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PAPER

Sampling to learn words: Adults and children sample words that reduce referential ambiguity

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Abstract

How do learners gather new information during word learning? One possibility is that learners selectively sample items that help them reduce uncertainty about new word meanings. In a series of cross-situational word learning tasks with adults and children, we manipulated the referential ambiguity of label-object pairs experienced during training and subsequently investigated which words participants chose to sample additional information about. In the first experiment, adult learners chose to receive additional training on object-label associations that reduce referential ambiguity during cross-situational word learning. This ambiguity-reduction strategy was related to improved test performance. In two subsequent experiments, we found that, at least in some contexts, children (3–8 years of age) show a similar preference to seek information about words experienced in ambiguous word learning situations. In Experiment 2, children did not preferentially select object-label associations that remained ambiguous during cross-situational word learning. However, in a third experiment that increased the relative ambiguity of two sets of novel object-label associations, we found evidence that children preferentially make selections that reduce ambiguity about novel word meanings. These results carry implications for understanding how children actively contribute to their own language development by seeking information that supports learning.

KEYWORDS
active learning, cross-situational word learning, mutual exclusivity, sampling, self-directed learning, uncertainty reduction

1 | INTRODUCTION

Why do we seek out new information during learning? One proposal is that information-seeking behavior is driven by uncertainty reduction (e.g., Kidd & Hayden, 2015). At least in some contexts, children may be motivated to gather information to reduce uncertainty after ambiguous or surprising events (Lapidow & Walker, 2020; Schulz & Bonawitz, 2007; Stahl & Feigenson, 2015). For instance, infants and children preferentially seek out information from social partners when they are more uncertain (Goupil et al., 2016) or when confronted with ambiguous or incomplete information (Bazhydai et al., 2020; Hembacher et al., 2020; Vaish et al., 2011). Understanding the nature of children's information-seeking strategies may provide key insights concerning how children are able to rapidly solve complex learning problems across development (Gopnik et al., 2017; Oudeyer & Smith, 2016).

A classic problem in word learning is how learners determine the meanings of words in potentially ambiguous situations (Quine, 1960). One solution is that children disambiguate word meanings by tracking co-occurrences of object-label pairs across multiple ambiguous situations (Smith & Yu, 2008; Suanda et al., 2014; Yurovsky & Frank, 2015). This proposal would be particularly powerful when combined with a drive to seek information that reduces uncertainty: if learners are motivated to sample object-label associations that remain ambiguous over the course of learning, this may substantially improve word learning outcomes (Hidaka et al., 2017; Keijser et al., 2019).

Computational analyses suggest that self-directed sampling can vastly simplify the task of learning new words and categories under uncertainty, as long as learners employ strategies that increase the frequency of word meanings that have higher uncertainty (Hidaka et al., 2017; Oudeyer, Kachergis, & Schueller, 2019; Settles, 2012). For example, in one computational model of object-label association learning (Hidaka et al., 2017), successfully learning an adult-sized vocabulary (around 60,000 words) required an unrealistic number of sampling trials when learning events were assumed to be drawn randomly from a Zipfian word distribution. However, when the model implemented an active learner that preferentially selected less frequently encountered object-label associations, learning sped up by several orders of magnitude. Other models have implemented active word learning in terms of curiosity mechanisms that preferentially sample objects that are expected to lead to the largest increases in accuracy (Twomey & Westermann, 2017). Sampling learning events based on active selection mechanisms leads to large increases in word learning speed and accuracy compared to randomly selected learning events, e.g. when learning to map labels to objects in visual scenes with multiple possible referents (Gelderloos et al., 2020; Keijser et al., 2019). These models suggest that at least in principle, mechanisms that make selections based on potential learning gain or uncertainty reduction can speed up and simplify the problem of tracking object-label associations.

What sampling strategies do learners use when faced with uncertainty about novel word meanings? Children are sensitive to referentially ambiguous situations, preferentially seeking information from social partners when confronted with referential ambiguity (Hembacher et al., 2020; Hembacher & Frank, 2017; Vaish et al., 2011). Children also show stronger word learning outcomes for objects they express more interest in (Ackermann et al., 2019; Lucca & Wilbourn, 2018). Among adult learners, active selection of label-object pairs during cross-situational word learning increases accuracy compared to a passive condition in which random sets of objects are presented (Kachergis et al., 2013). However, little is known about children's and adults' sampling strategies when given the opportunity to directly control their learning environment. What kind of word learning input do children actively seek? Investigating the types of information that learners sample during word learning, and how these information-seeking strategies emerge in development, can help us understand when and how active learning plays a critical role in learning novel words.

