Executive function and attention predict low-income preschoolers' active category learning

Katherine A. Adams[1] **(kat.adams@nyu.edu), George Kachergis**[2,3]
[1]Department of Applied Psychology, New York University
[2]Department of Artificial Intelligence, Radboud University
[3]Donders Institute for Brain, Cognition and Behavior

Abstract

Recent studies find that school-age children learn better when they have active control during study. Yet little is known about how individual differences in strategy or cognitive control skills may affect active learning for preschoolers, nor if experimental measures of active learning map onto real-world learning outcomes. The current study assesses 101 low-income 5-year-olds on an active category learning task, and measures of executive function, attention, and school readiness. We find that preschoolers use an informative sampling strategy for categories defined by stimuli features in 1D and when presented with a distractor dimension (2D). Children accurately classify in 1D, but show mixed performance in 2D. Attention predicts sampling accuracy, and working memory and inhibitory control predict classification accuracy. Performance in the active learning task predicts early math and pre-literacy skills. These findings suggest that trial-by-trial learning decisions may reveal insight into how cognitive control skills support the acquisition of knowledge.

Keywords: active learning; executive function; attention; cognitive development; education

Introduction

From the enthusiastic preschooler who asks "why?" to the infant who turns her head to attend to a novel toy, children learn by actively exploring the world around them. Experimental studies show that children are engaged problem-solvers and employ strategies such as hypothesis testing, for example playing more with a toy after being shown confounded information about how it works (Schulz & Bonawitz, 2007).

Research in cognitive science suggests that active information gathering boosts children's performance in learning experiments (Partridge, McGovern, Yung, & Kidd, 2015; Sim, Tanner, Alpert, & Xu, 2015). For example, Sim and colleagues (2015) recently found that 7-year-old children learn categories better after self-selecting examples of category membership than when passively presented with a random sequence of examples. Yet little is known about how variation in children's abilities to optimally sample information may affect learning outcomes. Do young children differ in their information sampling strategies? What skills help children be good active learners? How do experimental measures of active learning map onto real-world learning outcomes? These questions have important implications within cognitive science and may inform targeted education interventions, particularly for children from under-resourced backgrounds who are at increased risk for poor academic outcomes (Blair & Raver, 2014). This study takes a first step in addressing these questions by examining low-income preschool children's active sampling strategies in a category learning task. We then ask how individual differences in a series of executive function, attention, and school readiness measures relate to active learning performance.

Educational research has long been interested in how young children's abilities to actively attend and engage during learning affect academic outcomes. One set of factors identified are executive functions (EF), higher-order cognitive control skills such as the ability to hold items in working memory, inhibit a prepotent response, and flexibly shift attention. Higher EF is associated with higher socioemotional and cognitive skills, and predicts early math and pre-literacy skills (Blair & Raver, 2014). Similarly, individual differences in preschool children's sustained and selective attention are important predictors of cognitive and academic skill (Steele, Karmiloff-Smith, Cornish, & Scerif, 2012). The neural networks that underlie EF and attention undergo tremendous growth during the preschool years. Several successful preschool interventions capitalize on this neurocognitive plasticity by targeting EF and attention as a means to boost school readiness and close income-based academic achievement gaps (Ursache, Blair, & Raver, 2012). Importantly, these intervention programs promote children's active engagement in learning as a key mechanism to support both EF and academic skills. However, this research is limited both by conceptualizing active learning in global behavior terms and by operationalizing learning outcomes with static standardized assessments.

Active learning paradigms from the cognitive science and machine learning literature offer a higher resolution to examine how young children actively learn and employ cognitive control processes. Here, active learning is defined as allowing learners to generate or make decisions about the information they want to experience trial by trial (Gureckis & Markant, 2012). Trial-by-trial analyses of active information gathering can reveal meaningful variation in learning strategies. For example, Gureckis and Markant (2009) investigated adult learners' ability to gauge information value during an active search task similar to the children's game *battleship*. The authors found that participants' information generating behaviors took two forms: one relatively fast and undirected and another slower, more effortful, that exploited local information constraints. Moreover, response time and search efficiency differed across these "modes."

