Journal of Experimental Child Psychology 225 (2023) 105535

Contents lists available at ScienceDirect

Journal of Experimental Child Psychology

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

Explore versus store: Children strategically trade off reliance on exploration versus working memory during a complex task

Praveen Kenderla [a], Melissa M. Kibbe [a,b,*]

[a] Department of Psychological & Brain Sciences, Boston University, Boston, MA 02215, USA
[b] Center for Systems Neuroscience, Boston University, Boston, MA 02215, USA

ARTICLE INFO

Article history:
Received 31 March 2022
Revised 3 August 2022

Keywords:
Working memory
Visual search
Exploration
Cognitive effort
Cognitive development
Hypothesis-testing

ABSTRACT

During complex tasks, we use working memory to actively maintain goal sets and direct attention toward goal-relevant information in the environment. However, working memory is severely limited, and storing information in working memory is cognitively effortful. Previous work by Kibbe and Kowler [2011, *Journal of Vision, 11*(3), Article 14] showed that adults strategically modulate reliance on working memory during complex, goal-oriented tasks, varying the amount of information they store in working memory depending both on the cognitive demands of the task and on the ease with which task-relevant information can be accessed from the environment. We asked whether children, whose working memory and executive functions are undergoing significant developmental change, also use working memory strategically during complex tasks. Forty-six 8–10-year-old children searched through arrays of hidden objects to find three that belonged to a given category defined over the objects' features. We manipulated the cognitive demands of the task by increasing the complexity of the category. We manipulated the exploration costs of the task by varying the rate at which task-relevant information could be accessed. We measured children's search patterns to gain insights into how the children used working memory during the task. We found that as the cognitive demands of the task increased, children stored less information in working memory, relying more on exploration. When exploration was costlier, children explored less, storing more in working memory. These results suggest that

* Corresponding author at: Department of Psychological & Brain Sciences, Boston University, Boston, MA 02215, USA.
E-mail address: kibbe@bu.edu (M.M. Kibbe).

https://doi.org/10.1016/j.jecp.2022.105535

developing children, like adults, make strategic decisions about when to explore versus when to store during a complex, goal-oriented task.

Introduction

Children learn about the world through active participation in their environments (Miller, 2002) and must actively sample from the environment in order to accomplish goals. For example, a child searching their room for their blue bear toy needs to maintain information about the color and shape of the toy in working memory and actively search the environment for these features. As the child searches for the toy, they must also encode information about which locations they have already searched into working memory and maintain that information while moving on to search new locations, returning to previously visited locations as memory for these locations begins to fade.

A child putting together a picture puzzle faces an even more complex challenge. Now, their task is not to simply locate a single object but rather to locate multiple objects that work together to accomplish the goal of finishing the puzzle. In order to do so, the child must keep in mind the overall goal (complete the puzzle) and various sub-goals (e.g., find another green puzzle piece, find a piece that completes a portion of the puzzle) while actively searching among the puzzle pieces for pieces that accomplish these goals. A child solving a picture puzzle must coordinate holding multiple pieces of information in working memory (e.g., goals and sub-goals, features of the puzzle pieces already put together, possible features of missing puzzle pieces), exploration of the environment (e.g., searching through the remaining puzzle pieces, looking back at the in-progress puzzle to assess fit), testing hypotheses about candidate puzzle pieces, and making decisions about when to continue searching and when to stop searching and try a candidate piece. Indeed, the coordination of multiple cognitive and motor processes underlies countless goal-directed actions, from making a peanut butter and jelly sandwich (Hayhoe, 2000; Land & Hayhoe, 2001; Land et al., 1999) to solving complex geometry problems (Epelboim & Suppes, 2001).

How do children coordinate multiple cognitive and motor processes to accomplish goals? A child with the goal of solving the picture puzzle, for example, must consider the limitations of their cognitive and motor systems in order to make strategic decisions about when to rely on working memory and when to explore their environments. Working memory is severely limited during childhood and undergoes substantial development into the teenage years (Burnett Heyes et al., 2012; Gathercole et al., 2004; Heyes et al., 2016; Isbell et al., 2015; Ullman et al., 2014). Because of these limitations, as children explore their environments, more information is stored in working memory and the fidelity of earlier representations becomes noisier (Lewis-Peacock et al., 2018; Portrat et al., 2008). To strengthen these fading representations, previously viewed information needs to be revisited (Hollingworth & Maxcey-Richard, 2013; Zelinsky et al., 2011). Exploration of the environment thus serves to replenish and strengthen working memory representations (Ballard et al., 1995; Melcher, 2001; Melcher & Kowler, 2001; Pertzov et al., 2009). However, active exploration *also* can be costly (Araujo et al., 2001; Ballard et al., 1995) such as when information is not readily accessible or when retrieving information requires excessive motor effort (e.g., producing reaching actions or even very large saccades) (Araujo et al., 2001). Furthermore, during goal-directed tasks, the costs of reliance on memory and exploration must be weighed while also keeping in mind the overall goal that needs to be accomplished (e.g., solving the puzzle) and any interim goals (e.g., finding the puzzle piece that fits in a particular location). A child who is attempting to solve a puzzle is thus faced with a series of complex decisions that require the careful coordination of multiple cognitive processes and goal sets if they hope to accomplish their goal without expending excessive amounts of cognitive or motor effort. The aim of the current study was to examine whether and to what extent children are strategic in the way they coordinate reliance on memory versus exploration of the environment during complex, goal-oriented tasks.

Previous work has shown that adults strategically trade off reliance on memory versus reliance on exploration during complex, goal-directed tasks. For example, Ballard and colleagues (1995) asked adult observers to recreate a pattern of blocks using blocks in a virtual workspace and measured observers' gaze patterns as the observers completed the task. Instead of maintaining the entire block pattern in working memory and then recreating the block pattern based on that remembered pattern, observers repeatedly referenced the original pattern, encoding only information relevant in that moment. However, when the distance between the model block pattern and the recreated pattern increased, observers shifted their strategy to maintaining more information about the block pattern in working memory and making fewer saccades. These results suggest that, with an increase in exploration costs, observers store more information in working memory compared with when exploration costs are low.

The cognitive complexity of the task also can impose limitations and can tip the balance between exploration and working memory (Epelboim & Suppes, 2001; Kibbe & Kowler, 2011). When the cognitive demands of the task are low but the cost of exploration is high, such as searching a large room for a toy, a strategic searcher may rely more on working memory, holding more information about previously searched locations in mind to avoid the motor cost of searching those locations again. But as the cognitive demands of the task increase, such as when solving a complex picture puzzle, a strategic searcher may rely more on exploration, freeing up cognitive resources for the relatively more complex task of considering multiple possibilities simultaneously or testing hypotheses about candidate pieces.

Kibbe and Kowler (2011) parametrically manipulated the cognitive demands of a search task and measured the effect of these demands on trade-offs between reliance on exploration and reliance on working memory in adults. In their study, adult observers were presented with an array of nine hidden multi-featured objects, each defined by a color, shape, pattern, and orientation. Observers were asked to search through the objects, viewing them one at a time, to find three objects that belonged to a given category defined over the objects' features. The authors manipulated the cognitive demands of the task by varying the number of conjunctive and disjunctive rules that made up each of five categories. For example, the simplest category required observers to find three objects that all matched on a single feature (e.g., all were red, all were square), while the other three features were irrelevant. The most complex category required observers to find three objects that shared a single feature but differed completely on two features (e.g., all were red but one was a striped square, one was a solid circle, and one was a gridded diamond). They also manipulated exploration demands by varying the motor effector (lower-cost saccade vs higher-cost mouse click) and how long it took to view each object (i.e., immediately or after a 1-s delay). To examine how observers were trading off memory and exploration, they measured the number of times observers visited and revisited each location. They also measured the number of locations observers visited between visits to the same location. They found that as the cognitive demands of the task increased, observers relied more on exploration to accomplish the goal, visiting and revisiting objects more frequently as the complexity of the category increased regardless of motor effector or delay. When the cost of exploration was higher, such as when there was a delay between selecting a location and viewing the information at that location, observers relied more on working memory, visiting and revisiting fewer locations overall. These results suggest that adults strategically trade off reliance on exploration and working memory depending both on cognitive demands of the task and on exploration costs.