In the current experiments, we investigated whether adult and child learners actively seek information that will serve to reduce ambiguity about the meanings of novel words. We manipulated the ambiguity of novel object-label mappings by varying the degree to which object-label pairs co-occurred with one another during cross-situational word learning (Experiments 1 and 2) or whether children could use mutual exclusivity to disambiguate the referents of novel words (Experiment 3). The central question is whether adults and children preferentially sample the items that are most helpful in reducing uncertainty about novel object-label associations.

2 | EXPERIMENT 1

Experiment 1 was designed to determine whether adults seek information that aids in disambiguating reference. Participants completed a cross-situational learning task in which their goal was to learn a set of object-label associations by determining the referent of each label across training. Participants were then given the opportunity to select which object-label association they would observe on each subsequent learning trial. The central question was whether adults make selections that reduce referential ambiguity.

2.1 | Method

2.1.1 | Participants

We recruited 28 participants through Amazon Mechanical Turk (8 female; mean age: 31.4 years, SD = 7.25; all native speakers of English). Three additional participants were excluded for not passing an initial auditory attention check (2) or for restarting the experiment (1). Participants were paid $0.75 for completing the study.

2.1.2 | Stimuli

The objects were eight images of novel 'alien' creatures used in previous studies (Partridge et al., 2015). Eight novel words (*beppo*, *finna*, *guffi*, *kita*, *noopy*, *manu*, *sibu*, *tesser*) were recorded by a female native speaker of English and normalized in duration and average loudness. The association between each label and its target referent and the roles of the stimuli within a condition were randomized across participants. The stimuli were presented using jsPsych (de Leeuw, 2015). All stimuli and experimental scripts for Experiment 1 and all subsequent experiments can be viewed on the Open Science Framework (OSF) (https://osf.io/udmvh/).

2.1.3 | Design & Procedure

The experiment consisted of Training, Sampling, and Test Phases.

Training Phase

Participants completed 24 cross-situational learning trials (two blocks of 12 trials), presented in random order (Figure 1). Participants were instructed that their goal was to learn the association between eight novel labels and their referents. On each trial, participants were presented with two referents and two labels. The labels

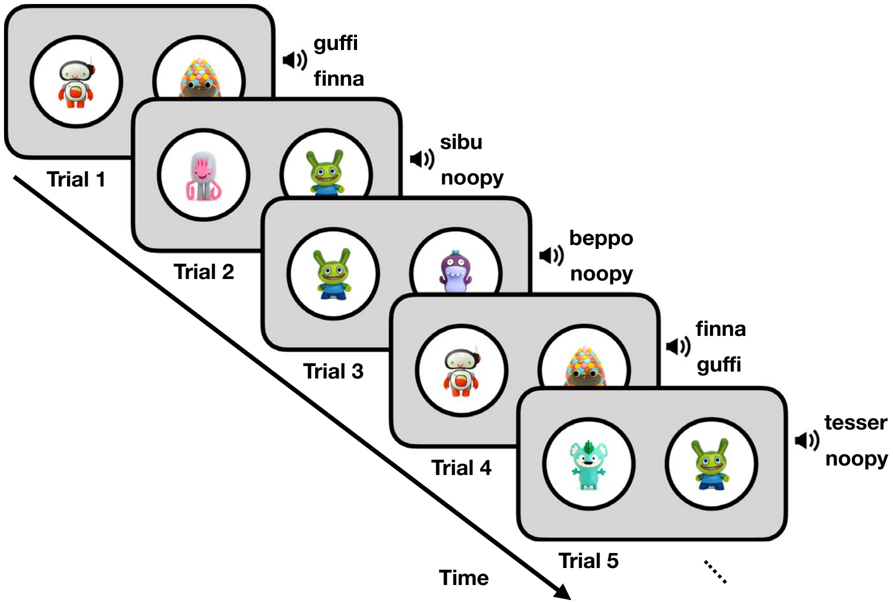

FIGURE 1 Overview over the training procedure.

