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Highlighting in Early Childhood: Learning Biases through Attentional Shifting

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Abstract

The literature on human and animal learning suggests that individuals attend to and act on cues differently based on the order in which they were learned. Recent studies have proposed that one specific type of learning outcome, the highlighting effect, can serve as a framework for understanding a number of early cognitive milestones. However, little is known how this learning effect itself emerges among children, whose memory and attention are much more limited compared to adults. Two experiments were conducted using different versions of the general highlighting paradigm: Experiment 1 tested 3- to 6-year-olds with a newly developed image-based version of the paradigm, which was designed specifically to test young children. Experiment 2 tested the validity of an image-based implementation of the highlighting paradigm with adult participants. The results from Experiment 1 provide evidence for the highlighting effect among children 3 to 6 years old, and suggest age-related differences in dividing attention among multiple cues during learning. Experiment 2 replicated results from previous studies by showing robust biases for both image-based and text-based versions of the highlighting task. The present study suggests that sensitivity to learning order emerges early through the process of cued attention, and the role of the highlighting effect in early language learning is discussed.

Introduction

The ability to adapt to unfamiliar situations based on knowledge from past experience is fundamental to human learning. For example, a child might be extra cautious at first when told to try an unknown food placed on their plate, particularly if this unfamiliar item is green and shaped like a vegetable. Making accurate predictions based on outcomes from previous encounters is a continuous learning process and relies on basic cognitive functions such as memory and attention for selecting important information from the environment and storing it for later use. However, recent work has shown a protracted course in the development of these most basic functions, particularly in regards to memory capacity and the distribution of attention among multiple cues, with rapid changes taking place during the preschool years (Bertrand & Camos, 2015; Fisher, Thiessen, Godwin, Kloos, & Dickerson, 2013; Ruff & Rothbart, 2001; Schneider, 2015). Understanding the nature of these changes in early childhood can provide insight into the basic learning mechanisms that are responsible for the gradual accumulation of knowledge over time at all ages of development (for similar developmental approaches in the spatial learning domain, see Darby, Burling, & Yoshida, 2014; Dixon, Zelazo, & Rosa, 2010). In the present study, we take what has previously been considered an adult-specific learning phenomenon, the highlighting effect, and compare differences in learning outcomes between preschool and primary school children on a customized version of the task.

Highlighting: A unique ordered learning bias

The highlighting effect is a special case of cognitive bias from a class of biases formed as a result of disproportionately learning multiple relationships over time. A typical task involves presenting a pair of cues alongside potential referents of these cues, with instructions for learning associations between cues and referents. Some of the cues may be repeated over time and shown with different referents, establishing redundancies when learning the relationships. Biases emerging from learning may sometimes be classified as irrational (Shanks, 1995) in the sense that learners show behaviors that link together some of the cues with one of the referents, even though *any* of the possible cues were equally likely to fit with any of the provided referents—likelihood is based on the frequency of occurrence from past exposure (Kruschke, 1996). These purportedly irrational behaviors might manifest themselves as biased preferences, such as looking preferences (Kruschke, Kappenman, & Hetrick, 2005; Pelley, Beesley, & Griffiths, 2011) or selection preferences (Kamin, 1968; Mackintosh, 1975), and are counterintuitive given expectations about the predicted learning outcomes.

Previous literature has typically used symbolic notation in the place of cues and outcomes (Kruschke, 2003). For example, the paired set of cues $A.B$, where B is one item and is always present with the other item A, will both correspond to some outcome. In this case the outcome is the referent X, which may be any event, label, object, etc. Theoretically, cues A and B should have equal weight for predicting the referent X, provided that they are always together when establishing their relationship. Biases start to form with the later introduction of a new set of paired cues $A.C$ indicating referent Y. One specific element of this pair, cue A, has already been previously established and is now repeated across both instances of learning. This leads to cue A being classified as highly ambiguous—since it unreliably refers both to X and Y at different points in time. Its repetitive nature does not provide much in terms of additional information during later learning instances. However, cues B and C have a direct, one-to-one relationship with their referent and are treated as unambiguous indicators of that referent (cue B is always learned in relation to X and never for Y, and vice versa for cue C). Testing novel combinations of cues that were seen during training reveals selection biases, which have emerged due to the order in which each of the relationships were shown. For instance, if given the repeated cue A in isolation, individuals will often choose referent X over the competing referent Y. This selection preference will take place despite A being seen the same number of times for $A.B \rightarrow X$ as $A.C \rightarrow Y$, in other words the $p(X|A)= p(Y|A)$=50%. Also, when pairing both the unambiguous cues together, such as $B.C$, participants will likely choose outcome Y, despite both referents being equally probable for selection, that is $p(X|B)= p(Y|C)$=100%.

Competing accounts for highlighting

In the extant literature, there are multiple competing explanations for the biased selection preferences. Among the list of possible explanations are inferences based on rule learning (Juslin, Wennerholm, & Winman, 2001; Wood & Blair, 2010) or causal relationships (T. Griffiths, Sobel, Tenenbaum, & Gopnik, 2011; Sobel & Munro, 2009) that each rely on assumptions about top-down processing and higher-level cognitive abilities being responsible for the biases, as well as explanations based on general cognitive mechanisms such as the involvement of memory and attention during associative learning tasks with adults (Hogarth, Dickinson, Austin, Brown, & Duka, 2008; Lamberts & Kent, 2007; Shanks, 1992). The domain-general mechanisms responsible for the highlighting effect are based on rapid shifts of attention during critical moments in time (Kruschke, 2011; Wills, Lavric, Hemmings, & Surrey, 2014) and are not based on explanations regarding abstract, rule-like representations. For example, given the structure of learning these relationships sequentially, that is, at Time 1: $A.B \rightarrow X$ and at Time 2: $A.C \rightarrow Y$, attention is redirected toward novel cues at Time 2, and correlations are established between new information and any corresponding referent being learned during this time. Attentional resources are thus actively and rapidly being focused toward potentially meaningful input, consequently strengthening or *highlighting* the link between C and Y. As a byproduct of redirected attention, and due to its redundancy, the association between cue A and outcome Y is weaker, preserving any previously established relationship (in this case, : $A.B \rightarrow X$).

The domain-general framework is of theoretical importance because it implies that the mechanisms responsible for this type of learning are applicable throughout all of development, including early childhood (Smith, 2001). However, previous work investigating the phenomenon in 8- and 9-year-old children have failed to observe the expected response patterns (Winman, Wennerholm, Juslin, & Shanks, 2005). These findings might be rooted in assumptions about the underlying mechanisms responsible for generating the biases, in that the behaviors are guided by top-down, inductive inferences or evaluations of one’s hypothesis space during decision making. These assumptions could lead to experimental design choices not particularly suitable for use with young children, such as written labels serving as cues, which are then used to make judgments about potential outcomes. Research on the development of inductive inferences from perceptual features has shown that children under 7 years old make inferences based on perceptual similarity among cues, and it is not until 11 years and older do they perform induction based on labels and knowledge-based processes (Sloutsky, Lo, & Fisher, 2001). Furthermore, associative learning models have shown that it is the order of learning visual features with labels that has an effect on the kind of predictions the model can generate about new events (Ramscar, Yarlett, Dye, Denny, & Thorpe, 2010), and work done primarily in the visual domain has demonstrated that active maintenance of items in working memory has a direct impact on rapidly shifting selective attention (Downing, 2000). This line of work suggests that lower-level mechanisms interacting with temporal information can account for the types of biases observed in the highlighting task without the need for explanations regarding higher-level cognitive capacities. In this study, we observe the patterns of biases in both young children and adults using a child-friendly version of the highlighting task based on perceptual features to establish cue-to-outcome relationships and the resulting biases.