Do these trade-offs occur in children in whom the cognitive systems underlying complex, goal-directed tasks are still developing? Children's working memory for visual information continues to develop through adolescence (Burnett Heyes et al., 2012; Gathercole et al., 2004; Heyes et al., 2016; Isbell et al., 2015; Ullman et al., 2014), and the executive functions that underlie complex goal completion also are undergoing significant development into adulthood (e.g., Anderson et al., 2010; Barnea-Goraly et al., 2005; Crone, 2009; Diamond, 2006; Gogtay et al., 2004). Development within these individual systems means changes not only in the functioning of these systems but also in the ways these systems interact. This means that for developing children, unlike for adults, the coordination of these processes is a continually changing process, which may make strategic use of working memory more challenging for children. However, children also are able to selectively attend to, encode, and refresh information in working memory (Shimi & Scerif, 2017), prioritize encoding task-relevant information over task-irrelevant information in working memory (e.g., Atkinson et al., 2019), and show metacognitive awareness of their own working memory limitations (Applin & Kibbe, 2021; see also Shimi et al., 2015), suggesting that some of the cognitive requirements for strategic use of working memory during complex tasks may already be in place by middle childhood.

In the current study, we asked whether children consider the cognitive and exploration demands of a complex, goal-directed task to strategically coordinate reliance on working memory versus exploration. Understanding whether these trade-offs occur in children can provide important insights into the way children make *active use* of working memory. Previous work has often assessed children's working memory capacity for visual information by using passive observation tasks such as asking whether children can detect a change in an array (e.g., Cowan et al., 2005; Riggs et al., 2006, 2011; Simmering, 2012) or by asking children to directly manipulate the contents of their working memory (e.g., the *n*-back task; Schleepen & Jonkman, 2009). Although these studies have been instrumental in uncovering the time course of working memory development (and instrumental in providing important continuity with adult tasks; e.g., Luck & Vogel, 1997), they did not require children to *use* their working memory in service of a goal. Whether the "capacity" of children's working memory flexibly shifts to accommodate the cognitive and motor demands of a complex task is currently unknown.

The category search task

We adapted the category search task of Kibbe and Kowler (2011) to examine whether and how children aged 8 to 10 years strategically trade off reliance on working memory versus exploration depending on the demands of a complex, goal-directed task. We investigated 8- to 10-year-olds because these children are undergoing developmental change in both working memory and executive functioning systems but are old enough to be able to learn the rules of the category search task. We told children that they were going to play a modified version of the "memory game" in which players search through arrays of upside-down cards, one at a time, to find cards that go together. In our task, children were shown sets of 9 cards on a computer screen and could click the card to reveal the image of an object on the other side. Each object was defined by four features (color, shape, pattern, and orientation) that could each take one of three values (e.g., square, circle, or diamond in the case of shape). However, instead of finding images that match, children were asked to find three objects that belonged to one of three categories defined over the objects' features.

As in Kibbe and Kowler (2011), we manipulated the cognitive demands of the task by varying the complexity of the category (Feldman, 2006; Jacob & Hochstein, 2008). The categories were formed using conjunctive and disjunctive rules over one or more of the objects' features. Conjunctive rules required the objects to share a feature value (i.e., all three objects are the same shape, color, pattern, *or* orientation). Disjunctive rules required objects to each have a different value of the same feature. For example, if three objects differed on color, one would be red, one would be blue, and one would be green. We manipulated the complexity of the categories by varying the number of features that defined the category (one or two) and by varying whether the category contained conjunctive rules (shared feature values) or disjunctive rules (different feature values) (Feldman, 2006; Jacob & Hochstein, 2008). This resulted in three category rules that were identical to the first three category rules used by Kibbe and Kowler (2011).[1]

We also manipulated the cost of exploration by varying how difficult it was to view the object. In a No Delay condition, children could view the object immediately upon clicking on its location. In a Delay condition, there was a 1000-ms lag between clicking and viewing, making exploration more costly because of the additional time it took to retrieve the relevant information.

We measured children's search patterns: the number of visits, number of revisits, and mean number of objects viewed between revisits to the same object (revisit distance). Each of these measures

[1] Kibbe and Kowler (2011) used five category rules with adult observers defined over one to three features of the objects. We reasoned that using all five rules, including the two most complex rules, might make the task too difficult for children.

gives us unique insights into children's strategies for solving the task. The number of visits is the overall rate of exploration: how many items children need to view before they make their final decision about which objects belong to a given category. The number of revisits gives the rate at which children are refreshing memory representations for earlier encoded items or are returning to increase certainty about objects as possible candidate members of a set of objects that satisfies the category.

The number of objects children visit before returning to an object that they already visited—revisit distance—gives us an estimate of the number of objects children are simultaneously considering in working memory. Previous work has used revisit distance to infer the amount of information that is being held in working memory (e.g., Epelboim & Suppes, 2001; Jacob & Hochstein, 2009; Kibbe & Kowler, 2011), and variation in revisit distance can reflect participants' search strategies. For example, Kibbe and Kowler (2011) found that participants visited about four to six objects between revisits, suggesting that they were simultaneously maintaining enough objects in working memory to consider multiple potential sets of objects that satisfied the category before refreshing the contents of working memory. Adults' revisit patterns in Kibbe and Kowler (2011) also suggested sophisticated use of strategies for using working memory more efficiently during search. First, adults' revisit distance varied with category complexity, increasing particularly when the category included a disjunction. Second, adults visited more objects between revisits when exploration costs were low. Kibbe and Kowler (2011) argued that, together, these patterns suggested that adults were testing hypotheses about potentially category-relevant features and storing only those features in working memory. Exploration then served to enrich existing representations as new hypotheses about potential sets were tested, particularly when it was less costly to explore. Given this previous work, we used revisit distance to infer the number of objects stored in working memory.

Critically, we designed each trial such that an ideal searcher, with perfect memory and unlimited cognitive resources, would need to visit only four to six objects before encountering three objects that belonged to the given category, regardless of the complexity of the category or the exploration demands of the task. Thus, any searching behavior beyond 4 to 6 visits will yield insights into the sources of limitation and strategies that children are using as the demands of the task are manipulated.

Predictions

There were several potential patterns of results that we could observe, but we reasoned that we might observe one of three more likely patterns. The first possible pattern is that children might not vary their search strategies depending on the demands of the task. Children might not yet have the adult-like ability to make strategic cognitive decisions about how to use developing working memory most efficiently to complete demanding tasks that require coordination of multiple cognitive processes. If this is the case, we may observe children making more errors (selecting objects that do not belong to the given category) as the cognitive demands of the task increase (i.e., as we increase the complexity of the category rule), but we would not observe differences in the number of revisits as a function of cognitive demands or exploration cost.

Another possibility is that children may modulate their search patterns based on only exploration cost or cognitive demands but not both. Under this possibility, children may be sensitive to only one of the dimensions on which the difficulty of the task was manipulated. For example, children may strategically shift toward relying more on working memory when exploration costs are high, showing sensitivity to the ease with which information can be accessed from the environment. However, children might not modulate use of working memory as the cognitive complexity of the task increases (i.e., relying more on working memory when cognitive complexity is lower and relying more on exploration when cognitive complexity is higher), suggesting that they are not able to make efficient use of working memory to meet the cognitive demands of the task.

A final possibility is that children, like adults, may strategically trade off reliance on exploration and memory depending on the cognitive and exploration costs of the task. Under this possibility, we would expect that children should rely more on exploration as the cognitive demands of the task increase, visiting and revisiting more objects as the category becomes more complex, and rely more on working memory as the exploration costs of the task increase, visiting and revisiting fewer objects when there is a delay to view each object.

Method

Participants

Participants were 46 8- to 10-year-old children assigned to one of two conditions: No Delay (n = 23; mean age = 9.23 years, SD = 0.83; 11 girls) or Delay (n = 23; mean age = 9.33 years, SD = 0.92; 8 girls). Caregivers reported that their children were Asian (n = 2), Black (n = 5), more than one race (n = 4), Pacific Islander (n = 1), or White (n = 30) or did not report their children's race (n = 4). Of the participants, 8 were reported as being Hispanic/Latine. Sample size was determined prior to data collection. Previous work using this method with adults (Kibbe & Kowler, 2011) included 7 or 8 participants per condition and observed large effect sizes. We reasoned that children's behaviors may be more variable. A power analysis using G*Power suggested a total sample size of 44 participants for a 3 (Task Complexity) $\times$ 2 (Exploration Costs) mixed analysis of variance (ANOVA) design (main effects and interactions; $1 - \beta$ =.95, α =.05) assuming a medium effect size (n = 22 per between-participants condition). A total of 46 children were tested due to overscheduling. An additional 3 children participated in the Delay condition, but their data were not included in the analysis due to a computer malfunction (n = 1), failure to complete the task (n = 1), or failure to reach a sufficient number of correct responses (at least 1 per category) to meet inclusion criteria (n = 1). Children participated in a quiet laboratory space at Boston University.