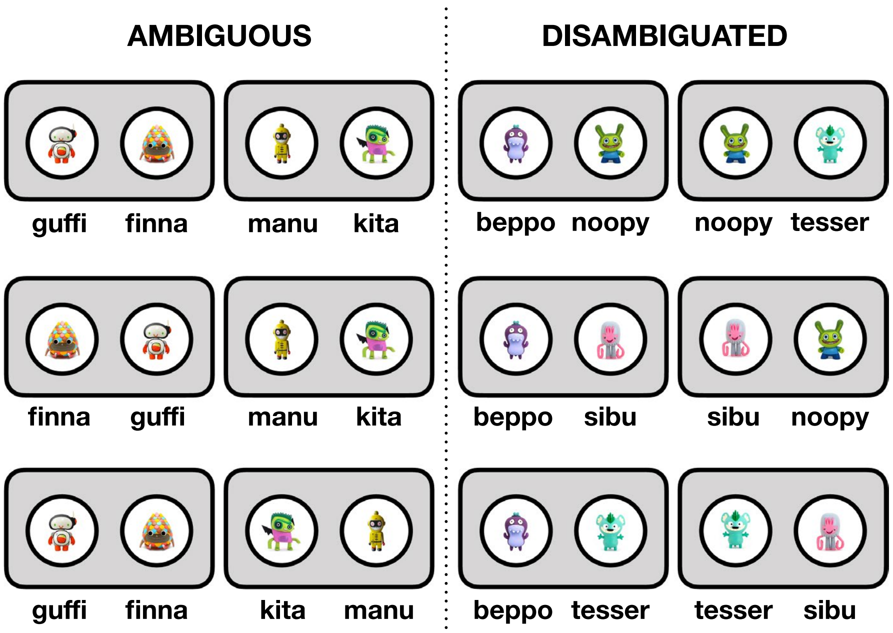

FIGURE 2 Overview over one block of the Training Phase.

appeared sequentially in random order, both visually and auditorily. Consequently, the association between a particular label and its referent remained ambiguous on any single trial, but could be disambiguated by aggregating information across trials. Each object and its label occurred six times across the 24 training trials.

We manipulated whether or not the object-label associations became disambiguated across training trials. Half of the object-label pairs remained ambiguous: two sets of two items were yoked together such that they were never disambiguated across training (ambiguous items; Figure 2, left panel). The other half of the object-label pairs were disambiguated across the training trials; each occurred with three different object-label pairs across trials (disambiguated items; Figure 2, right panel). Note that regardless of item type, each individual object and label appeared equally frequently. Due to this manipulation, half of the label-object pairs remained highly uncertain at the onset of the Sampling phase, while the other half were (potentially) disambiguated.

Sampling Phase

Participants next completed four sampling trials. On each trial, all eight objects appeared in randomized locations. Participants were instructed to select which of the eight items they wanted to hear on the next cross-situational learning trial. After participants made a selection, a second object was chosen at random from the remaining objects. The two objects and their labels then appeared together in a cross-situational word learning trial with the same structure as in the training phase.

Test Phase

Participants' knowledge of the object-label associations was probed in an 8-AFC recognition test. On each test trial, all eight objects appeared in randomized locations on the screen, along with one of the eight labels. Participants were asked to select the object that went with the label. No feedback was provided. Participants were tested on each label in random order, for a total of eight test trials.

2.2 | Results

The data and scripts documenting the data analysis for all experiments are openly available on the Open Science Framework (https://osf.io/udmvh/). These materials include a walkthrough of all analyses reported in the manuscript, including further modeling details and supplementary analyses described in the Results section (accessible through a web browser at the following link: https://mzettersten.github.io/crossAct/analysis/Crossact.html).

2.2.1 | Sampling choices

We used the lme4 package version 1.1–21 in R to fit a logistic mixed-effects model testing participants' likelihood of making an ambiguous selection against a chance level of 0.5 (chance level was 0.5, since the probability of selecting an ambiguous item by chance was 4/8 = 0.5; note that since logit(0.5)=0, the test of our main hypothesis is represented by whether the intercept in the logistic mixed-effects model differs from zero), including by-participant and by-item random intercepts (Bates et al., 2015; R Development Core Team, 2019). The model was specified as follows:

$$\text{ambiguous selection} \sim 1 + (1|\text{participant}) + (1|\text{item})$$

Participants were more likely to choose ambiguous items than disambiguated items, $b = 0.62$, Wald 95% CI = [0.06, 1.17], $z = 2.16$, $p = 0.03$. Participants chose an object from the ambiguous set on 62.5% (95% CI = [50.8%, 74.2%]) of trials (Figure 3a).

To test the robustness of participants' preference for sampling ambiguous items, we also tested subjects' average proportion of ambiguous selections against the chance level of 0.5 in a non-parametric statistical test. A Wilcoxon signed-rank test found that the distribution of ambiguous selections significantly diverged from chance, $V = 152$, $p = 0.02$.