Why study development?

The highlighting effect is similar to other important developmental phenomena focusing on sequential learning contexts and domain-general processes. For example, work done in the areas of habituation (Perone & Spencer, 2013; Schöner & Thelen, 2006), mutual exclusivity (Merriman, Bowman, & MacWhinney, 1989), online word recognition (Fernald, Thorpe, & Marchman, 2010; Swingley & Aslin, 2000), and contextually cued attention (Chun & Jiang, 1998; Smith, Colunga, & Yoshida, 2010), among others, can be considered to contain elements of biased preferences due to learning multiple cue-to-outcome relationships across time. Each of these examples involve the reallocation of attention toward one or more cues when provided with an abundance of information, and the dynamic nature of this process over time is driven by ones previous learning history (Johnson, Spencer, & Schöner, 2009; Thelen & Smith, 1996). Memory for previously learned relationships interacts with new information through mechanisms of cue competition (Desimone & Duncan, 1995; Yurovsky, Yu, & Smith, 2013) and are also subject to interference effects, such as when new information partially or fully overwrites memory for old information (Bower, Thompson-Schill, & Tulving, 1994; Darby & Sloutsky, 2015; Howe, 1995). Gradations in attentional control and memory capacity at specific stages of development can influence how these mechanisms interact with one another to create a series of unique learning trajectories. Assessing developmental differences in highlighting task performance between preschool and primary school children provides an opportunity to present a case for gradations among the related learning literature (Gibson & Rader, 1979).

While the highlighting effect provides an ideal context for studying the mechanistic origins of biased learning in different developmental phenomena, its relevancy within the developmental literature is rarely addressed. One of the few considerations is from within the domain of early word learning (Ellis, 2006; Regier, 2005; Yoshida & Burling, 2012). For example, assume that a child initially learns that a *wug* creature's defining features are both a tail and wings, then later learns that a *dax* creature also has a tail but has claws instead of wings, it is during the time in which the child learns about the *dax* that the relationship between the most defining feature (claws) and the *dax* might be strengthened, or *highlighted*. Variations in associations between individual features and creatures can lead to unexpected biases when presented with ambiguous feature combinations, such as how the child might predict a *dax* when asked which creature consists of both wings and claws or predict a *wug* when asked only about a creature with a tail. Under this scenario, highlighting-like phenomena could be a likely candidate for explaining some of the disambiguation difficulties in early word learning. For example, adjective learning takes place at a much later age than noun learning (Gasser & Smith, 1998), and is also the case that in the English language, adjectives maintain a temporal role within a sentence structure, as well as being ambiguous in isolation—that is, when not modifying a noun in a sentence (Mintz & Gleitman, 2002). A more complete understanding of the mechanisms driving the mastery of adjectives and word learning is one justification for the need to employ learning paradigms such as the highlighting task, tasks that are amenable and effective for understanding the processes taking place during temporally ordered learning (Yoshida & Burling, 2012).

Overview of approach

In this study, we conducted two separate experiments of the highlighting paradigm with both children and adults to further investigate the relationship between domain-general cognitive processes and biased learning outcomes, and to assess how ordered learning preserves critical pieces of information across multiple learning instances and across multiple developmental periods. We implemented a standard temporally ordered learning structure (learning of some relationships before moving on to others) common among many iterations of the highlighting task (Kruschke, 1996) and measured selection biases (or asymmetrical preferences) after training participants with this structure. One important manipulation of the training structure is that training be constrained to be equal in frequency for both initial and later learning instances, so that when biases are observed after shown ambiguous combinations of previously learned cues, these biases cannot be attributed solely to the frequency of learning previous relationships. In Experiment 1, we tested children from 3 to 6 years old on their ability to establish the learning biases typically seen under the highlighting task, with an additional emphasis on the selection preferences between preschool and primary school children. In Experiment 2, we tested adult participants on both our child-friendly implementation of the task and a standard version typically administered in the adult learning literature. This within-subjects design was used to establish that the two perceptually different types of tasks were comparable in generating the expected response biases.

Experiment 1

Experiment 1 tests for biased object preferences in young children. We propose that the learned biases are established by forming associations between a single referent and a subset of one or more cues from a pair of cues, and that the pattern of biases can be explained by an interaction between the order in which relationships are learned and the nature of cue overlap throughout learning. The current experimental hypothesis is that children will show evidence of the highlighting effect, and that associations from sets of paired cues might be more fragile due to age-related differences in cognitive capacities, such as differences in memory capacity and the distribution of attention among cues. Hence, we expect to observe younger and older children responding differently on the critical testing items as opposed to treating them equally, reflecting their cognitive capacity state at some point in development.

Participants

We recruited children from the surrounding University of Houston community and within the Greater Houston Area. Thirty-three children ages 38.4 to 71.4 months (M=55.5) participated in the task in exchange for a small gift at the end of the session. An additional eight children also participated, but we removed them from the analysis for failure to adequately learn $A.B$ and $A.C$ sets by the end of the training phase (either they did not reach the testing phase or the final training accuracy for either set was <67%; there were no differences due to age or stimulus type).

Stimuli and Materials

Our implementation of the highlighting task consisted of a sample of illustrated images presented on a 19” touch screen monitor with a resolution of 1280 × 1024. We designed a series of nine images (common objects) to serve as paired cues (cues that, when presented together, refer to another distinct type of image). For each child, we selected three of the nine images and assigned them to the role of predictive cue A, B, or C. We reused these object illustrations throughout the task. Two of the objects were always presented as pairs, side-by-side at the top of the screen. Additionally, we created a separate sample of six images (animals) and used these as referents for the paired objects. We selected two of the six animals and assigned them the role of referent X or Y, and displayed them side-by-side along the bottom of the screen (see Figure 1 for an example of the task screen). We pre-selected groups of images to avoid the situation of strong pre-existing associations between specific groups of objects and animals. Table S4 and corresponding Figure S4 show a complete breakdown of the groups used in the study and how they were assigned to specific cues and referents.

Procedure

Two main phases of the task were administered to the children, training then testing. We provided verbal instructions along with a familiarization phase before starting the training phase (see Table S5 for the list of instructions used for this task). Participants began the task with six familiarization trials designed to instruct them on using the touch screen monitor. Children were required to drag a pair of triangles at the top-center of the screen toward one of two boxes presented along the bottom of the screen. They then pressed a button on the top right corner to accept their response and were then provided with corrective feedback before moving on to the next trial.