Benefits of active control during information gathering are that learners can ask targeted questions to avoid redundant examples or content too difficult, creating learning situations to best fill their personal knowledge gaps (Gureckis & Markant, 2012). Active control also supports learning by enhancing the encoding of episodic representations which increases the likelihood of retrieving information about the experienced stimuli from memory (Markant, Ruggeri, Gureckis, & Xu, 2016). Adult learners can benefit from even subtle control over timing by coordinating the presentation of new information with their optimal attentional state so they are alert and ready to encode (Markant, DuBrow, Davachi, & Gureckis, 2014). Moreover, active control during memorization is associated with increased coordination in the neural networks that support executive control, attention, and memory encoding (Markant et al., 2016).

A limitation to active learning is that benefits can vary based on learners' abilities and task demands. For example, learners may be biased when sampling data, creating an uninformative feedback loop. Markant (2016) manipulated the hypothesis generation process in a series of category learning tasks to assess the impact on adults' ability to learn simple and complex rules. Results showed successful active learning depended on a match between the target rule and salient perceptual and abstract features of the task stimuli, and poor learning was due to generation of hypotheses that followed a non-relevant rule. That is, adult participants benefited from active learning opportunities under complex task demands when they were able to shift their attention to relevant rules or dimensions while ignoring others–a central EF skill.

To our knowledge, no studies to date have examined the coordination of EF and attention in children during active learning. Moreover, very little is known about how individual differences in active learning relate to sampling strategies or school readiness. Identifying the mechanisms supporting successful active learning may inform both cognitive science theory and educational interventions to support school readiness. The current study addresses these research gaps by examining active learning in a large sample of low-income preschoolers using a multi-dimensional category learning task, as well as a well-validated battery of EF, attention, and school readiness measures.

Method

Participants

One hundred and one preschoolers (M = 61m; Range = 55-67m; Male = 46) were tested as part of a school readiness study run in collaboration with two Head Start preschool centers. Participants came from low-income backgrounds, with an average reported yearly income of $11,968 (Range = 733-34,486). The sample was predominantly African American (N = 86).

Children were tested in their preschools by trained assessors using a touchscreen laptop. Administration of the tasks was divided over two testing days within a one week period. EF tasks were administered on day 1, and the category learning task and school readiness assessment were administered on day 2.

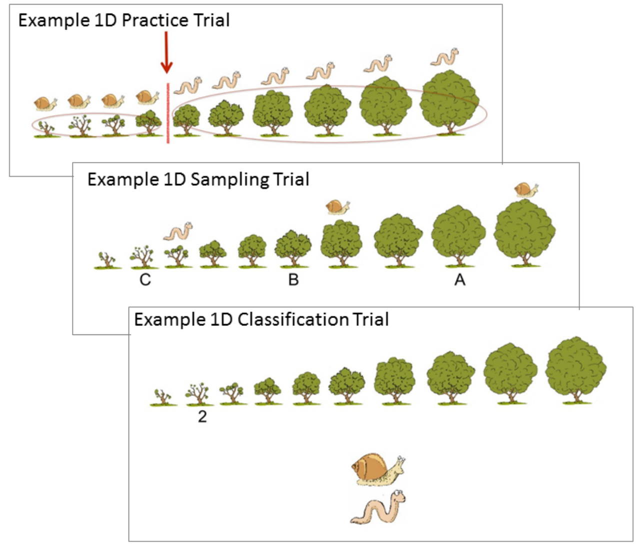

Figure 1: Examples of 1D trials varying by size dimension.