2.2.2 | Test performance

Overall, participants showed learning of the object-label pairs, accurately selecting the correct referent (M = 65.6%, 95% CI = [52.7%, 78.6%], chance=12.5%). Participants' accuracy was significantly greater than chance in a logistic-mixed effects model including by-participant and by-item random intercepts and specifying an offset corresponding to the logit of chance performance, $z = 6.26$, $p < 0.001$. To compare accuracy for items that remained ambiguous during training to accuracy for items disambiguated during training (Figure 2), we fit a logistic mixed-effects model predicting trial-by-trial accuracy from item type (centered; ambiguous=0.5; disambiguated = −0.5), including

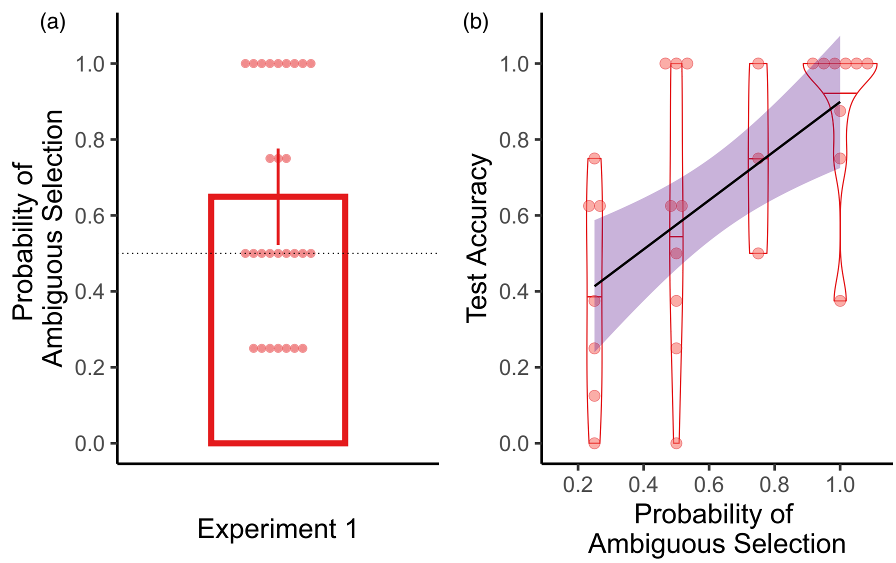

FIGURE 3 (a) Proportion of more ambiguous items selected in Experiment 1. Error bar represents the 95% CI of the model predictions. (b) Relationship between choosing more ambiguous items and test accuracy in Experiment. Dots and violin plots represent the distribution of individual participants' test accuracy. Error bands represent 95% CIs.

by-participant and by-item random intercepts and a by-participant random slope for item type. We specified the model as follows:

$$\text{correct choice} \sim 1 + \text{item type} + (1 + \text{item type}|\text{participant}) + (1|\text{item})$$

Accuracy for ambiguous items (M = 63.4%, 95% CI = [54.6%, 72.2%]; corrected within-participants; Morey, 2008) was marginally lower than accuracy for items that were disambiguated during training (M = 67.9%, 95% CI=[59.1%, 76.6%]), $z = -1.65$, $p = 0.10$.

2.2.3 | Relationship between sampling selections and test performance

Participants who chose more objects from the ambiguous set during the sampling phase accurately identified more words at test, $r(26) = 0.58$, 95% CI = [.27, .78], $p = 0.001$ (Figure 3b).

2.3 | Discussion

In a cross-situational learning task, adult participants chose to learn more about object-label pairs that remained ambiguous throughout training. In the Supplementary Materials (section S1), we report an additional in-lab experiment replicating this result: adult participants preferentially sampled object-label associations that were ambiguous at the end of the Training Phase. These studies provide evidence that adults seek to reduce ambiguity about object-label associations when given the opportunity to control their learning experience.

Intriguingly, we found that participants' sampling behavior was correlated with their test accuracy: participants who chose more ambiguous items during the Sampling Phase also more accurately identified object-label associations. However, the directionality of this correlation is unclear. One possibility is that learners were more accurate on the test because they sampled more ambiguous items. Another possibility is that successfully learning novel words during training makes it more likely that learners will subsequently focus on ambiguous items during the Sampling Phase. In the supplementary in-lab replication experiment (see S1 for further details), we found preliminary evidence supporting the latter explanation– as participants become more successful at learning the novel label-object associations, they also become more likely to seek out information about ambiguous items. This finding underscores the point that uncertainty is dependent on past learning: which items are perceived as most uncertain will vary depending on how well participants have learned the new words. In the current experiment, adult participants were generally successful in learning the underlying label-object associations and actively sought out information about items that remained ambiguous during training.