Training procedure—After familiarization with the setup, participants proceeded to the training phase with the goal of learning the correct referents (animals) for a set of paired objects. It is during the training phase that any biases are expected to be established. A single object pair (predictive cues) and its referent was learned first before moving on to another set of paired objects and its corresponding referent. The first relationship $A.B \to X$ we will refer to as Set 1, and the second relationship $A.C \to Y$ as Set 2. We instructed children to drag the object pair placed at the top-center of the screen down to one of the referents placed at opposite ends along the bottom of the screen (see Table S5 for these instructions). That is, children placed the predictive cues in the appropriate box, with each box displaying the image of one of the referents (Figure 1). Both possible referents were always displayed along the bottom of the screen, and the horizontal orientation of objects and referents were randomized across all trials. Dragging either one of the objects downward toward a box led to both items moving across the screen synchronously to illustrate a coupled relationship between pairs of objects and to avoid separating objects into different boxes during a trial. We provided auditory feedback using either cheers (correct) or a buzzing sound (incorrect) after the children made their final referent selection. A gradual progression (between early learning of Set 1 and late learning of Set 2) took place by designing three distinct phases of training: Early, Mixed, and Late (see Table 1 for a summary on how this was structured). We tracked their progress during each phase to guarantee that participants learned the items throughout the training session. The total number of training trials per participant depended upon his/her performance in each phase. The starting number of trials in each phase and the final total were taken from Kruschke's (2009) canonical design. The canonical design allowed for children to become equally exposed to the different sets ($A.B \rightarrow X$ and $A.C \rightarrow Y$) while keeping intact the progression from early to late learning (Table 1). All participants progressed through each training phase without interruption, and were not informed when one type of phase progressed to the next.

A participant began Early training with four consecutive Set 1 trials (2 blocks) before assessing accuracy. If a participant reached at least 75% accuracy after these initial four trials, he/she moved on to the Mixed phase, otherwise we added an additional block of trials until both of those trials were correctly answered. The Mixed phase served as a gradual introduction to the Set 2 association, and during this phase we displayed three trials from Set 1 and one trial from Set 2 (1 block). Accuracy was again assessed with a criterion of 75% for the Mixed phase, and additional blocks were added as necessary. We recorded the total number of blocks for determining the length of the Late training phase. We based the final number of blocks in the Late training phase on the sum of the total number of Early and Mixed blocks (Table 1). The Late training phase started with a minimum of twelve trials (3 blocks), nine of them being from Set 2, and three from Set 1. If a participant required no additional blocks throughout all of training, the exact number of Set 1 training items learned during training was ten, with the number of Set 2 training items also equaling ten. The average number of Set 1 training for all participants was 11.97, which was also the same for training set Set 2 (See Table S7 for a breakdown within each phase).

Testing procedure—Before the start of the testing phase, we informed participants that they were about to see pictures of what they previously saw, and to try their best at choosing one box for their final selection (Table S5). We presented testing items similar to that of training, except that we now showed the participants novel cues (either novel combinations of objects or objects as single cues—no longer paired together). The same previously used training pairs were also intermixed with the new testing trials for comparison purposes. Each type of the six test cues presented in Table 2 were randomly assigned and repeated five times, resulting in a total of 30 testing trials per participant. Unlike the training session, participants were not provided with feedback after each test trial, and the completion of each trial immediately led to the next one.

Results

We derived accuracy measurements for each test item by calculating the proportion of correct responses from the total number of test trials completed for each child. For the novel, untrained items, we recorded a response as correct or incorrect based on the expected answer choice obtained from previous literature (Table 2). We then estimated the probability of a particular frequency of responses by fitting a Bayesian hierarchical logistic regression model with a logit link function and binomial likelihood using the following set of predictors: type of testing cue (e.g., $A.B, \ldots, B.C$), the child's age, the image group used (Figure S4), the interaction of test cue × age (age-related effects for each test cue) and the interaction of image group × test cue (as a control for image-related effects on response). The choice of the use of a hierarchical regression model allowed us to vary the testing cue type coefficients by child, meaning that we fitted different intercepts and test cue parameters for each individual, which were estimated from a common covariance matrix. This was to account for dependencies such as the correlation of responses from the same individual due to repeated measures for each test cue type.

We fit the fully Bayesian implementation to the generalized linear mixed model, which allows for estimating a probability distribution for each of the parameters given the data we collected instead of a single estimate as in frequentist approaches. Due to shrinkage and deriving a *distribution* of parameter values, we can apply the appropriate set of contrasts required for the multiple comparisons without the need for type I error correction methods (Gelman, Hill, & Yajima, 2012). Highest density intervals (HDI, or credible intervals) are used when reporting results and are based on the most dense regions of the posterior distributions of parameters, which are estimated from the model (Kruschke & Liddell, 2015). See the Analysis section for Experiment 1 in the supplementary materials for additional model details.

Evidence of the highlighting effect in children—When considering all children used in the analysis as a whole, the results show strong evidence for biased object preferences in children, which are established from the temporally ordered training session. Figure 2a displays the accuracy (proportion of correct responses) collapsed across children for each type of testing trial. Performance on the trained cues ($A.B \rightarrow X$=.78) and ($A.C \rightarrow Y$=.69) was well above chance performance of .50 (equal preference for either referent), demonstrating that the child's accuracy on the training items persisted well into testing, and despite the testing phase mixing trained cues with novel occurrences. The single cues were also above chance ($B \rightarrow X$=.63, $C \rightarrow Y$=7.8). These trials have an unambiguous, one-to-one correspondence given that they were never paired with more than one referent (unlike cue A). However, there was evidence of accuracy differences between the two single, unambiguous cues. That is, we observed a significant difference between the C and B test trials (the difference in accuracy between the association of $C \rightarrow Y$ and $B \rightarrow X$ was .15, 95% HDI = [.66, .22]), indicating a robust highlighting effect for the later learned unambiguous cue, and how strongly highlighted items could lead to better learning of implicit relationships (cues individually correspond to referents just as they do when shown in pairs). The increase in association for $C \rightarrow Y$ also directly influences how children respond to the ambiguous set of testing trials, A and $B.C$ (Kruschke, 2003). We observed a strong bias for the early learned referent X when tested on the ambiguous, single cue ($A \rightarrow X$ = .73), and a weaker bias toward the later learned referent Y when given the ambiguous pair of cues ($B.C \rightarrow Y$=.58). Together, these set of results reflect the expected trends as seen in the adult highlighting literature (Kruschke, 2009; Kruschke et al., 2005). Our results showing that the strength of the bias is not equal among the two ambiguous test items gives some insight into the nature of what makes each test item considered uniquely ambiguous. Given children's changing cognitive capacities along different points in development, they may treat these two items differently than what is typically expected in adults (adults often respond to $B.C \rightarrow Y$ and $A \rightarrow X$ with similar frequency).