Stimuli

On each trial, children were presented with 3 $\times$ 3 arrays of black-outlined squares (3.71° $\times$ 3.71° visual angle). Clicking on each square revealed an object at that location (3.43° $\times$ 3.33° visual angle). Objects were made up of four trinary features: color (red, green, or blue), shape (square, round, or diamond), pattern (solid, striped, or grid), and orientation (indicated by the position of a hole in the object; up, down, or side). There were 82 possible objects (identical to those used in Kibbe & Kowler, 2011). Fig. 1 shows three example objects, each with a different value for each feature.

Text at the bottom of the screen (black 10-point Courier font) reminded children of the category for that trial. To make their final selections, children clicked a black-outlined button at the top of the screen that contained the text "Click here and select locations" (in the same black 10-point Courier font). Once clicked, the button outline turned red and the text changed to "Select objects." Introduction screens for each category were presented before each trial to indicate the relevant category for that trial. These screens contained text describing the category and an image of a sample object with each feature labeled.

Stimuli were presented using the Psychophysics Toolbox (Brainard, 1997) in MATLAB R2018b. To train children on the categories and the task, we also created a training demonstration slideshow

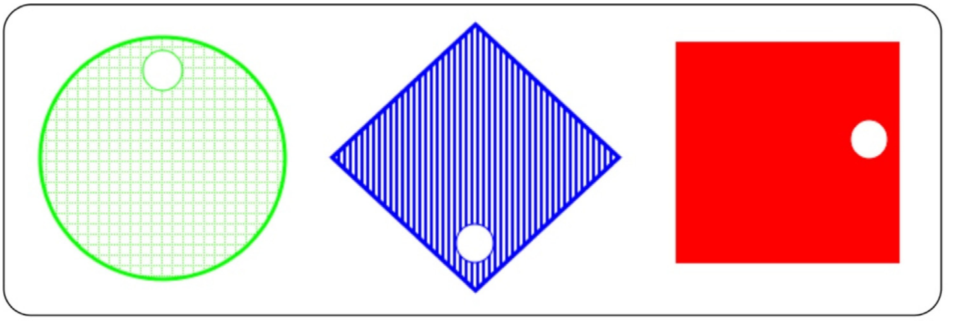


Fig. 1. Example objects, each with a different value for each of the four features (color, shape, pattern, and orientation).

using Microsoft PowerPoint (see "Procedure" section). Both programs were run on a Dell Latitude 13.3-inch laptop computer with a resolution of 1366 × 768 pixels and a refresh rate of 60 Hz.

Categories, exploration costs, and trial structure

We manipulated the *cognitive demands* of the task by varying the number of features that defined the category (one or two) and by varying whether the category contained conjunctive rules (shared feature values) or disjunctive rules (different feature values) (Feldman, 2006; Jacob & Hochstein, 2008). This resulted in three categories with increasing complexity: Share One (Category S): find three objects that share one feature (the other three features do not matter); Share Two (Category SS): find three objects that share two features (the other two features do not matter); and Share One, Differ One (Category SD): find three objects that share one feature and differ on one feature (the other two features do not matter). See Fig. 2 for examples of sets of objects that satisfy each category.

Children completed three trials for each category. Each trial was constructed so that children had roughly the same probability of encountering a correct set of three objects regardless of the complexity of the category. On each trial, there were 9 to 12 possible correct sets that satisfied the category, and a random search would reveal a correct set within four to six object visits. That is, each object belonged to multiple potential sets (e.g., a single object could share the same shape as some objects in the array while sharing the same color as different objects in the array). A searcher could randomly select four to six objects to have a 100% chance of encountering three objects that would satisfy the category rule. Thus, continued searching beyond four to six visits reflects limitations on working memory for objects already visited (e.g., remembering only a subset of the features from each object and therefore failing to recognize that one had already encountered a category-satisfying set).

We manipulated *exploration cost* by assigning children to one of two conditions. In the No Delay condition, objects were visible immediately after they were clicked. In the Delay condition, there was a 1000-ms delay to view the objects after clicking. Thus, for children in the Delay condition, retrieving the relevant information took longer, making exploration more costly.

Procedure

The task proceeded in three phases: training, practice, and category search task. The full scripts for the training and practice phases and the training slideshow are available at https://osf.io/rzkfy/?view_only=6daf4447027140b7a2ffa9de70e0b8bf.

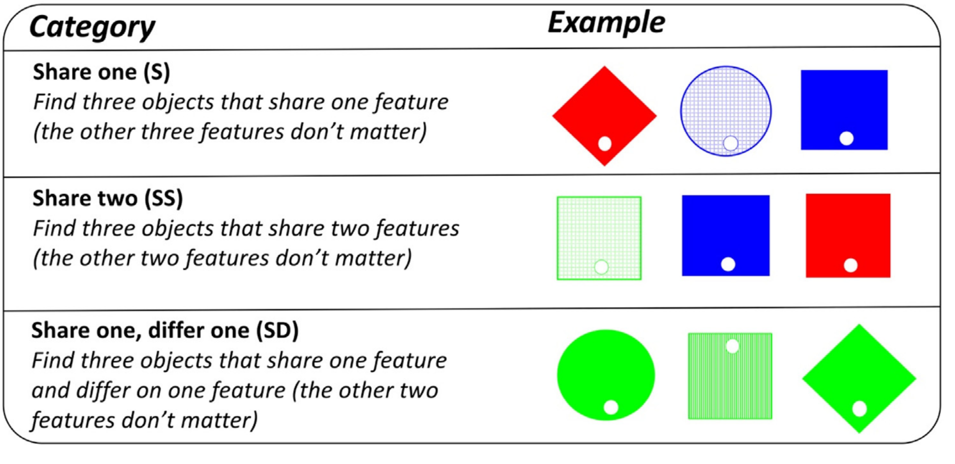


Fig. 2. The three categories and examples of each category. In these examples, for Category S the three objects share the same orientation, for Category SS the three objects share the same orientation and the same shape, and for Category SD the three objects share the same color but all are different shapes.

Training

We first told children that they were going to play a memory game. We described a typical memory game in which the player flips over cards to find pictures that match. Most children reported being familiar with this game. We then told children that that they were going to learn the rules of the game. Children were told that they could ask questions during the training.

We next familiarized children with the objects that would appear in the game. We showed children three example objects (Fig. 1) and walked children through the four features of the objects (shape, color, pattern, and orientation) and their possible values. To ensure that children could identify all the features of the objects, we next presented children with three different example objects, one at a time, and asked them to name all the features of the objects. Children were given corrective feedback on their responses.

We then told children that they were going to learn rules about how the objects go together in the memory game. We introduced children to the three categories in a fixed order. Children were shown the first rule—Share One (Category S)—and were told, "You have to find three objects that *share one feature.* That means that they are all the same color, *or* all the same shape, *or* all the same pattern, *or* all the same orientation. But it doesn't matter what their other features are. As long as they *share at least one feature,* they work. Okay?" We then showed children four sets of three objects presented one at a time. Two of the sets satisfied the category and two did not. We asked children to decide whether each set of objects fit the category and to explain why or why not. Children were given corrective feedback on each set.

The experimenter then introduced the two other categories in the same way. For the second category rule—Share Two (Category SS)—children were told that they needed to find three objects that share *two* features. For the third category rule—Share One, Differ One (Category SD)—children were told that they needed to find three objects that shared one feature "but also *differ* on one feature. That means that they all have to be different. So, for example, the objects could all be red, but one is a circle, one is a square, and one is a diamond. Or, they are all striped, but one is red, one is blue, and one is green. Does that make sense? As long as the objects share one feature and are completely different on one feature, they work." Children were again shown four examples for each category rule (two that satisfied the rule and two that did not) and were asked to judge whether they fit the category and to explain why or why not. Children were given corrective feedback throughout.