3 | EXPERIMENT 2

Next, we asked whether children (4–8 years of age) also seek out information that reduces ambiguity during cross-situational learning. As in Experiment 1, one set of novel object-label associations could be inferred based on the object-label pairs they co-occurred with during training, while another set of words remained ambiguous. Children were then given the opportunity to sample object-label associations presented in isolation. The central question was whether children would prefer to select object-label associations that remained ambiguous at the end of the Training Phase.

3.1 | Method

3.1.1 | Participants

We recruited 38 participants (M = 5.9 years, SD = 1.19, range = 4.1–8.1 years; 19 female) at a local children's museum. Two additional participants were excluded due to inattention (e.g., not attending during task instructions and/ or requiring a high degree of experimenter support; results including these individuals follow the same pattern).

3.1.2 | Stimuli

The object stimuli included the eight 'aliens' from Experiment 1 (Partridge et al., 2015) and two cartoon images of familiar animals (penguin, dog). Eight novel words (*biffer*, *deela*, *guffi*, *sibu*, *tibble*, *leemu*, *zeevo*, *pahvy*) and two familiar words (*penguin*, *dog*) were recorded by a female native speaker of English and normalized in duration and average loudness. The association between the novel labels and target referents, as well as the particular roles of the novel label-referent stimuli, were randomized across participants. The stimuli were presented using jsPsych (de Leeuw, 2015).

3.1.3 | Design & Procedure

Children were tested individually in a quiet room in the local children's museum on a 10.1" Samsung Galaxy Note tablet. An experimenter guided children by giving instructions at the beginning of each phase. The experiment was presented as a game in which a cartoon bear named Teddy would first teach children the names of new alien friends, and then ask children to help her find her friends. The experiment began with a Practice Phase (see supplementary materials S2 for details), followed by the main experiment consisting of three phases: Training, Sampling, and Test.

Training Phase

Participants completed nine cross-situational learning trials (three blocks of three trials each). On each training trial, participants saw two referents appear on the screen on either side of the Teddy character and heard the labels of the two objects presented sequentially in random order. Next, the objects switched locations in a brief animation, and participants heard the same two labels presented in the same order. We included this trial repetition with flipped locations in order to reduce children's tendency to interpret the labeling event as moving from left to right on the screen.

As in Experiment 1, we manipulated whether the object-label associations could be disambiguated across training trials (Figure 4). Each object-label pair occurred on three cross-situational training trials. Four of the objects occurred with three different object label pairs (disambiguated items). The remaining two object-label pairs always occurred with one another (ambiguous items), such that children never saw evidence allowing them to link the two words unambiguously with their respective referents.

Sampling Phase

After completing the training phase, participants completed four sampling trials. On each sampling trial, all six referents appeared in randomized locations on the screen. Participants were instructed to select which of the six items they wanted to learn about next (Figure 4). When participants tapped one of the six referents, a brief animation moved the item to the center of the screen while the remaining items disappeared, and the referent was subsequently labeled in isolation.

Test Phase

Participants' knowledge of the object-label associations was probed in a 6-AFC recognition test. On each test trial, all six referents appeared in randomized locations on the screen surrounding the Teddy character. When participants tapped Teddy in the center of the screen, they heard one of the six labels. Participants were instructed to help Teddy by selecting the friend she was looking for. No feedback was provided after a choice. Participants were tested on each label in random order, for a total of six recognition test trials.

3.2 | Results

3.2.1 | Sampling choices

We fit a logistic-mixed effects model testing whether children's likelihood of selecting an ambiguous item differed from chance (0.33, since the probability of randomly selecting an ambiguous item was 2/6 = 0.33), including by-participant and by-item random intercepts. Contrary to our prediction, children did not select ambiguous

