed evidence of gist memory; they showed greater memory when considering the novel-space lures as compared with the same-space lures. In addition, calculating memory (discrimination sensitivity) with only the novel-space lures was also found to drive the trade-off between memory and categorization performance, as a trade-off was not observed when calculating memory using only the same-space lures.

In experiment two, the children also learned to categorize at the same pace as the adults but with lower overall accuracy. However, their memory was significantly lower than the adults and was not different from chance overall. Also unlike the adults, there was no relationship between their category learning and their memory, but there was a moderate interaction between categorization accuracy and time of exposure (trial number) during the categorization task in predicting memory. This pattern was the opposite of that found in adults, as memory for correctly categorized items increased as categorization trials increased, while memory for incorrectly categorized items was better for items that were categorized early-on. Children also showed evidence of gist memory, showing greater memory when considering the novel-space lures as compared with the same-space lures. However, gist memory scores were significantly lower than adults. Finally, gist memory scores trended towards a trade-off with category learning.

In some ways, observing a trade-off in category learning and item memory is not surprising. Findings from a number of different literatures (e.g., category learning, gist memory, selective attention) point to a loss of resolution along irrelevant dimensions (Brainerd et al., 2008; Simons, 2000; Sloutsky & Fisher, 2004) as being important for abstraction in general, and category learning in particular. Yet, until now, little had been done to address the question directly. We
show this trade-off very clearly in the adults. In children, we observe a moderate trade-off only when calculating memory using the highly distinct lures, likely because their memory is so poor for these items, particularly when using same-space lures. This makes sense given that children are known to have worse memory than adults (Rubin, 2000). We therefore find that these processes are likely to be in competition and that learning novel non-verbalizable categories (as we have here) is better when memory for items is worse.

The different ways in which time interacts with categorization accuracy to predict memory in children and adults is not as straightforward. It is not entirely clear why children would remember errors better before learning has happened while adults would remember errors better after developing expertise. One possibility may be that while adults can proactively prepare for stimuli exposure, for instance preemptively directing eye gaze to the relevant location on the screen, young children tend to be more reactive to exposure as it occurs, for instance finding the relevant location after the stimulus has already appeared on screen (Chatham, Frank, & Munakata, 2009). This may mean that adults could proactively control their focus of attention to systematically test out categorization rules during learning. This would help explain their equal memory for correctly and incorrectly categorized items early in the task, as both are equally informative in a systematic approach to learning which could temper a potential reactive response to error. On the other hand, children lack this control, and an error in a learning context might signal greater reactive processing which could, in turn, boost their memory for those items. Adults’ boost in memory for late errors may simply reflect a surprise response, since they are mostly experts at that point in the task. A surprise may result in a more childlike, reactive response, resulting in a boost in memory. Of course, these explanations are quite speculative and would benefit from future work addressing these possibilities more directly.

While we discussed abstraction broadly, the children’s data may point to feedback-driven abstraction and gist-based abstraction being different processes. As mentioned, children’s learning speed on the categorization task was comparable to adults, while their gist memory was significantly poorer. This suggests that children’s abstraction might be late developing in general (given their poor gist representation for the shape space), but that when abstraction is facilitated by feedback (as in the category learning phase), abstraction is more possible for young children. This is supported by the neuroscience literature, which finds that feedback-driven learning is dependent on the dopaminergic system within striatal regions (Aron et al., 2004), and the
striatum has been found to develop in childhood (Sowell, Trauner, Gamst, & Jernigan, 2007). In comparison, abstraction more generally is thought to be dependent on multiple regions including the prefrontal cortex (Miller & Buschman, 2007), known for having a protracted development (Giedd et al., 1999). This developmental asymmetry could account for the difference seen in children’s performance across abstraction tasks.

Despite this pattern of data having important implications for understanding how learning and memory interact in both adults and children, conclusions regarding item memory were limited by floor effects, particularly in the children. A study with more variable and memorable stimuli would help clarify memory outcomes and how these relate to category learning. Moreover, while selective attention may be an important contributor to our findings, having been posited as contributing to the trade-off pattern, the current study did not directly manipulate or measure attention. As such, claims of its effects are theoretically-based and cannot be confirmed. Finally, the children who participated in this study were recruited at a science museum and are largely from high SES families. Their data may not be representative of the broader population.

While some adults showed poor learning and good item memory, there was an interesting pattern where, as a group, adults learned to categorize well and also form a gist representation in a dimension that was not related to the learning task. This makes sense given that abstraction is where we derive meaning, which is often more informative than specific details. For instance, if a vehicle is speeding towards you, it is fairly inconsequential what colour the vehicle is. On a more practical note, consider how abstract language can be, with turns of phrase often making little sense when taken at face value. However, while this points to adults being great abstractors, the trade-off between category learning and gist memory may suggest that focus tends to be limited to one type of abstraction at a time.

Finally, these data suggest that children are also capable of abstraction, but that this ability is still developing across the elementary school years. Children’s gist memory was worse than adults, and their categorization was less accurate overall. That said, they were, as a group, able to abstract in the task and along a dimension irrelevant to it. These findings support the work pointing to an early ability to abstract, and they show no evidence of the item-level focus posited by the opposing studies. Again, floor effects may have obscured any possible difference in item-focus between children and adults. Perhaps children would be more item-focused with a different
type of stimulus. Nonetheless, these findings support that children are capable of abstraction.

Taken together, this study supports the assertion that learning category-level information comes at the cost of learning item-level information, both in adults and, to a lesser extent, children. This trade-off in learning is likely symptomatic of the finite cognitive resources available at any one time. As such, it may represent an adaptive mechanism for learning effectively and efficiently. Yet, it remains a notable function of our cognition, and perhaps something to keep in mind, that we are never really getting the whole picture.
References


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