Category Task

Materials The category task (a modified version from Sim et al., 2015) was presented as a multi-slide questionnaire using the Qualtrics survey system. First, Block 1D presented two forests of trees that varied by one stimuli feature. The color row showed 10 images, identical in size and shape, but with varied leaf color, ranging from orange to green (left to right). The size row of 10 images were identical in color and shape, but progressed in size from smallest to largest (left to right). Block 2D presented a 7-by-6 grid of trees that varied horizontally by size (smallest on the left) and vertically by color (orange on top). In this task, worms and snails live in different groups of trees. The goal of the task is to classify trees based on the type of animal that lives there. Small worm and snail icons were displayed above exemplar trees in the sampling phase, and appeared as two larger button choices at the bottom of the screen in the test phase.

Procedure The 1D and 2D blocks each began with a demonstration phase, followed by two testing sequences which switched the dimension of categorization. In the 1D block, the first sequence featured the color row of stimuli and the second used the size row. In the 2D block, the first sequence was categorized by the size dimension and the second by color. Each sequence began with a 2-trial sampling phase followed by a classification phase (4 1D trials, 8 2D trials).

Block 1D *Demonstration phase.* To introduce the task, children were told to pretend they were scientists and figure out where two types of animals, worms and snails, liked to live. First, children were shown the the 1D color row. To demonstrate an example categorization of the trees, children were shown a small worm or snail icon above each and every tree (see Fig. 1). A red circle appeared around the group of trees with worms and another around the group with snails to emphasize that the animals were grouped separately. Children were asked to point to the category boundary, described as the "edge between the trees where the worms and the snails live." Once the child guessed, they were shown the boundary with a red arrow. This sequence was repeated with the 1D size row of trees and a new category boundary. Following the Sim et al. (2015) task design, these practice trials were meant to establish that (1) the animal icon above the tree indicated that the animal lived in that tree, (2) there was an invisible category boundary that divided the trees into two groups, and (3) the category boundary moved with each new forest.

Sampling phase. Children were first presented with the 1D color row of trees. In sampling trial 1, a worm and a snail icon appeared over 2 exemplar trees. The letters A, B, and C appeared under possible trees to sample. One sampling option was informative to find the category boundary, while the other two were non-informative because their category membership could be inferred by the position of the exemplars. By limiting learners to three sampling options, we increased our power to differentiate informative vs. uninformative sampling strategies over fewer trials, reducing noise and task demands for this very young sample.

To complete the sampling selection, the child was prompted, "Here's where a worm lives and here's where a snail lives. If you want to find the edge between the trees, would you want to learn about what lives in tree A, B, or C?" Once the child touched the sampling tree option of their choice, the selection was automatically logged in the Qualtrics database. Sampling trial 2 revealed the correct worm and snail icons above the three sampling tree options of the previous trial, and three new trees were shown as sampling options (see Fig. 1). Children selected a sampling option and the task advanced to the classification phase.

Classification phase. Children were presented with the 1D color row of trees without exemplars. At the bottom of the screen, a larger image of a worm and snail were shown vertically aligned. To reduce task demands, only 4 of the 10 trees were queried for classification. On each classification trial, the test trial number (1-4) appeared underneath one of the trees as a cue to guess the category membership of that tree. Children indicated their response by touching either the worm or snail response icon. Together, these responses demonstrated where each child believed the category boundary was generally located.

The sequence of sampling and classification phases was repeated for the 1D size row of trees, with a new category boundary and locations for exemplars and test trials.

Block 2D To introduce the 2D block, children were shown the 6x7 grid of trees and instructed, "In big forests, you have to find out if the worms and snails live in groups based on the SIZE of the trees or the COLOR of the trees. They only care about the size OR color!" The demonstration phase was identical to that in the 1D block (see Fig. 2). Sampling and classification phases in 2D followed the same procedure as 1D. Children were not told whether color or size was the relevant dimension for categorization.