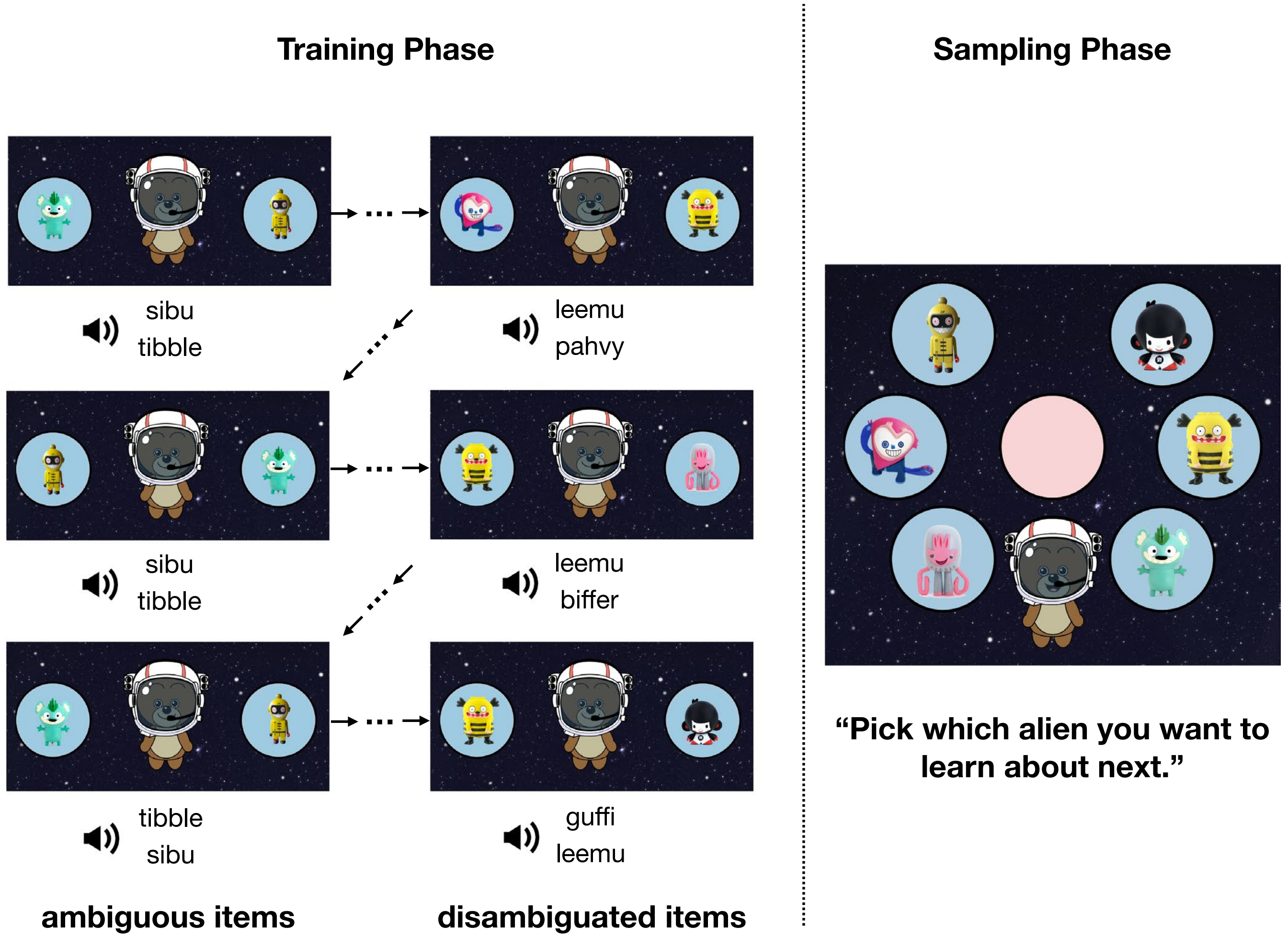

FIGURE 4 Overview over the design of the Training and Sampling Phase in Experiment 2.

object-label associations more frequently than would be expected by chance during the Sampling phase, $b = -0.02$, Wald 95% CI = [−0.36, 0.32], $z = -0.12$, $p = 0.91$. Participants chose an object from the ambiguous set on 32.9% of trials (95% CI=[27.1%, 38.7%]; Figure 5). A Wilcoxon signed-rank test conducted on children's proportion of ambiguous selections yielded comparable results ($V = 409$, $p = 0.57$). In order to investigate whether children's sampling preferences changed with age, we fit a logistic mixed-effects model predicting the likelihood of selecting ambiguous items from age, including by-participant and by-item random intercepts. Children's propensity to select an ambiguous item was unrelated to age, $b = 0.004$, Wald 95% CI = [−0.28, 0.29], $z = 0.03$, $p = 0.98$.