Age-related differences in selection biases—To account for developmental differences among the set of cues tested we analyzed performances between preschoolers and primary school children. We collapsed all preschool children 4.5 years and younger (mean age = 47.4 mos.; range = [38.4,54]; $n = 14$) into a "young" group, and collapsed primary school children older than 4.5 years (mean age = 61.5 mos.; range =[55.5,71.4]; $n = 19$) into an "old" group. Based on mean accuracy for each test item for each group, we calculated differences scores (old –young) to analyze group contrasts (shown as points in Figure 2b). Accuracy proportions for both the young and old groups are shown in Table 3. The largest difference in accuracy we observed was for the single cue B, where we found better performance in older children for this cue. The older group of children were more likely to remember that the single cue B unambiguously corresponds to the early referent X, with a difference in proportion of .10 (95% HDI =[−.001, .21]). We found that younger children performed better on the ambiguous pair of cues, $B.C$. Younger children were more likely to choose the later learned referent Y when tested on $B.C$, a difference of .06 (95% HDI = [−.04, .17]). These results suggest that older children were more likely than younger children to maintain the relationship of cue B corresponding to the early referent X, and thus more likely to learn the correct, implied relationships between cues and referents despite never learning them separately.

Attentional distribution among early training items—Developmental differences between each of the testing cues may be attributed to differences in how children remember the early learned relationships, specifically how they might have treated paired cues as separate entities. In order to investigate the role of memory versus distributed attention among the early trained relationships, we looked at the accuracy of the single test items A and B to observe how performance on these items impacts other critical test items. Three groups of children were formed based on (1) a child's mean accuracy on the A test trials was equal to their accuracy on the B test trials, (2) $A > B$, or (3) $A < B$. The $A = B$ group indicates that the cues A and B—learned during the start of training—were each equally likely to correspond to X. Despite never being taught in isolation, children were able to learn implied relationships between these cues and the early referent, in addition to maintaining these associations well into testing. Groups $A > B$ and $A < B$ indicate that at least one cue from the pair was *not* equally associated with the corresponding referent, thus performance on each during testing differed considerably from one another. Table S6 in the supplementary materials displays the sample size, mean age, and accuracy proportions on all test items for each of these three groups.

The results from Figure 2c indicate that the extent of the selection biases seen in testing are dependent upon how the child attended to the single cues A and B during their training of the association $A.B \rightarrow X$. For the group consisting of participants where $B > A$, we observed no highlighting effect and found no evidence of biases whatsoever for any of the ambiguous test items. These results would be expected if individuals learned all implicit relationships and selected referents with equal probability when given ambiguous information. For the $A > B$ group, where we observed an unusually strong bias for X when given the ambiguous cue A, we also observed a 34% increase in accuracy for cue $C \rightarrow Y$ over $B \rightarrow X$, indicating a strong highlighting effect for C. We also observed a bias for referent Y when given the ambiguous pair of cues $B.C$, 12% higher than expected by chance. Lastly, for the $A = B$ group we did not observe the same discrepancy between B and C performances as we did in the $A > B$ group, and instead observed a small difference between $C \rightarrow Y$ and $B \rightarrow X$, as typically seen in the adult highlighting literature. However, this still resulted in strong biases for both $B.C \rightarrow Y$ (17% higher than chance) and $A \rightarrow X$ (30% higher than chance). These results suggest that children's differential learning of early pairs of cues has a direct influence on the likelihood of them forming selection biases during later learning.

Discussion of Experiment 1

Referential biases observed in children—The findings from Experiment 1 demonstrate that children as a whole show the expected selection biases when provided with ambiguous cues and when provided with a child-friendly version of highlighting task. That is, children strongly preferred the earlier learned referent when given the repeated cue A (despite this cue being shown with both referents), and preferred the later learned referent when given the combination $B.C$ (despite each individual cue already having a direct, one-to-one mapping with its corresponding referent). The case of A biased toward X is particularly interesting because the magnitude of this effect was approximately 10% larger than what is typically seen in adults, and demonstrates how attention was frequently redirected away from A when learning the relationship $A.C \rightarrow Y$. Primacy or recency effects (memory retention for early information only or late information only) cannot account for the results obtained in this study because if either scenario were the case, children would have preferred only one of the referents at all times—either the early or the late referent—when given ambiguous items. Instead, children formed different biases for both the early *and* late referents, which suggests different mechanisms resulting in the asymmetric associations across the two ordered learning instances.

The role of memory and attention in forming biases—We also observed that the extent of the biases depended on how well the child attended to individual cues during the early training set. If cues A and B were not treated equally when learning the initial relationship of $A.B \rightarrow X$, then this significantly affected their accuracy during testing. We found that during testing, older children were more likely to infer the correct relationship of $B \rightarrow X$ than younger children. This may be because memory capacity differences are expected in children of different ages, particularly for older children being able to remember associations that were established much earlier in training. Alternatively, developmental differences may also be attributed to how children of different ages distribute attention across multiple items during early learning. When children strongly preferred $B \rightarrow X$ much more than $A \rightarrow X$, we observed no evidence of selection biases for any of the ambiguous testing items. This situation may imply that memory for A as a predictor of X, was poor during training, or that more attentional resources were allocated toward cue B during this time. However, if memory for A was in fact degrading over time and throughout training, then children should instead show biases for $A \rightarrow Y$, which is more in line with a recency effect explanation. Children were much more likely to associate $A \rightarrow X$, or prefer both referents equally when given the options X, and Y,, and it was never the case that A strongly refers to the late item Y,. Thus, it is likely that the early learned relationships at the start of training were reliably maintained in memory over time and that any type of biases that may be formed are due to differences in attentional allocation, particularly during early learning. Furthermore, the accuracy of the ambiguous pair $B.C \rightarrow Y$ provides weight to the argument for distributed attention among items in children (or lack thereof). If limited memory capacity was solely responsible for the results obtained in children, we should have observed a much stronger preference for Y, when given the pair $B.C$ than what is observed, given that B would have been largely forgotten, and C, was only seen late in training. However, the $B.C$ bias was the weaker of the two ambiguous items for both preschool and primary school children. Lastly, the two different types of ambiguous items might affect attentional distribution in different ways. If children are able to distribute attention *equally* among multiple items, then they can also evaluate these items separately and individually when making selection preferences. Attention can be distributed between objects in the ambiguous $B.C$ case, whereas for the single ambiguous item A , this is not even possible. Equal distribution of attention is particularly likely if B is a strong competitor, and thus, the highlighting effect may be attenuated under ambiguous situations with additional, potentially informative cues. This may explain the lower performance for the $B.C$ test item in general, and in particular for older children with greater attentional distribution ability.

These results suggest that memory, but attentional development in particular, plays an important role in the formation of these biases. Specifically, competition between pairs of cues, the redirection of attention toward novel, more informative sources of information and away from previously established sources, can result in some items having a strong relationship with current events, in contrast to those cues that don’t receive as much attention.

Experiment 2

Our results are inconsistent with the results from a study showing that children as old as 8 to 9 years failed to show the highlighting effect under more adult-like, diagnostic conditions (Winman et al., 2005). One may argue that our child-friendly version of the highlighting task may not be compatible with a more standard version, and the nature of the highlighting effect is specific to a task context in which participants make inferences about causal outcomes given a set of predictive cues. If this is the case, the selection biases observed in Experiment 1 are not the same as the highlighting effect, and we should observe measurable differences in the biases formed when compared to the standard task using diagnostic conditions (Kruschke, 2009; Medin & Edelson, 1988).