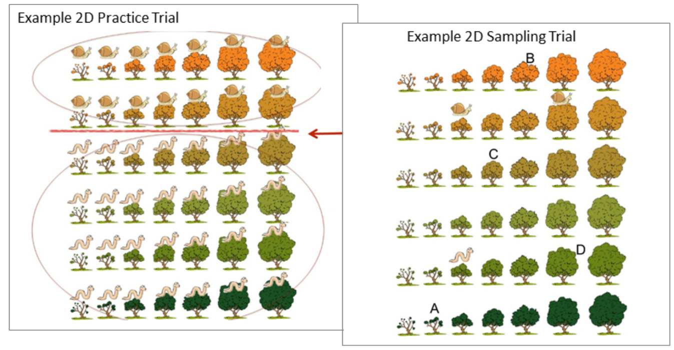

Figure 2: Examples of 2D trials with horizontal category boundary (classification trial not shown).

The first 2D sequence had a category boundary determined by tree size, following a vertical axis. Sampling trial 1 featured 3 category exemplars and 4 sampling tree options. The location of the exemplars made categorization only possible by the vertical dimension (i.e. by size). One sampling option was informative to the vertical category boundary. The category membership of the three other non-informative options could be inferred by the locations of the exemplars. After 2 sampling trials, children completed 8 classification test items. The number of exemplars, sampling options, and classification trials were increased compared to the 1D block to include a variety of positions across the 2D grid.

The second 2D sequence had a category boundary determined by tree color, following a horizontal axis (see Fig. 2). This dimensional switch (i.e., requiring attention to horizontal relations between exemplars to infer category boundary, not vertical as in past trials) is a feature of dimensional card sort games, classic EF tasks which require the participant to flexibility shift attention to the new relevant dimension and inhibit response to the old dimension.

Coding Selection trials were coded as correct if the child selected the option informative to finding the category boundary. Aggregate scores were computed for overall task accuracy and overall sampling and classification accuracy, and for sampling and classification accuracy on 1D vs. 2D blocks.

EF, Attention, and School Readiness Tasks

Working Memory. Digit Span is a widely used executive function task that assesses children's working memory (WM). Children are instructed to repeat number sequences of sequentially longer length in forward and backward conditions. Children in this sample were largely unable to repeat sequences backwards, so only correct responses on the forward condition are reported here.

Attention and Inhibitory Control. In the Continuous Performance Test (CPT), one hundred pictures are randomly presented on a touch screen one at a time for 300 ms followed by blank response screen for 1500 ms. Children are instructed to touch the screen as soon as an animal appears. Stimuli include 20 presentations of the target stimuli (animals) and 80 presentations of nontarget stimuli (objects). We report reaction time on correct touches to targets, a measure of attention processing speed (APS). We reverse-coded percent of missed responses to targets (omission error) and incorrect touches to distractors (commission error) as indices of sustained attention (SA) and inhibitory control (IC), respectively.

Math and Pre-Literacy Skills. The Woodcock Johnson III Tests of Achievement (WJ-III) is a well-validated assessment of school readiness skills. The Applied Problems subtest assesses children's early mathematical reasoning. The Letter Word subtest requires children to identify letters and words to measure their pre-literacy skills. A sum of the total correct answers is computed for each subtest and then translated into a standardized W-Score.

Results

Sampling Performance

We first ask if preschoolers can strategically sample in a category learning task. In the 1D block, children are significantly above chance in accurately choosing the informative sampling option (M = .48, chance = .33; $t(99) = 4.06$, $p < 0.001$). Within the 1D block, mean sampling accuracy is not different for color (M = .45) and size (M = .51), $t(99) = -1.37$, p = .18. Children also chose the informative sampling option in the 2D block ($M = .35$, chance = .25; $t(98) = 3.5$, $p = 0.001$). Within the 2D block, mean sampling accuracy is also not different for color (M = .33) and size (M = .37), $t(99) = -1.07$, p = .29. We find that sampling accuracy in 1D is related to sampling accuracy in 2D, $r = .26$, $p = .01$.

Figure 3 shows participants' mean accuracy on sampling questions (left panel) and subsequent categorization questions (right panel) by stimulus dimension and dimension of the sampling space.