3.2.2 | Test performance

To investigate participants' test performance, we fit the same logistic mixed-effects models as in Experiment 1 (including the identical random effects structure). Overall, participants showed significant learning of the object-label pairs, choosing the correct object to go with a label at above-chance levels (chance = 0.167; the probability of selecting a target object if choosing completely at random), M = 38.6%, 95% CI = [30.7%, 46.5%], $z = 6.46$, $p < 0.001$. Surprisingly, children performed more accurately on the ambiguous items (M = 48.7%, 95% CI = [40.0%, 57.4%]) than on the disambiguated items (M = 33.6%, 95% CI = [24.8%, 42.3%]), $b = 0.68$, Wald 95% CI = [0.08, 1.28], $z = 2.23$, $p = 0.026$. When tested on ambiguous items, children had a strong preference to select one of the two ambiguous objects (61.8% of trials, 95% CI = [51.4%, 72.3%]) rather than the four disambiguated objects (chance = 0.33). When tested on disambiguated items, children tended not to choose the two ambiguous objects, selecting them on only 18.4% of trials (95% CI = [8.0%, 28.9%]).

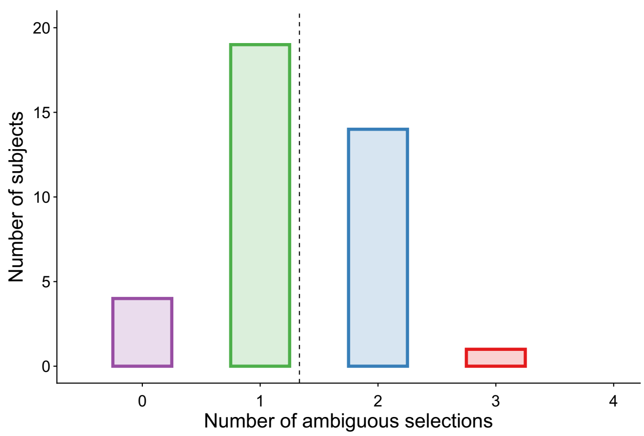

FIGURE 5 Children's sampling choices in Experiment 2. The plot depicts the number of subjects (out of 38) selecting 0, 1, 2, 3, or 4 ambiguous items across the four sampling trials. The dashed line represents the expected value if items are sampled randomly.

3.2.3 | Relationship between sampling selections and test performance

We investigated the relationship between children's selections during the Sampling Phase and their subsequent test accuracy on sampled (vs. non-sampled) items. To do so, we fit a logistic mixed-effects model predicting children's test accuracy from item type (centered; ambiguous = 0.5; disambiguated = −0.5), sampling choice, i.e. whether or not the item was chosen by a participant during the Sampling Phase (centered; sampled = 0.5; not sampled = −0.5), and their interaction, including by-participant and by-item random intercepts, and a by-participant random slope for item type. There was a significant effect of item type, $b = 0.83$, 95% Wald CI = [0.15, 1.50], $z = 2.41$, $p = 0.016$. There was also a significant effect of sampling choice, $b = 0.89$, 95% Wald CI = [0.23, 1.55], $z = 2.66$, $p = 0.008$ (see Figure S3.3 in the supplementary materials for additional details). This indicates that participants performed more accurately on test items that they had previously selected during the Sampling Phase (M = 45.2%, within-participant 95% CI = [34.6%, 55.7%]) than on items they did not sample (M = 26.8%, within-participant 95% CI = [16.2%, 37.3%]). There was no significant interaction between item type and sampling choice, $p = 0.48$.

As in Experiment 1, we also tested whether children's tendency to select items from the ambiguous set predicted their test accuracy, and found no evidence that a higher number of ambiguous items selected was associated with better learning, $r(36) = 0.22$, 95% CI = [−0.11, 0.50], $p = 0.18$.

3.3 | Discussion

Unlike adult learners, children did not show a tendency to select object-label associations that remained ambiguous during training. While children did not exhibit a bias toward sampling ambiguous items, children tended to have higher test accuracy for items that they selected during the Sampling Phase, suggesting that sampling behavior was linked to subsequent learning. Surprisingly, children performed better on ambiguous object-label associations than on object-label associations that were disambiguated across training trials. There are likely two reasons why children showed higher accuracy on the ambiguous items. First, since the two ambiguous items always co-occurred with one another, the training could help learners constrain the set of possible competitors for a given ambiguous label to two objects (compared to four possible objects for the disambiguated items). Indeed, children appeared to constrain their choices to the two objects that co-occurred on ambiguous trials when tested on their respective labels and rarely chose these objects when tested on the labels that occurred with the disambiguated objects.