The goal of Experiment 2 was to address the possibility that the image-based implementation of the highlighting task we administered in Experiment 1 resulted in biases that were fundamentally different compared to adult-oriented designs of the highlighting paradigm, questioning the generalizability of the developmental findings documented in Experiment 1. We tested adults on the same image-based task used with children in Experiment 1 and on a standard, text-based version of the highlighting task (Kruschke, 2009; Medin & Edelson, 1988) to rule out this possibility. The primary difference between designs was the content matter for learning cue-referent associations, with one task based on associations between sets of images, and the other based on textual information. We

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compared testing cues common to both the image-based and text-based designs in order to evaluate the selection preferences from the two tasks as equally as possible, with the expectation that the adults will form similar biases when given both tasks.

Participants

Forty-seven adults (mean age =23.8; range =[18,38]) with normal to corrected vision from the University of Houston and the Greater Houston Area participated in both the image-based and text-based task designs. All participants received some form of compensation for their time by either providing them with partial course credit or a $5 gift card as a form of payment.

Stimuli and Materials

The stimuli for the image-based version of the highlighting task were identical to stimuli used with children from Experiment 1. For the standard text-based task, we displayed cues and referents as typed text surrounded by outlined boxes, shown on the same touch screen monitor used for the image task. Following the task structure used by Kruschke (2009), participants partaking in the text task viewed two different sets of early learned items and two different sets of late learned items—as opposed to just one of each as in the previous experiment. We use subscripts to identify different sets. For example: $A_1.B_1 \rightarrow X_1$ denotes early Set 1, $A_2.B_2 \rightarrow X_2$ early Set 2, $A_1.C_1 \rightarrow Y_1$ late Set 1, and $A_2.C_2 \rightarrow Y_2$ late Set 2. The cues in this version of the task are defined by known symptoms instead of images while referents correspond to novel diseases in place of animals. We took symptom and disease terms from (Medin & Edelson, 1988), the complete list can be viewed in Table S9 from the supplementary materials. We randomly sampled six of the symptoms and assigned them to the role of paired cues and sampled four diseases to take the place of referents. We displayed two symptoms per trial with the vertical orientation of the text randomized. We showed all four possible diseases at all times at the bottom of the screen with the order also randomized across trials. Figure S6 in the supplementary materials illustrates the layout of the stimuli for a single trial as seen on the touch screen monitor.

Procedure

Each adult participant completed both the image-based and text-based version of the task. The order of each task was randomly assigned between participants. The procedure used for the image-based version of the task in Experiment 2 was identical to the one used in Experiment 1, except that the adults performed the task three times, each time viewing a distinct group of images (and each time learning new sets of associations), thus exhausting all possible groups from the set shown in Figure S4. We counterbalanced the order of the image groups for each participant. Responses were collapsed across image groups for each test cue type and for each participant.

Text-based procedure—Training for the text-based task was similar to the image-based design. We presented written instructions before initiating training (see Table S10). The temporal training structure for the text version was the same as in the image-based version (progression through Early, Mixed, and Late phases). We chose a larger, fixed number of training trials to adhere to previous studies as much as possible, instead of assessing accuracy after blocks of trials and adding more as necessary. As previously mentioned, the early learning phase presented sets of items $A_1.B_1 \rightarrow X_1$ and $A_2.B_2 \rightarrow X_2$ instead of a single set. The mixed and late learning phases contained the early learned items as well as $A_1.C_1 \rightarrow Y_1$ and $A_2.C_2 \rightarrow Y_2$. Each phase had a predetermined frequency of training trials. The early learning phase contained a total of 16 learning trials with both early sets presented 8 times each. The mixed learning phase contained a total of 32 trials with 24 being early items (12 each) and 8 late items (4 each). The late phase contained a total of 64 trials with 16 early items (8 each) and 48 late items (24 each). In total there were 112 training trials split between four different relationships that were learned across temporally ordered phases. Participants simply touched the correct disease within the rectangular boundary to make a response when items were presented during each trial. We provided participants with corrective feedback after their response.

After training in the text task, we displayed written instructions before starting the testing phase (Table S10). The text-based testing procedure was identical to the training procedure with the exception of the different combinations of cue(s) and no corrective feedback for each trial. Learning multiple sets of early and late items allowed for testing novel cue combinations between distinct sets. For example, participants could be shown a list of symptoms such as $A_1.B_1\ C_2$ or $A_2.B_2\ C_1$ and asked to choose the appropriate disease. In this particular situation, combinations of symptoms were shown that overlapped between different sets. We presented these types of cues during testing to maintain consistency with previous literature, but they were not of particular interest during analysis since the goal was to compare analogous test cues between the different types of highlighting designs. We administered a total of 60 testing trials per participant, 8 trials of test item $A.B$ ($A_1.B_1$ = 4, $A_2.B_2$ = 4), 8 trials of $A.C$, and 4 trials each of every other test cue(s) shown in Table S11 in the supplementary materials. More trials of $A.B$ and $A.C$ were added during testing in order to better evaluate adequate learning of the training items.

Results

Learning criteria for adults—Performance on novel test items can only be accurately assessed if participants learned the correct cue-to-referent associations during training. For the text-based version of the task, we calculated accuracy for the test items $A.B$ and $A.C$ and we required at least 6 out of 8 correct responses for each item and for each individual (Kruschke, 2009). Unlike the fixed number of trials in the text-based design, the length of the image task training varied according to participant performance, with a mean of 60.4 trials completed for each participant, collapsed across image groups. We assessed whether or not participants learned the training items for the image-based design based on the last phase of training, similar to Experiment 1. We observed a noticeable difference in performance between the text task and the image task, with 13 adults removed from the analysis due to failure to adequately learn the training items $A_1.C_1$, $A_2.B_2$, and $A_2.C_2$ in the text-based version. After these removals, accuracy for the image-based design was assessed, and only 1 *additional* participant beyond the already removed participants from the text design failed to learn the training events during the late training phase during this task. Removals due to these learning criteria resulted in a total of 33 adult participants used in the subsequent analysis.

Testing performance in adults—We obtained frequencies of correct responses for each type of test item, which were totaled across all image groups in the image task and across all sets in the text task. For example, a single participant's score on test item *A.B* for the image-based task is the sum of all *A.B* trials from the first, second, and third image groups, while their score for *A.B* on the text-based task is the sum of test trials $A_1.B_1$ and $A_2.B_2$. The results, averaged across all participants, are presented in Tables S11 and S12. Only test trials common to both tasks were compared in the analysis.

The same approach in terms of statistical analysis and class of model fitted was identical to that of Experiment 1. The frequency of correct responses out of the total number of trials was used as the outcome variable in the model, and was obtained from each of the participants' performance on each of the six types of testing cues (*A.B*, *A.C*, … *B.C*), for each type of task (*text*, *image*), along with the interaction between the cue type and task type factors. The coefficients for these effects were free to vary by person and standard deviations and correlations between coefficients were accounted for in the model. See the Analysis section for Experiment 2 in the supplementary materials for more details on model formulation.