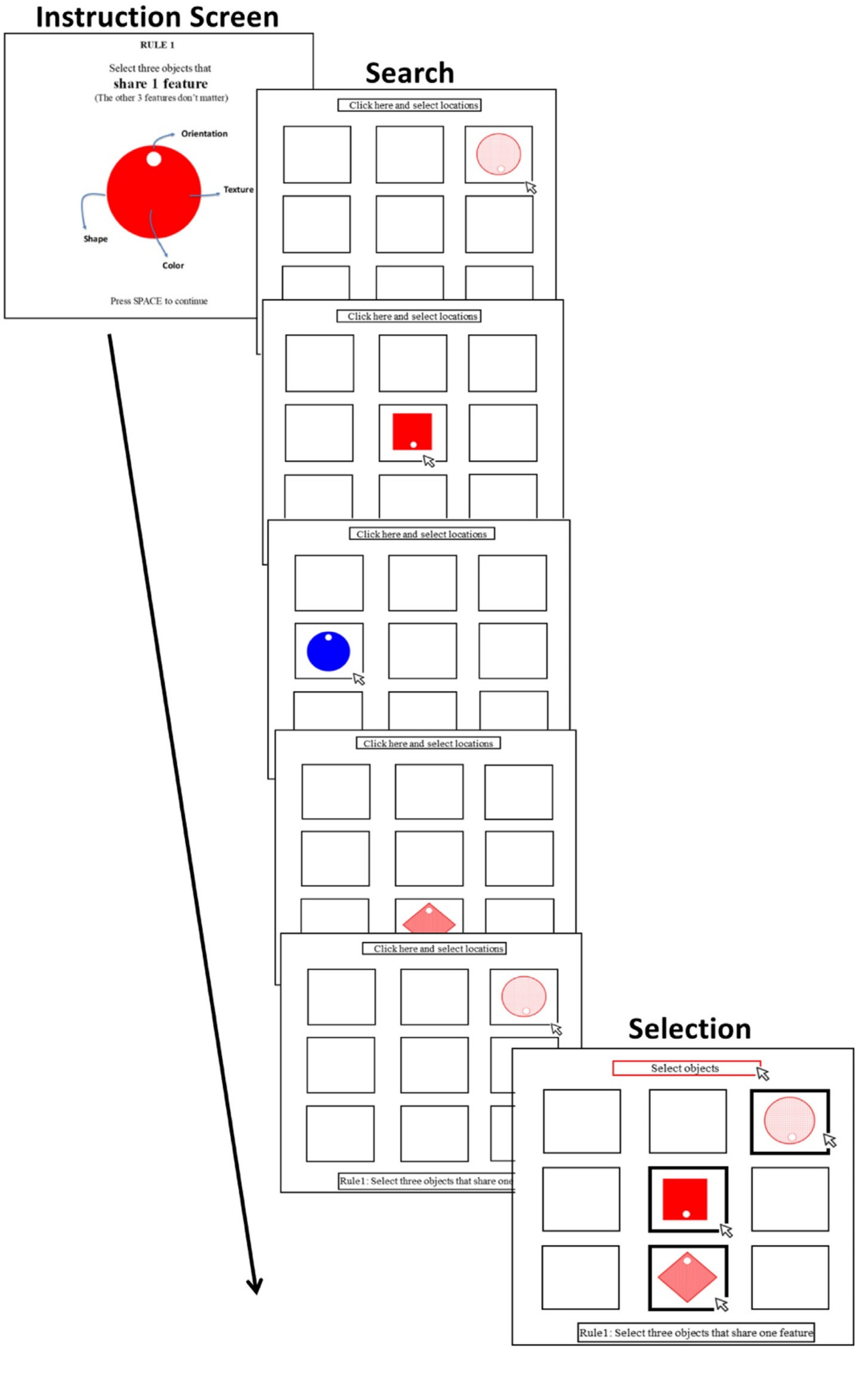
There was no strict criterion for success on the training. The experimenter moved on to the next training trial when children were able to explain how the objects satisfied the category. All children were able to complete the training and demonstrated understanding of the objects and categories.

Practice

Children were next given the opportunity to practice searching through objects and selecting sets. Practice trials proceeded exactly as the test trials would proceed in the main category search task except that the experimenter provided children with instruction throughout (detailed below).

Each trial consisted of three parts: Instruction Screen, Search, and Selection (see Fig. 3). Children first viewed the Instruction Screen, which depicted the category for that trial and a picture of an example object with features labeled. Children could view the Instruction Screen until they pressed the space bar to begin the trial.

Next, children viewed the Search screen, which consisted of a 3×3 array of black-outlined squares. Children could click on these squares with the mouse to reveal the object hidden in that location. For children in the No Delay condition, clicking on a location revealed the object at that location immediately. For children in the Delay condition, the object appeared 1000 ms after its location was clicked. Objects were then visible for 500 ms and were only visible one at a time; if another location was clicked during the 500-ms period, no object was revealed at that location. Children could search as much as they wanted until they found three objects that they thought satisfied the category. They then clicked the Selection button at the top of the screen to make their selections. Any object clicked after the Selection button was pressed remained visible to indicate that it had been selected. Thus, after the button was clicked, children could no longer search. Once three objects were selected, the trial ended and the program advanced to the next trial.


Instruction Screen
RULE 1
Select three objects that
share 1 feature
(The other 3 features don't matter)
Orientation
Texture
Shape
Color
Press SPACE to continue
Search
Click here and select locations
Click here and select locations
Click here and select locations
Click here and select locations
Click here and select locations
Selection
Select objects
Rule1: Select three objects that share one feature

Children completed three practice trials, one for each category. The experimenter introduced each category, oriented children to the layout of the objects, showed children that the relevant category rule was written at the bottom the screen, and walked children through how to click objects to view them, how to click the Selection button when they were ready to select objects, and then how to click the objects they wanted to select. The experimenter also answered any questions children had during the practice trials and let children know whether the set they ultimately selected was correct or incorrect. To ensure that children understood the task and felt confident in their ability to complete the task, once the training program was complete, the experimenter gave children the opportunity to complete the practice again (5 of the 46 children opted to do one additional practice run). Children were successful at selecting three objects that satisfied the given category in the practice trials (No Delay mean percentage correct: 87%; Delay mean percentage correct: 94%).

Category search task

The main category search task proceeded as in the practice trials except that participants were not given feedback or instruction from the experimenter. Children completed three trials of each category presented in blocks (nine total trials). Blocks were presented in a fixed order: Category S, Category SS, and Category SD.[2] Objects in each trial were presented in random locations for each participant. Fig. 3 shows an example Category S trial.

The entire task, including training, practice, and category search task, took about 20 min to complete.

Dependent measures and predictions

We had four primary measures of interest. First, we measured whether children made errors by determining whether the sets of objects children ultimately selected on each trial satisfied the category. We predicted that if variation in exploration patterns across categories and conditions reflects strategic trade-offs between exploration and memory necessary to complete the task, error rates should be roughly equivalent across conditions and categories and should not be dependent on children's search behaviors.

Second and third, to examine how children trade off reliance on exploration versus working memory, we measured visits (the number of objects viewed on each trial) and revisits (the number of times children visited an object they had already viewed). We were interested in *both* visits and revisits because these can serve different functions. Visits are a metric of total exploration, whereas revisits can serve the function of refreshing children's memory for items that they have previously viewed. If children trade off reliance on exploration versus working memory depending on the demands of the task, we predicted that children would visit and revisit more locations as cognitive demands increased (i.e., when a feature or a disjunctive rule was added to the category), reflecting greater reliance on exploration as the cognitive demands of the task increased. This pattern would be reflected in a main effect of task complexity. If children trade off reliance on exploration versus working memory depending on the exploration costs of the task, we predicted that children would visit and revisit fewer locations overall in the Delay condition versus the No Delay condition, suggesting greater reliance on working memory when the cost of exploration was higher. This pattern would be reflected in

Fig. 3. An example Category S trial. Children first viewed the instruction screen, which described the category for that trial, and then searched for the objects that belonged to the category. To make their final response, children clicked the button at the top and then clicked on the objects they wanted to select. In this example, five objects were visited and one object was revisited before the final selection of three objects was made.