Classification Performance

Overall, children are above chance in correctly classifying test items in 1D (M = .66, chance = .5; $t(99) = 6.3$, p < 0.001) but not in 2D (M = .51, chance = .5; $t(98) = .97$, p = .337). Mean classification accuracy in the 1D block is significantly higher than mean classification accuracy in the 2D block ($t(97) = 5.14$, p < .001). Within the 1D block, mean classification accuracy is significantly higher for color (M = .71) than for size (M = .63), $t(99) = 2.23$, p = .03. Within the 2D block, children are at chance on the size condition (M = .47, chance = .5; $t(98) = -1.35$, p = .18) but interestingly above chance on the subsequent color condition, which includes a dimension switch on the category boundary (M = .55, chance = .5; t(98) = 2.15, p = .034). Mean classification accuracy is significantly higher for color in the 2D block than for size ($t(98) = 2.24$, p = .03). Note that effects of size vs. color dimensions should be interpreted with caution, as the blocks were presented in fixed order.

Does Sampling Predict Classification?

We next ask if sampling accuracy benefits subsequent classification accuracy, as suggested in previous active category learning studies with both adults and school-age children. Surprisingly, sampling accuracy is not related to classification accuracy. Children who choose the most informative sampling strategy in 1D are not better at 1D classification, $r = .06$, $p = .58$, nor are 2D sampling and classification accuracy related, $r = -.03$, $p = .81$. Comparing classification accuracy on 1D of good samplers ($M_{acc} > .7$) vs. poor samplers ($M_{acc} < .3$) yielded no significant differences, $t(72.9) = .84$, $p = .41$, nor for good vs. poor samplers in 2D, $t(35.7) = .2$, $p = .84$.

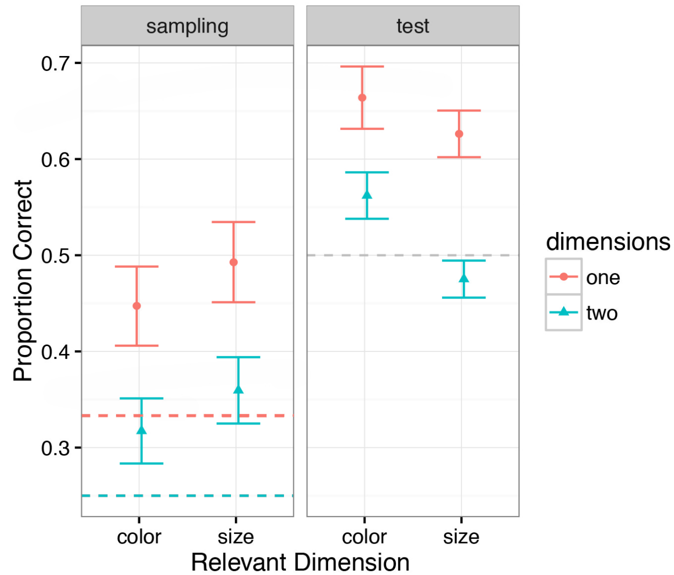

Figure 3: Accuracy on sampling questions (left) and categorization test (right) for each relevant stimulus dimension (color/size) and dimensionality of the stimulus space. Dotted lines show chance (sampling chance: 1D=33%, 2D=25%).

Relations Between EF and Active Learning

We next examined the role of executive function and attention in predicting active learning performance using a series of exploratory logistic mixed-effects regression models to the item-level with subject as a random factor. Age, sex, EF, and attention measures were fixed predictors. Prior to analyses, we scaled and centered all variables. Table 1 presents descriptives of executive function, attention, and school readiness measures.

First, we predicted overall accuracy, including both sampling and classification trials (N = 2,632; R syntax: `Correct ~ age + sex + WM + APS + SA + IC + (1|Subject)`). There was a significant positive effect for WM ($\beta = .11$, $Z = 2.11$, $p = .04$), showing that participants with higher working memory perform better overall in the task. Next, we predicted accuracy on all sampling trials (N = 676), adding overall classification accuracy as an additional fixed predictor (R syntax: `Correct ~ age + sex + WM + APS + SA + IC + class Acc + (1|Subject)`). There was a significant positive effect

Table 1: Descriptives of Executive Function, Attention, and School Readiness Measures.