The results shown in Figure 3 display the 95% highest density intervals (HDI) from the posterior distributions of the test item parameters for both the image and text tasks. The HDI (thin horizontal line) corresponds to the probability of choosing the correct response given one of the test items, with the mean of the posterior displayed to the right of the figure. All responses were above chance performance of 0.5 (based on the expected choice selections given a particular cue(s), see Table 2). The results show that there are no meaningful differences in performance between the image-based and text-based tasks when comparisons are made between each type of test item—the 95% HDI's between cues of the same type are all overlapping. When comparing overall mean accuracy between the two tasks (collapsed across all test items) accuracy was consistently higher in the image-based version by an average of 3% but not reliably different from zero (HDI =[−0.6%, 8.7%]). In addition, the effect sizes of the selection biases observed in adults for the ambiguous items was similar to the proportions seen in previous literature (see the following for comparison: Kruschke et al., 2005; Lamberts & Kent, 2007). These results indicate that responses are consistent between tasks and the biases observed in the image-based version cannot be attributable to differences in forming associations for objects → animals and between inferences made about symptoms → diseases. The consistency in responses between the image-based and text-based designs indicate that the two tasks are comparable, and that the image-based study was effective in eliciting the kind of selection biases typically seen in past highlighting literature.

General Discussion

The fragile nature of ambiguous associations in children

In the present study, we documented young children's asymmetric learning of relationships which consisted of multiple objects referring to some outcome, and observed biased selection preferences due to the order in which these relationships were learned. We provided evidence suggesting that a simple image-based task used for learning the multiple relationships was similar in function to the standard highlighting task typically used in inducing these biases. Age-related effects were observed between preschool and primary school children in that the older children were more likely to learn the implied relationships seen during training. Their accuracy was higher when tested on the association between the early learned cue B and its referent X, despite only learning this relationship alongside the paired cue A. These results reflect older children's ability to adequately shift attention between cues when learning multiple cue $\rightarrow$ referent relationships over time. When the early learned pair of cues were equally associated with their referent, we observed biases similar to that of adult performance. In addition, differences in distributed attention between paired cues in the early training set likely resulted in differences in biases for test items with multiple ambiguous cues, such as the pair $B.C$, which was never shown during training. Cue competition continues to play a role during the presentation of multiple ambiguous cues during testing and influences immediate selection preferences. If the highlighting effect can be described as the focus of attention primarily on the cue C when learning $A.C \rightarrow Y$, and this leads to biases when given ambiguous information such as $B.C$, then competition between $B.C$ might take place but largely in favor of the highlighted cue C. If attention is not equally distributed during early training, with attention being directed mainly toward the cue B during this time, the opposite effect may occur, resulting in stronger competition between the ambiguous pair of cues, and thus unbiased selection preferences. In general, the degree to which attentional resources are placed upon the repeated cue A when learning the early association $A.B \rightarrow X$ directly influences the balance of competition between paired cues during late learning of $A.C \rightarrow Y$, and thus determines the strength of biases when shown ambiguous testing items. We also concluded that the role of memory seems to have less of an immediate influence when assessing the differences between preschoolers and primary schoolers, given that biases were observed asymmetrically for both early and late referents. Yet, its contribution is still important for retaining the associations across time and during the processing of overlapping cues. Further experimentation is necessary to fully understand the limits of memory capacity in preserving associations over much longer periods of time and the effect this has on selection biases.

Similar mechanisms for the two versions of the highlighting task

Experiment 2 showed evidence that adults form the same biases in outcomes when tested on either the text-based version of the highlighting task, the implementation often used in previous literature, or the image-based version we developed specifically for children. The consistency in accuracy proportions between the two tasks for the adults demonstrates that learned biases can occur outside of a symptom-diagnosis context and under conditions of predominately visual associations. Since adults performed similarly, particularly for the ambiguous testing items, we can conclude that the differences we see between younger and older children are likely due to changes in development as opposed to design choices we used in our implementation of the highlighting task. Lastly, we can conclude from the adult data that if the same processes are at work when diagnosing diseases and when predicting animals from random objects, it is unlikely that children as young as three years old are also employing the same type of higher level, rule-like strategies during selection.

Cued Attention and Word Learning

Highlighting, and temporally cued attention in general, has previously been suggested to have a prominent role in early word learning (Gogate & Hollich, 2010; Regier, 2005; Smith et al., 2010; Yoshida & Burling, 2012). For example, as young as six months old, auditory labels are indicated to cue attention to objects (Bergelson & Swingley, 2012). Cue competition driving selective attention is a powerful mechanism for generating looking preferences toward novel objects and establishing robust correlations that persist over time and under ambiguous contexts (Desimone, 1998). Ambiguity resolution can also take place at much smaller timescales, where attention is redirected moment to moment as new information competes with past information. In adults, attention is dynamically reallocated as the auditory information continues to unfold over time, eventually stabilizing on a final selection (Spivey, Grosjean, & Knoblich, 2005).

Words and labels commonly refer to objects in the environment, and these objects can have multiple properties. An object can have both a common label, such as a noun, and a descriptive property, such as an adjective. Given that older children in our task were more likely to learn the implicit relationships by distributing attention across paired cues, these results may provide insight into the delay in children fully understanding the nature of adjectives until about four years old (Waxman & Klibanoff, 2000). During the early stages of adjective learning, looking-while-listening studies demonstrate how young children use multiple, ordered labels to efficiently direct attention to the correct object when referenced (Fernald et al., 2010). When two different objects share a common label, but differ in their properties (e.g., blue car and red car), the order in which these two objects are learned can bootstrap the learning of new, less frequently observed properties during later learning. In another recent study demonstrating the effect of early learned associations in the context of novel adjective learning, the authors suggest that early learned object-word pairings later help novel pairings to compete for attention (Yoshida & Hanania, 2013).