[2] This was the same approach taken by Kibbe and Kowler (2011). We reasoned that fixing the order so that categories increase in complexity (corresponding to how children were trained on the categories at the outset) would reduce confusion. Because children completed only three trials per category, we also reasoned that task fatigue would not be a major factor in children's performance.

a main effect of exploration costs. We also might observe that the cognitive and motor demands interact to affect children's search behavior. For example, we might observe that exploration costs would affect children's search behavior only when cognitive demands are lower, and therefore children have more working memory resources available to store more in working memory when the search is costlier. This pattern would be reflected in an interaction between task complexity and exploration costs.

Finally, we examined revisit distance: the number of objects children viewed between visiting an object and then revisiting that object. Revisit distance can serve as a proxy for the number of items stored in working memory. We did not have strong predictions for children's revisit distance patterns in our study. It is possible that children's patterns may be similar to those of adults. That is, children may opt to visit more objects between revisits, storing less information about each object, when exploration costs are lower. This pattern would be reflected in a main effect of exploration costs. However, children's working memory also is more limited than that of adults, which may limit the number of potential sets children can consider at once and therefore could affect their revisit strategies. Children also may rely on less sophisticated strategies (e.g., storing all the features of the objects in working memory regardless of category complexity or exploration cost), in which case we would observe no differences in revisit distance across categories and/or conditions.

Data are available at https://osf.io/rzkfy/?view_only=6daf4447027140b7a2ffa9de70e0b8bf. All dependent variables are reported.

Results

Analysis approach

We conducted separate repeated-measures ANOVAs on children's error rates and mean visits, revisits, and revisit distance for each category with Task Complexity (Category S, SS, or SD) as a within-participants factor and Exploration Cost (No Delay or Delay) as a between-participants factor. We include both frequentist and Bayesian ANOVAs here. We followed up any significant effects with planned comparisons using two-tailed *t* tests and Bayes factor analysis for all results. Bayes factor analysis yields the odds in favor of or against the null hypothesis (e.g., that there is no effect of task complexity or exploration cost on children's visits, revisits, or revisit distance). Here, we report Bayes factor as odds of the null hypothesis over the alternative hypothesis. A Bayes factor greater than 0 indicates support for the null, less than 0 indicates support for the alternative, and close to 0 indicates that there is not clear support for one hypothesis over the other (see Gallistel, 2009, for more information about interpreting Bayes factors).

One child's behaviors on one trial were not recorded due to a computer glitch. We also removed two additional trials prior to data analysis (one in the No Delay condition and one in the Delay condition) because children reported accidentally selecting an object they did not plan to select (objects could not be unselected).

Errors

Errors were defined as selecting three objects that do not satisfy the category. Overall, errors were low, accounting for 9.66% of trials. We conducted a repeated-measures ANOVA on the percentage of trials in which children made errors for each category with Task Complexity (Category S, SS, or SD) as a within-participants factor and Exploration Cost (No Delay or Delay) as a between-participants factor. This revealed no main effect of Task Complexity, $F(2, 88) = 0.22$, $p = .802$, $\eta_p^2 = .005$, no main effect of Exploration Cost, $F(2, 88) = 0.26$, $p = .613$, $\eta_p^2 = .006$, and no Task Complexity $\times$ Exploration Cost interaction, $F(2, 88) = 0.79$, $p = .457$, $\eta_p^2 = .018$. A Bayesian repeated-measures ANOVA revealed that the null model was the best-fitting model, 3.6 times more likely than a model including Exploration Cost only, 11 times more likely than a model including Task Complexity only, 43 times more likely than a model including both main effects, and 192 times more likely than a model including main effects and interaction. Fig. 4 shows children's mean proportions correct for each category in both the No Delay and Delay conditions.

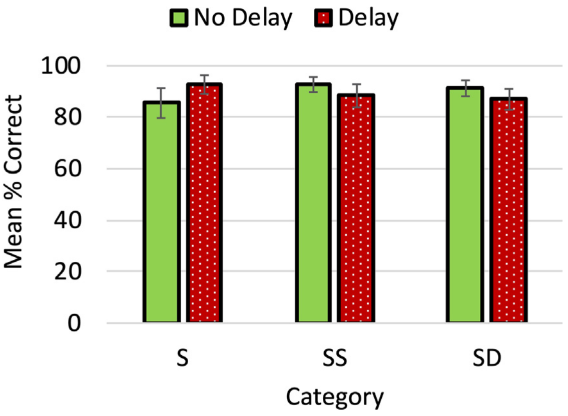


Fig. 4. Children's mean percentages correct across categories for the No Delay and Delay conditions. A correct response was defined as selecting three objects that satisfied the category rule on that trial. Categories: S, Share One; SS, Share Two; SD, Share One, Differ One.

These results suggest that children were able to understand and complete the task and that any differences in exploration behavior observed as a function of category complexity or exploration cost did not contribute significantly to differences in error rates across these variables. The following analyses were conducted only on trials in which participants selected a correct set. Participants contributed an average of 2.7 trials per category.

Visits and revisits

We asked whether children's exploration behavior (visits and revisits to objects) varied as a function of task complexity and/or as a function of exploration cost. For each child, we computed the mean number of visits and revisits across the three trials for each category. The distribution of these means deviated significantly from normal, violating ANOVA assumptions. Inspection of the data revealed that some children had trials in which the number of visits was higher than 3 standard deviations above the mean for that category. Therefore, we removed these trials from analysis. This resulted in five trials removed from the No Delay condition (two trials from Category S, two trials from Category SS, and one trial from Category SD; contributed by 3 children) and six trials removed from the Delay condition (two trials from Category S, two trials from Category SS, and two trials from Category SD; contributed by 4 children). Fig. 5 shows the data with outlying trials removed. See online supplementary material for a figure showing the data with outlying trials included.

A repeated-measures ANOVA revealed a significant main effect of Task Complexity, $F(2, 86) = 13.39$, $p < .001$, $\eta_p^2 = .237$, a main effect of Exploration Cost, $F(1, 43) = 18.87$, $p < .001$, $\eta_p^2 = .305$, and no Task Complexity $\times$ Exploration Cost interaction, $F(2, 86) = 2.61$, $p = .079$, $\eta_p^2 = .057$. A Bayesian repeated-measures ANOVA confirmed these results; the model with Task Complexity and Exploration Cost was the best-fitting model and was more than 450,000 times more likely than the null model. We followed up the main effects with planned paired-samples *t*-test comparisons (alpha corrected to .017) and Bayes factor analyses. We found that mean visits increased significantly between the category defined over one feature and both categories defined over two features (Category S vs SS: $t(44) = -4.45$, $p < .001$; Category S vs SD: $t(44) = -3.64 p < .001$), with Bayes factor revealing substantial support for the alternative hypothesis (Category S vs SS: $BF_{01} = .003$; Category S vs SD: $BF_{01} = .030$). Although there was no significant difference in mean visits between the two-feature categories [Category SS vs SD: $t(45) = 1.60$, $p = .116$] and Bayes factor analysis yielded only anecdotal support for the null hypothesis ($BF_{01} = 2.55$). Children also visited substantially more objects in the No Delay condition versus the Delay condition, $t(44) = -3.90$, $p < .001$, $BF_{01} = .012$), and children visited more objects overall in the No Delay condition across categories, suggesting that the delay imposed a cost that influenced