	Mean (SD)	**Range**
Digit Span (% correct forward)	44% (13)	0-67%
CPT Omission Errors (%)	47% (28)	0-100%
CPT Commission Errors (%)	12% (14)	0-78%
CPT Reaction Time (ms)	824 (166)	474-1364
WJ-III Applied Probs (W-Score)	407 (17)	350-440
WJ-III Letter Word (W-Score)	333 (20)	276-369

for attention processing speed (APS) (β = .38, Z = 2.57, p = .01), showing that participants with faster attention processing are more accurate at sampling. We then predicted accuracy on all classification trials (N = 1956), substituting in overall sampling accuracy as an additional fixed predictor. There was a significant positive effect for WM (β = .12, Z = 2.14, p = .03), showing that participants with higher working memory are more accurate at classification.

We next ran the models by 1D and 2D blocks. Predicting 1D sampling (N = 339) with 1D classification accuracy as the additional fixed predictor revealed no significant effects. For 1D classification trials (N = 598) with 1D sampling accuracy as the additional fixed predictor, there was a surprising significant negative effect for sustained attention (SA) ($\beta = -.37$, $Z = -1.98$, p = .048), such that children who were less responsive to targets during a sustained attention task had better classification accuracy in the 1D block.

Predicting to 2D sampling (N = 337) with 2D classification as the additional fixed predictor also revealed a positive effect of attention processing speed (β = .357, Z = 2.026, p = .043). For 2D classification trials with 2D sampling accuracy as the additional fixed predictor, there was a significant effect of inhibitory control (IC) (β = .131, Z = 2.087, p = .037), showing that children who are better at inhibiting a prepotent response are more accurate at 2D classification.

Predictors of School Readiness

How does active learning performance relate to school readiness? To examine this question, we use an exploratory linear mixed-effects model fit by REML (nlme package) at the subject level to predict to math and pre-literacy scores on the WJ-III assessment. First, we predict to math scores using subject as a random effect, and age, sex, EF, attention, and overall sampling and classification accuracy as fixed predictors (R syntax: `math ~ age + sex + WM + APS + SA + IC + class Acc + Sampling Acc, random= ~ 1|subject`). We found significant positive effects for overall sampling accuracy ($t(77) = 3.85$, $p < .001$), and overall classification accuracy ($t(77) = 2.64$, p = .01), suggesting that children who are better at active learning in the category task are have better early math skills over and above the contributions of EF, attention, and demographics.

We ran the same exploratory linear mixed-effects model to predict pre-literacy scores but did not find any relations between pre-literacy and sampling or classification accuracy. We modified the predictors, collapsing over sampling and classification trials to examine the effect of overall active learning performance. Here, we find that overall accuracy in the active learning task is a positive predictor of pre-literacy skills ($t(78) = 2.03$, p = .046).

Discussion

We found that 5-year-olds from low-income backgrounds use an informative sampling strategy in an active category learning task. Preschoolers are able to accurately classify the category membership of test items in 1D, but show mixed performance in the 2D classification blocks. Sampling accuracy across dimensions hangs together: children who choose the most informative option in 1D are also better at sampling in 2D. However, children who are good at classification in 1D are not more likely to be good at classification in 2D. Contrary to past active learning studies, we do not find that better sampling accuracy benefits classification accuracy in either 1D or 2D blocks. However, individual differences in children's EF and attention skills shine a light on potential cognitive control processes that support success in active learning. We found that attention processing speed largely supports sampling accuracy and better working memory is linked to higher accuracy on classification. Notably, better inhibitory control supports classification accuracy when the categories are presented with a distractor dimension (2D).