These studies indicate that competitive processes may be mediated through one's learning history, and that looking preferences within these contexts depend on the degree of mastery of nouns and adjectives at different periods of development. They also suggest that the biases derived through ordered learning can help to resolve conflict under highly ambiguous contexts. Therefore, the biases observed in highlighting paradigms are not merely obstacles that need to be overcome in order to obtain some greater understanding about the *true* underlying relationships, but they serve as a means to preserve past information while new information is also attended to and learned just as well.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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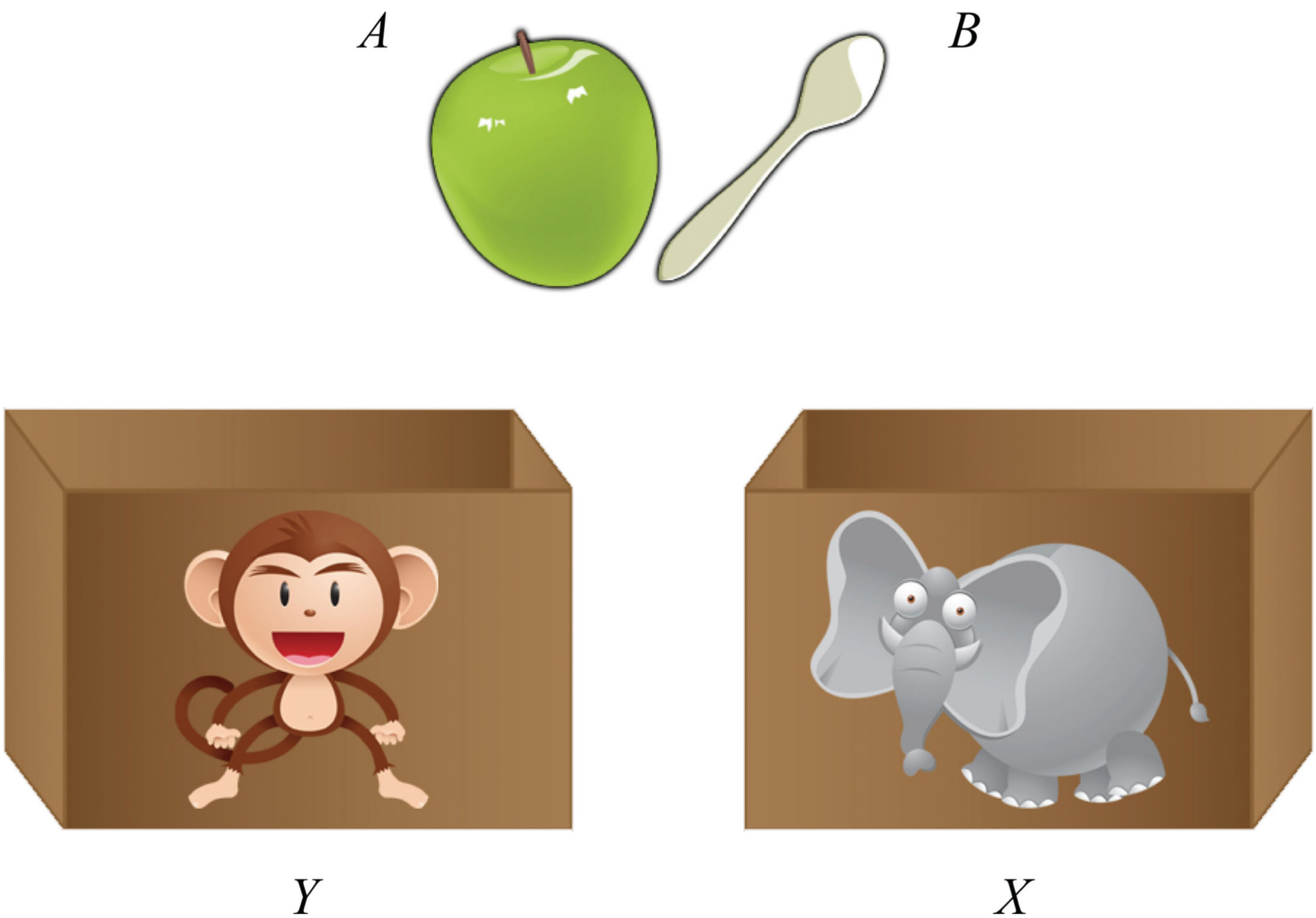

Figure 1.
Example of a selection of cues and referents for the image-based version of the highlighting task. The symbol for each type of cue is marked with a letter next to the image (not shown in the actual task). The figure depicts image group 2 of 3 (see Figure S4 for others). Objects such as the spoon and apple serve as paired cues, while the elephant and monkey are potential referents.

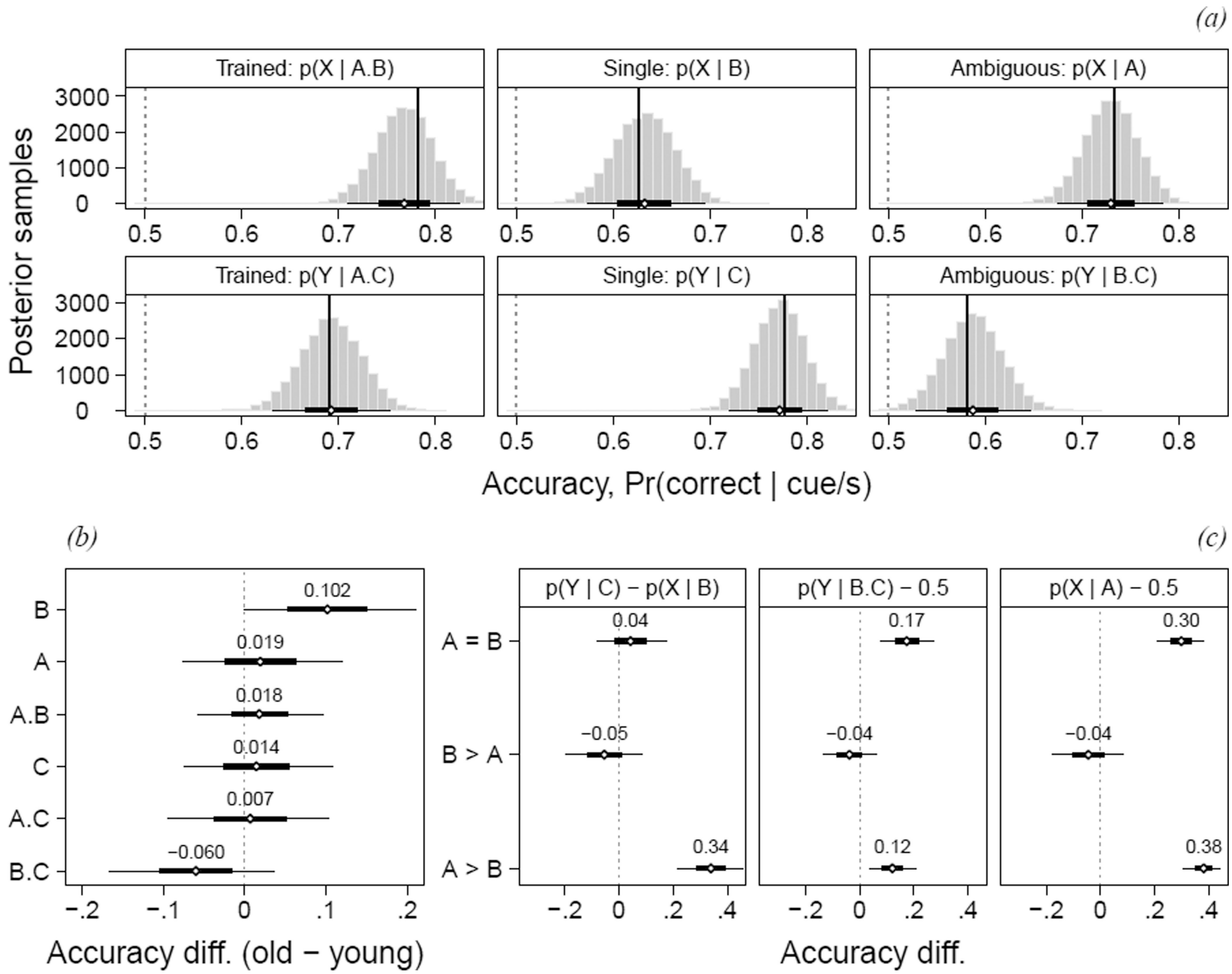

Figure 2.