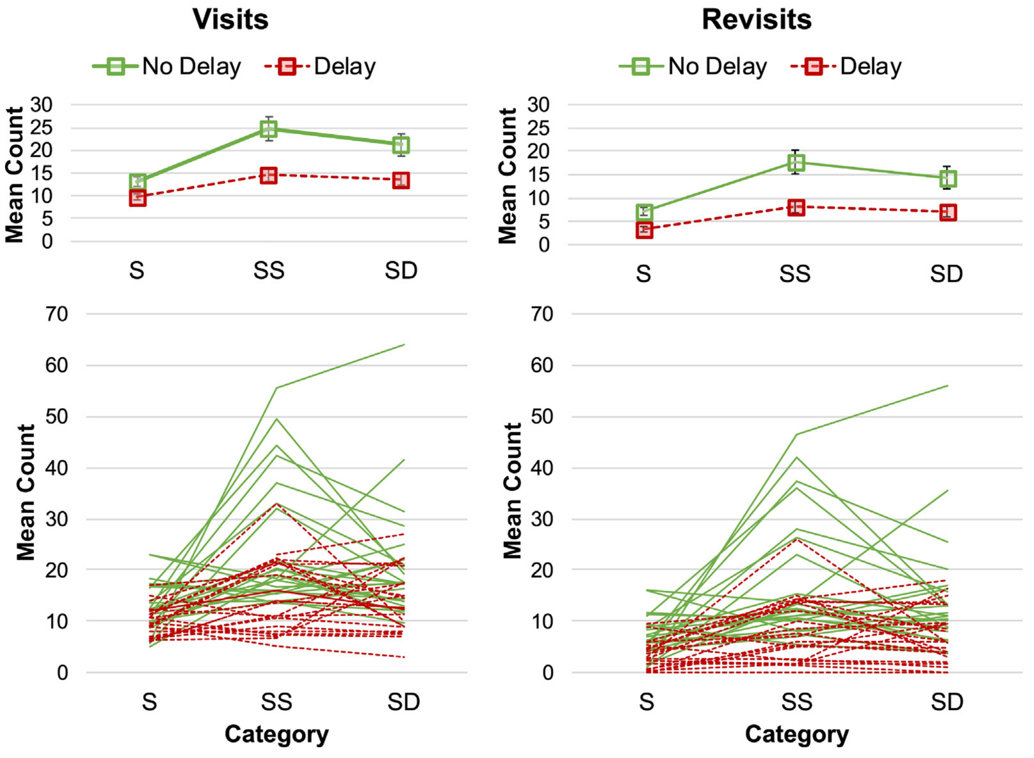


Fig. 5. Mean number of objects visited (left panel) and revisited (right panel) as a function of category complexity and exploration cost. The top panels show visits or revisits for each category averaged across trials and across children. The bottom panels show individual children's means for each category averaged across trials. Error bars represent standard errors. Categories: S, Share One; SS, Share Two; SD, Share One, Differ One.

Table 1
Children's mean (and standard deviation) visits, revisits, and revisit distance for each level of task complexity and exploration cost.

	Exploration cost	Task complexity		
		Category S	Category SS	Category SD
Visits	No Delay	13.12 (4.94)	24.71 (12.67)	21.16 (11.76)
	Delay	9.80 (3.18)	14.64 (7.18)	13.61 (6.10)
Revisits	No Delay	7.16 (4.13)	17.72 (12.21)	14.38 (11.57)
	Delay	3.35 (2.75)	8.21 (6.37)	7.09 (5.31)
Revisit distance	No Delay	3.85 (1.16)	3.95 (1.11)	3.71 (0.68)
	Delay	3.93 (1.29)	4.13 (1.08)	4.85 (1.11)

Note. Categories: S, Share One; SS, Share Two; SD, Share One, Differ One.

children's exploration behavior consistently regardless of cognitive demands. See Table 1 for mean visits for each category in both the No Delay and Delay conditions.

A similar pattern was observed for revisits. We observed a significant main effect of Task Complexity, $F(2, 86) = 13.89$, $p < .001$, $\eta_p^2 = .244$, a significant main effect of Exploration Cost, $F(1, 43) = 18.80$, $p < .001$, $\eta_p^2 = .304$, and no Task Complexity $\times$ Exploration Cost interaction, $F(2, 86) = 2.14$, $p = .124$, $\eta_p^2 = .047$. A Bayesian repeated-measures ANOVA revealed that the best-fitting model included Task Complexity and Exploration Cost, and this model was more than 770,000 times more likely than the null model. Follow-up pairwise comparisons revealed that revisits increased significantly when a feature was added to the category [Category S vs SS: $t(44) = -4.57$, $p < .001$; Category S vs SD: $t(44) = -3.67$, $p < .001$), with Bayes factor yielding decisive support for the alternative hypothesis (Category S vs SS: $BF_{01} = .002$; Category S vs SD: $BF_{01} = .027$). Between the two two-feature categories, we observed no significant differences in revisits (Category SS vs SD: $t(45) = 1.69$, $p = .098$), although again Bayes factor yielded only anecdotal support for the null hypothesis ($BF_{01} = 2.23$). Children revisited substantially more objects when exploration costs were lower versus higher, $t(44) = -4.01$, $p < .001$, $BF_{01} = .009$), regardless of category, suggesting that the delay imposed a consistent cost to exploration regardless of task complexity (see Table 1).

Revisit distance

We examined the number of objects children viewed before returning to revisit an object. For each child, we computed mean revisit distance across the three trials for each category. Trials in which

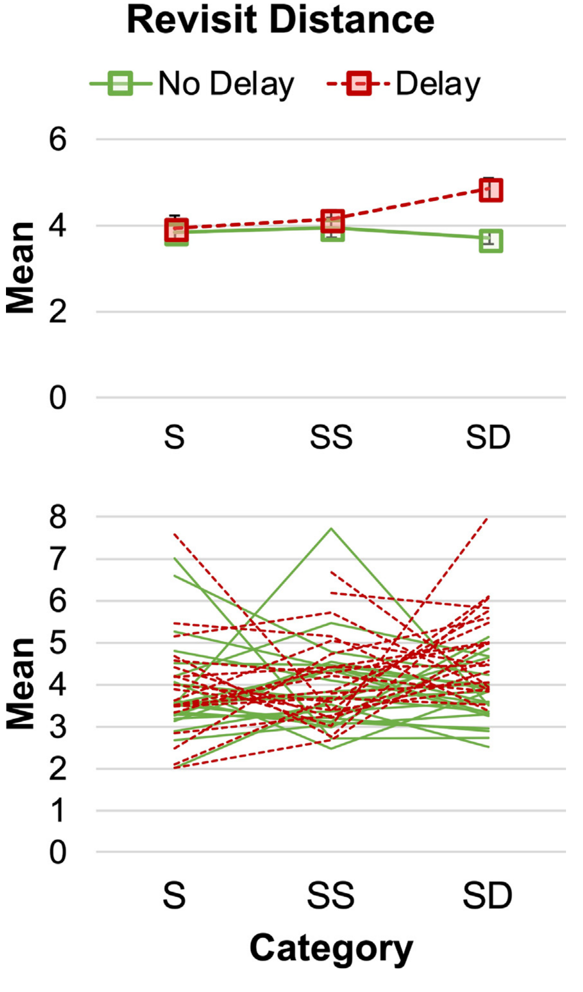


Fig. 6. Mean numbers of objects viewed between visiting an object and revisiting that same object as a function of category complexity and exploration cost. The top panel shows mean revisit distance for each category averaged across trials and across children. The bottom panel shows individual children's revisit distance for each category averaged across trials. Error bars represent standard errors. Categories: S, Share One; SS, Share Two; SD, Share One, Differ One.

children did not revisit any items were not included in the analysis. We submitted children's mean revisit distance to a repeated-measures ANOVA with Task Complexity (Category S, SS, or SD) as a within-participants factor and Exploration Cost (No Delay or Delay) as a between-participants factor. We observed no main effect of Task Complexity, $F(2, 78) = 1.62$, $p = .205$, $\eta_p^2 = .040$, a small main effect of Exploration Cost, $F(1, 39) = 5.70$, $p = .022$, $\eta_p^2 = .128$, and a small Task Complexity $\times$ Exploration Cost interaction, $F(2, 78) = 3.87$, $p = .025$, $\eta_p^2 = .09$. A Bayesian repeated-measures ANOVA revealed that the data provided similar support for the models including Exploration Cost only, Task Complexity $\times$ Exploration Cost interaction, and the null model, and all these models were about 5 times more likely than the models including the main effect of Task Complexity. Comparing the No Delay and Delay conditions, children revisited roughly the same numbers of objects on Category S and Category SS trials (both $BF_{01} > 3.95$), but for Category SD they visited more objects between revisits in the Delay condition compared with the No Delay condition (independent-samples $t(42) = 4.16$, $p < .001$, $BF_{01} = .006$), suggesting that they were holding more information in working memory when both cognitive demands (Category SD) and exploration costs (delay) were highest. Fig. 6 shows mean revisit distance across categories for each condition (see also Table 1).