Previous published work has found active learning benefits in categorization tasks for 7-year-olds (Sim et al., 2015), but little research has examined preschool-aged children. One concern was that younger children would struggle with the metacognitive organization needed to plan and follow an informative sampling strategy. Despite variability, our data show that many preschool children made queries that were informative to finding a category boundary.

It may be that categorization within a 2D space was especially difficult to navigate for children at this age, however we found that children had above chance classification accuracy within the 2D block after the dimensional rule switch from a vertical to horizontal category boundary. Although surprising, one possibility is that children became accustom to categorization within a 2D space over multiple trials, and thus increased accuracy was partially due to practice. A limitation to this study is that the task order was fixed, and thus size vs. color performance is confounded with practice effects. It is interesting to note that practice effects may be present in the 2D condition despite the added complexity of a categorization switch. Additional study is needed to understand how variation in boundary options and stimuli characteristics may affect children's active category learning.

Exploratory analyses examining the role of executive function and attention skills add nuance to understanding children's performance in this task. We found that attention processing speed supports children's sampling strategies. The link between attention processing and active learning benefits is discussed in Markant et al. (2014), who found that learners benefit from even minimal control of timing during learning by matching the presentation of information to their optimal attentional state. It is possible that those children who were able to maintain a ready state of attention processing were better able to encode information about sampling parameters than those whose attention processing was slower.

We found that higher working memory supports both overall task accuracy and classification across 1D and 2D blocks. Working memory may help children to remember the relative locations of exemplars within the 1D and 2D spaces, which is necessary to infer both the category boundary and test items' class. Inhibitory control significantly predicts classification accuracy in the 2D block. Dimensional shifting requires the learner to inhibit a learned response or rule and attend to new information. To attend to the category boundary and correctly classify exemplars in a 2D space, this task requires children to determine how exemplars related to each other along the relevant dimension, while ignoring relations on the non-relevant dimension. These exploratory findings suggest that inhibitory control may help children attend to relevant features under complex learning demands.

The lack of relation between category learning sampling and classification is at odds with previous studies which found better sampling led to better performance in active learning (e.g., Ruggeri et al., 2016). In fact, our design was meant to decouple sampling performance from categorization performance: the category memberships of all sampling choices are revealed once the selection is made. Thus a child who makes a bad selection is not penalized–they see the exemplar of the informative choice as well as the uninformative choices. Because we were limited to a fixed task across all administrations, this design allowed us to make sure all children's sampling choices were revealed and that they all saw the same information about the boundary leading into the classification phase. Thus, this design removed the necessity of good sampling to support classification accuracy within the task. We found that children's memory skills, likely related to remembering the location of exemplars, appeared to play a more important role in classification accuracy.

Our results also suggest that children's performance in the active learning task is related to their early math and preliteracy skills. Both overall sampling and overall classification accuracy significantly predict math scores, above and beyond demographics, executive function, and attention skills. Overall active learning accuracy predicts pre-literacy skills. These exploratory findings suggest that trial-by-trial performance in a lab-based measure of active learning may be related to children's acquisition or implementation of academic knowledge. Children's development and use of learning processes and problem solving strategies may rely in part on cognitive control skills. The benefits of good active learning skills may cascade overtime to support children's acquisition and practice of domain-specific knowledge. Importantly, these correlational data are only the first step in investigating active learning in relation to school readiness and additional research should examine this potential link, as it could be highly informative to educational intervention efforts.

While most education and developmental researchers examine EF and learning by way of standardized school readiness tests, the current study's findings suggest that details of children's trial-by-trial learning decisions may reveal important details of how cognitive control skills support the acquisition of knowledge. We note several limitations to this study. First, the sample is low-income and the restricted range of socio-economic status (SES) may lower generalizability, although examining the relations between learning processes and school readiness is of particular importance for this population. We plan follow-up studies including a high income cohort to examine the relations between SES, cognitive control skills, and active learning. Second, this work is both correlational and uses concurrent measures. Our future studies include experimental active learning paradigms for young children that vary aspects of cognitive control processes to better tease apart the role of EF and attention on active learning.

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