For all plots, the gray dotted vertical line marks chance performance (selecting X and Y equally), or no difference (zero value). Thin horizontal lines display the 95% highest density interval (HDI), while the thick horizontal lines display one standard deviation of the posterior distribution. The point in the center is the posterior mean. For consistency between plots, accuracy scores are always presented along the horizontal axis. (a) Histograms correspond to the distribution of posterior accuracy, the probability of choosing the expected referent given a specific test item. Solid black vertical lines indicate the observed mean accuracy computed from the data (unmodeled). (b) Difference in mean accuracy proportions between older children and younger children for each test item. Negative values indicate younger children performed better, thus positive values indicate better performance for older children. The difference score is displayed above the HDI. (c) The extent of the highlighting effect (panel 1) and other selection biases (panels 2,3) given how children performed on cues *A* and *B*. Panel 1 is the difference between two test cues, panels 2 and 3 are differences from chance.

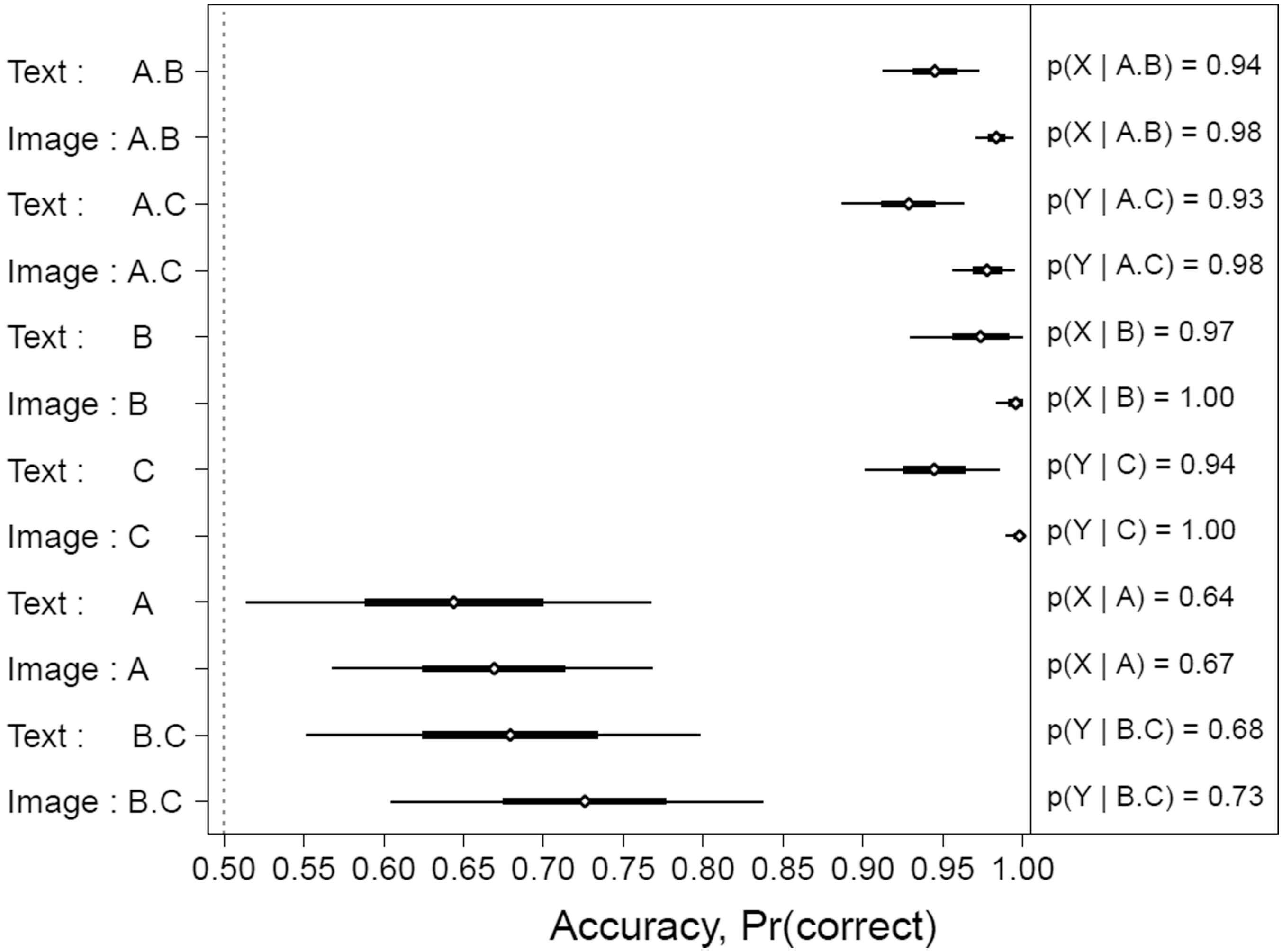

Figure 3.

Adult performance for the image- and text-based versions and for each testing cue from the highlighting task. Chance performance is marked at 0.5. The thin horizontal lines are the 95% HDI of the posterior distribution constructed from the estimated model parameters. The thicker horizontal line is one standard deviation of the same posterior. The center point is the posterior mean. The value of the posterior mean is displayed on the right, along with the expected choice given each type of cue(s).

Table 1

Highlighting training structure. Participants moved from learning A.B → X (Set 1) toward learning A.C → Y (Set 2). Accuracy was assessed at the end of each training phase and additional blocks were added as necessary. The total number of blocks in the Early and Mixed phases was recorded to determine the final number of blocks in the Late training phase. The number of blocks and trials shown represents the minimum that participants were exposed to if they met the accuracy criteria throughout the entire training session.

Phase	Total blocks	Item type & trials per block	Total trials
Early	$E = 2$	A.B → X (×2)	4
Mixed	$M = 1$	A.B → X (×3), A.C → Y (×1)	4
Late	$L = E + M = 3$	A.B → X (×1), A.C → Y (×3)	12

Table 2

Expected selection biases. The first two items are the trained items, introduced again during testing.

Test cue(s)	***A.B***	***A.C***	***B***	***C***	***A***	***B.C***
Corresponding referent	X	Y	X^*	Y^*	X^*	Y^*

Items with an * indicate the expected referent to be associated with the novel cue(s) that were provided during testing. Accuracy scores were based on these expectations.

Table 3

Accuracy for each testing cue separated by age group. Accuracy scores are based on the proportion of selecting the expected response out of the total number of repeated trials of the same kind. Difference scores are shown in Figure 2.

Test item	Expected response	Younger children	Older children
A.B	*X*	0.79	0.78
A.C	*Y*	0.69	0.69
B	*X*	0.55	0.68
C	*Y*	0.76	0.79
A	*X*	0.71	0.75
B.C	*Y*	0.64	0.54