Discussion

We investigated 8- to 10-year-old children's ability to strategically trade off between reliance on exploration and reliance on working memory during a cognitively demanding naturalistic task. Children were asked to search through arrays of nine hidden, multi-featured objects to find three objects that satisfied categories defined over the objects' features. We manipulated the cognitive demands of the task by manipulating the complexity of the category, adding a conjunctive rule (share one feature) or a disjunctive rule (differ on one feature) to the category. We manipulated the exploration cost of the task by introducing a delay to view the objects. Children successfully performed the task, making few errors. To examine trade-offs between exploration and working memory, we measured the number of times children visited and revisited objects and the number of objects children viewed between revisits to the same object (revisit distance).

We found that children searched more as the cognitive complexity of the task increased; children visited and revisited more objects when the category included a two-feature rule versus when the category included only a one-feature rule. Children also searched more when exploration costs were lower; children visited and revisited fewer objects in the Delay condition compared with the No Delay condition, suggesting that children relied more on working memory when exploration costs increased.

Critically, error rates were similar regardless of task demands or exploration costs; children were just as successful at finding correct sets when they visited and revisited fewer objects versus when they visited and revisited more objects. We also kept the probability of encountering a correct set constant across trials; if children were storing complete, high-fidelity representations of each object in working memory, they would need to visit an average of four objects before finding a set of three objects that satisfied the rule. However, children's exploration patterns suggest that they were not using this strategy. Even for the simplest category in the Delay condition (in which children visited the fewest objects overall), children visited about 10 objects on average ($\sim$4 of which were revisits) before making their selection, and this increased to about 15 objects ($\sim$8 of which were revisits) for the share two category. Therefore, it is unlikely that children were storing complete, high-fidelity, and enduring representations in working memory. Children's increased searching when cognitive demands were high, and when exploration costs were low, instead suggests that children were strategically storing less information in working memory when it is easier to exploit the environment for that information.

What were children storing in working memory? One possibility is that children, like adults, were using a strategy of encoding a subset of the features—those that seem to be likely candidates to satisfy the category—and were revisiting objects to update their representations as they test new hypotheses about candidate features. The addition of a feature to the category (e.g., Share Two vs Share One) required children to consider more hypotheses about which features of which objects may satisfy the category, placing significant demands on working memory. Children's increased searching with increasing cognitive demands suggests that they were choosing to revisit previously viewed objects, rather than storing high-fidelity representations of the these objects in memory, in order to free working memory resources for considering multiple hypotheses simultaneously. As children formulate hypotheses about candidate sets on each trial, they may search for particular features. For example, children completing a share two (Category SS) trial might first encode [red (color), square (shape)] and form a hypothesis to look for another [red (color), square (shape)] object. After visiting several more locations, they might revise their target features to [red (color), diamond (shape)]. The process of efficiently searching for features, and then updating hypotheses about candidate features, requires sampling from visited objects and then visiting new objects and revisiting previously viewed objects as new features are considered.

Another possibility is that all features of each object may be automatically encoded into working memory but that task-irrelevant features are actively removed as hypotheses about candidate features are considered (Lewis-Peacock et al, 2018). Active removal of task-irrelevant information results in freeing up space in working memory. Future studies should look into whether selectivity of task-relevant features operates at encoding or the maintenance stage of working memory.

It is interesting that children searched similarly across both two-feature categories despite the fact that the category containing the disjunctive rule was more complex (Feldman, 2006; Jacob & Hochstein, 2008) and produced increased searching relative to conjunctive rules in adults (Kibbe & Kowler, 2011). This may suggest that children are using a different strategy than adults when approaching two-feature rules. For example, adults may compress or cluster shared features in working memory, representing this information more efficiently (Huffman, 1952; Miller, 1956), whereas children may store the features of each object independently, resulting in similar search patterns regardless of the complexity of the rule. Further comparative work is needed to better identify developmental differences in children's and adults' approaches to complex tasks.

The number of objects children visited between revisits was similar across categories for the most part but increased when the cognitive demands and exploration costs of the task were highest. This suggests that children might not have been simply filling their working memories to a fixed upper limit on every trial (Ballard et al., 1995; Droll & Hayhoe, 2007; Kibbe & Kowler, 2011) but instead were strategically loading information into working memory depending on the requirements of the task at hand. When the category contained a disjunctive rule but the cost of revisiting previously viewed objects was high, children may have considered more objects simultaneously as they searched for combinations of target features even as they may have stored fewer features of each object in working memory, requiring more visits and revisits. It is possible that the divergence in revisit distance we observed would continue if the cognitive and exploration demands of the task were further manipulated. Future work would explore this possibility.

Overall, our results suggest that children, whose working memory and executive functioning abilities are undergoing developmental change, can actively sample the environment based on internally generated task-specific hypotheses (Corbetta & Shulman, 2002; Droll & Hayhoe, 2007; Kibbe & Kowler, 2011) and modulate their approach to a complex task depending on both cognitive and exploration demands. Crucially, our task did not make explicit demands on working memory; we did not ask children to remember sets of items, nor did we measure explicit recall or recognition. Instead, we used a task that mimics real-world tasks by allowing children to generate and update their own hypotheses and plan their own means to achieve the task goals. This meant that we were able to measure children's working memory use in active service of a goal. Our results suggest that children are storing just enough information in working memory to achieve these goals (information from about four or five objects, depending on whether the category contained a disjunctive rule, similar to adults). Although this number is similar to the results of many studies of working memory that have found that its capacity for explicit storage is about three to five items in children, we speculate that our data do not exclusively reflect a capacity limit for working memory. Rather, we speculate that the number of items held in working memory is in part governed by the task requirement of finding a set of *three* objects. Indeed, we speculate that if the task required finding two or four objects, we would observe that the distance between revisits would be modulated accordingly, suggesting that working memory is being used as needed rather than filled to a fixed capacity. Future work would examine how task requirements affect the number of items stored in working memory during naturalistic tasks.

This work has potential implications for understanding how children use working memory to support the acquisition of new knowledge and problem solving in the real world. Working memory capacity is correlated with academic achievement (Blankenship et al., 2015), and there are individual differences in the capacity of working memory both across childhood and into adulthood (Alloway et al., 2009; Camos, 2008; De Weerdt et al., 2013; Gathercole et al., 2006a, 2006b). It is possible that there also are individual differences in the efficient use of working memory during complex tasks, such as solving math problems and learning to read, which may moderate the relationship between working memory capacity and academic achievement. Training studies aimed at improving working memory capacity in children with low working memory has resulted in little transfer to academic achievement (Melby-Lervåg & Hulme, 2013; Sala & Gobet, 2017). Interventions that target optimization strategies may be a promising avenue for future research.

Data availability

Data are available on OSF (link provided in manuscript).

Acknowledgment

The authors thank Jannellie Rivera for her assistance with data collection.

Open practices statement

Data and training materials are available at the Open Science Framework (https://osf.io/rzkfy/?view_only=6daf4447027140b7a2ffa9de70e0b8bf).

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jecp.2022.105535.

References

Alloway, T. P., Gathercole, S. E., Kirkwood, H., & Elliott, J. (2009). The cognitive and behavioral characteristics of children with low working memory. *Child Development, 80*(2), 606–621.

Anderson, V., Anderson, P. J., Jacobs, R., & Smith, M. S. (2010). Development and assessment of executive function: From preschool to adolescence. In V. Anderson, R. Jacobs, & P. J. Anderson (Eds.), *Executive functions and the frontal lobes* (pp. 157–188). Psychology Press.

Applin, J. B., & Kibbe, M. M. (2021). Young children monitor the fidelity of visual working memory. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 47*(5), 808–819.

Araujo, C., Kowler, E., & Pavel, M. (2001). Eye movements during visual search: The costs of choosing the optimal path. *Vision Research, 41*(25–26), 3613–3625.

Atkinson, A. L., Waterman, A. H., & Allen, R. J. (2019). Can children prioritize more valuable information in working memory? An exploration into the effects of motivation and memory load. *Developmental Psychology, 55*(5), 967–980.

Ballard, D. H., Hayhoe, M. M., & Pelz, J. B. (1995). Memory representations in natural tasks. *Journal of Cognitive Neuroscience, 7*(1), 66–80.

Barnea-Goraly, N., Menon, V., Eckert, M., Tamm, L., Bammer, R., Karchemskiy, A., Dant, C. C., & Reiss, A. L. (2005). White matter development during childhood and adolescence: A cross-sectional diffusion tensor imaging study. *Cerebral Cortex, 15*(12), 1848–1854.

Blankenship, T. L., O'Neill, M., Ross, A., & Bell, M. A. (2015). Working memory and recollection contribute to academic achievement. *Learning and Individual Differences, 43*, 164–169.

Brainard, D. H. (1997). The Psychophysics Toolbox. *Spatial Vision, 10*(4), 433–436.

Burnett Heyes, S., Zokaei, N., van der Staaij, I., Bays, P. M., & Husain, M. (2012). Development of visual working memory precision in childhood. *Developmental Science, 15*(4), 528–539.

Camos, V. (2008). Low working memory capacity impedes both efficiency and learning of number transcoding in children. *Journal of Experimental Child Psychology, 99*(1), 37–57.

Corbetta, M., & Shulman, G. L. (2002). Control of goal-directed and stimulus-driven attention in the brain. *Nature Reviews Neuroscience, 3*(3), 201–215.

Cowan, N., Elliott, E. M., Saults, J. S., Morey, C. C., Mattox, S., Hismjatullina, A., & Conway, A. R. (2005). On the capacity of attention: Its estimation and its role in working memory and cognitive aptitudes. *Cognitive Psychology, 51*(1), 42–100.

Crone, E. A. (2009). Executive functions in adolescence: Inferences from brain and behavior. *Developmental Science, 12*(6), 825–830.
De Weerdt, F., Desoete, A., & Roeyers, H. (2013). Working memory in children with reading disabilities and/or mathematical disabilities. *Journal of Learning Disabilities, 46*(5), 461–472.
Diamond, A. (2006). The early development of executive functions. In E. Bialystok & F. I. M. Craik (Eds.), *Lifespan cognition: Mechanisms of change* (pp. 70–95). Oxford University Press.
Droll, J. A., & Hayhoe, M. M. (2007). Trade-offs between gaze and working memory use. *Journal of Experimental Psychology: Human Perception and Performance, 33*(6), 1352–1365.
Epelboim, J., & Suppes, P. (2001). A model of eye movements and visual working memory during problem solving in geometry. *Vision Research, 41*(12), 1561–1574.
Feldman, J. (2006). An algebra of human concept learning. *Journal of Mathematical Psychology, 50*(4), 339–368.
Gallistel, C. R. (2009). The importance of proving the null. *Psychological Review, 116*(2), 439–453.
Gathercole, S. E., Alloway, T. P., Willis, C., & Adams, A. M. (2006a). Working memory in children with reading disabilities. *Journal of Experimental Child Psychology, 93*(3), 265–281.
Gathercole, S. E., Lamont, E. M., & Alloway, T. P. (2006b). Working memory in the classroom. In G. Phye (Ed.), *Working memory and education* (pp. 219–240). Academic Press.
Gathercole, S. E., Pickering, S. J., Ambridge, B., & Wearing, H. (2004). The structure of working memory from 4 to 15 years of age. *Developmental Psychology, 40*(2), 177–190.
Gogtay, N., Giedd, J. N., Lusk, L., Hayashi, K. M., Greenstein, D., Vaituzis, A. C., Nugent, T. F., III, Herman, D. H., Clasen, L. S., Toga, A. W., Rapoport, J. L., & Thompson, P. M. (2004). Dynamic mapping of human cortical development during childhood through early adulthood. *Proceedings of the National Academy of Sciences of the United States of America, 101*(21), 8174–8179.
Hayhoe, M. (2000). Vision using routines: A functional account of vision. *Visual Cognition, 7*(1–3), 43–64.
Heyes, S. B., Zokaei, N., & Husain, M. (2016). Longitudinal development of visual working memory precision in childhood and early adolescence. *Cognitive Development, 39*, 36–44.
Hollingworth, A., & Maxcey-Richard, A. M. (2013). Selective maintenance in visual working memory does not require sustained visual attention. *Journal of Experimental Psychology: Human Perception and Performance, 39*(4), 1047–1058.
Huffman, D. A. (1952). A method for the construction of minimum-redundancy codes. *Proceedings of the IRE, 40*(9), 1098–1101.
Isbell, E., Fukuda, K., Neville, H. J., & Vogel, E. K. (2015). Visual working memory continues to develop through adolescence. *Frontiers in Psychology, 6*. Article 696.
Jacob, M., & Hochstein, S. (2008). Set recognition as a window to perceptual and cognitive processes. *Perception & Psychophysics, 70*(7), 1165–1184.
Jacob, M., & Hochstein, S. (2009). Comparing eye movements to detected vs. undetected target stimuli in an Identity Search Task. *Journal of Vision, 9*(5). Article 20.
Kibbe, M. M., & Kowler, E. (2011). Visual search for category sets: Tradeoffs between exploration and memory. *Journal of Vision, 11*(3). Article 14.
Land, M. F., & Hayhoe, M. (2001). In what ways do eye movements contribute to everyday activities? *Vision Research, 41*(25–26), 3559–3565.
Land, M., Mennie, N., & Rusted, J. (1999). The roles of vision and eye movements in the control of activities of daily living. *Perception, 28*(11), 1311–1328.
Lewis-Peacock, J. A., Kessler, Y., & Oberauer, K. (2018). The removal of information from working memory. *Annals of the New York Academy of Sciences, 1424*(1), 33–44.
Luck, S. J., & Vogel, E. K. (1997). The capacity of visual working memory for features and conjunctions. *Nature, 390*(6657), 279–281.
Melby-Lervåg, M., & Hulme, C. (2013). Is working memory training effective? *A meta-analytic review. Developmental Psychology, 49*(2), 270–291.
Melcher, D. (2001). Persistence of visual memory for scenes. *Nature, 412*(6845). Article 401.
Melcher, D., & Kowler, E. (2001). Visual scene memory and the guidance of saccadic eye movements. *Vision Research, 41*(25–26), 3597–3611.
Miller, G. A. (1956). The magical number seven, plus or minus two: Some limits on our capacity for processing information. *Psychological Review, 63*(2), 81–97.
Miller, P. H. (2002). *Theories of developmental psychology*. Macmillan.
Pertzov, Y., Avidan, G., & Zohary, E. (2009). Accumulation of visual information across multiple fixations. *Journal of Vision, 9*(10). Article 2.
Portrat, S., Barrouillet, P., & Camos, V. (2008). Time-related decay or interference-based forgetting in working memory? *Journal of Experimental Psychology: Learning, Memory, and Cognition, 34*(6), 1561–1564.
Riggs, K. J., McTaggart, J., Simpson, A., & Freeman, R. P. (2006). Changes in the capacity of visual working memory in 5- to 10-year-olds. *Journal of Experimental Child Psychology, 95*(1), 18–26.
Riggs, K. J., Simpson, A., & Potts, T. (2011). The development of visual short-term memory for multifeature items during middle childhood. *Journal of Experimental Child Psychology, 108*(4), 802–809.
Sala, G., & Gobet, F. (2017). Working memory training in typically developing children: A meta-analysis of the available evidence. *Developmental Psychology, 53*, 671–685.
Schleepen, T. M., & Jonkman, L. M. (2009). The development of non-spatial working memory capacity during childhood and adolescence and the role of interference control: An n-back task study. *Developmental Neuropsychology, 35*(1), 37–56.
Shimi, A., Nobre, A. C., & Scerif, G. (2015). ERP markers of target selection discriminate children with high vs. low working memory capacity. *Frontiers in Systems Neuroscience, 9*. Article 153.
Shimi, A., & Scerif, G. (2017). Towards an integrative model of visual short-term memory maintenance: Evidence from the effects of attentional control, load, decay, and their interactions in childhood. *Cognition, 169*, 61–83.
Simmering, V. R. (2012). The development of visual working memory capacity during early childhood. *Journal of Experimental Child Psychology, 111*(4), 695–707.

Ullman, H., Almeida, R., & Klingberg, T. (2014). Structural maturation and brain activity predict future working memory capacity during childhood development. *Journal of Neuroscience, 34*(5), 1592–1598.
Zelinsky, G. J., Loschky, L. C., & Dickinson, C. A. (2011). Do object refixations during scene viewing indicate rehearsal in visual working memory? *Memory & Cognition, 39*(4), 600–613.