Second, anecdotally, we observed that many children explicitly pointed to specific objects during training while listening to each label and even repeated the respective label for each object. This behavior may indicate that some children were generating explicit hypotheses about each word mapping (Trueswell et al., 2013). If a child formed a specific hypothesis about the mapping between the two labels and objects on the first ambiguous trial, they would subsequently hear evidence that would appear to confirm their hypothesis: the two labels and the two objects would occur together again on the subsequent two training trials. "Hypothesis-testers" would never experience evidence disconfirming their initial hypotheses. Crucially, one consequence of learners approaching the task in this manner is that the two object-label associations deemed "ambiguous" according to the experimental design may have actually appeared notably less ambiguous to children performing the task than the putatively disambiguated items. Thus, in our next study, we adapted the task to create a learning situation in which one set of object-label associations would be more clearly ambiguous from the perspective of the child learner.

4 | EXPERIMENT 3

In Experiment 3, we sought to increase the likelihood that children would perceive some novel object-label associations as more ambiguous than others. We used mutual exclusivity to increase the ease with which children could infer word-referent pairs for one set of novel objects (Lewis et al., 2020; Markman & Wachtel, 1988) while maintaining the ambiguity of a second set of novel word-referent pairs (as in the previous experiments). By giving children the opportunity to infer the referents for novel objects occurring on mutual exclusivity trials, we aimed to make it easier for children to recognize the ambiguity of consistently co-occurring object-label associations.

4.1 | Method

4.1.1 | Participants

We recruited 56 new participants (M = 5.5 years, SD = 1.18, range = 3.3–7.9, 33 female) at a local children's museum.[1]

Two additional participants were excluded due to interruptions to the experiment (n = 1) or not completing the study (n = 1).

4.1.2 | Stimuli

The novel stimuli consisted of six images and recordings composed of a subset of the items used in Experiment 2. In addition, 4 cartoon images of familiar animals (cow, dog, monkey, pig) along with audio recordings of their respective labels were used. Stimuli were recorded by the same female native speaker of English and normalized in duration and average loudness.

4.1.3 | Design & Procedure

The procedure and testing conditions were identical to Experiment 2.

Training Phase

Participants completed nine cross-situational learning trials (three blocks of three trials each) with six object-label pairs, two familiar object-label pairs (e.g., pig and dog) and four novel object-label pairs chosen randomly from the set of novel stimuli. As in Experiment 2, two referents appeared on the screen on each trial paired with two labels presented in random order. Two novel object-label associations always occurred with one another (ambiguous items), mirroring the ambiguity manipulation from Experiments 1 and 2. The two remaining novel object-label associations served as mutual exclusivity items; each novel object-label pair was yoked to a familiar object-label pair (i.e., one alien always occurred with the dog image, while the other always occurred with the pig image). We reasoned that children should be able to disambiguate reference for the mutual exclusivity items (i.e., when seeing an image of a dog and a novel "alien", on hearing the words *leemu* and *dog*, children would successfully infer that *leemu* referred to the novel alien). This would make it more likely that the ambiguous items would be perceived by child learners as having relatively high referential uncertainty. As in previous experiments, all novel objects and their labels occurred equally frequently across the training phase.

Sampling Phase

Participants next completed two sampling trials. On each trial, the four novel objects appeared on the screen and children were instructed to choose which object they wanted to learn more about. The procedure was otherwise identical to Experiment 2.

Test Phase

Participants' knowledge of the six words from the training phase (4 novel, 2 familiar words) was tested in a 6-AFC recognition task in the same procedure as in Experiment 2.

4.2 | Results

4.2.1 | Sampling choices

We fit a logistic-mixed effects model testing whether children's likelihood of selecting an ambiguous item differed from chance (chance level was 0.5, since the probability of selecting an ambiguous item by chance was 2/4 = 0.5), including by-participant and by-item random intercepts. As predicted, children preferentially selected ambiguous object-label associations during the Sampling phase, $b = 0.55$, Wald 95% CI = [0.15, 0.95], $z = 2.71$, $p = 0.007$ (Figure 6a). Participants chose an object from the ambiguous set on 63.4% of trials (95% CI = [54.4%, 72.4%]) (chance level=0.5). A Wilcoxon signed-rank test yielded similar results ($V = 330$, $p = 0.006$). In order to investigate whether the propensity for making ambiguous selections increased with age, we fit a logistic mixed-effects model predicting the likelihood of an ambiguous selection from Age, including by-participant and by-item random intercepts. Unlike Experiment 2, there was a significant effect of Age, $b = 0.46$, Wald 95% CI = [0.10, 0.82], $z = 2.48$, $p = 0.013$ (Figure 6b).

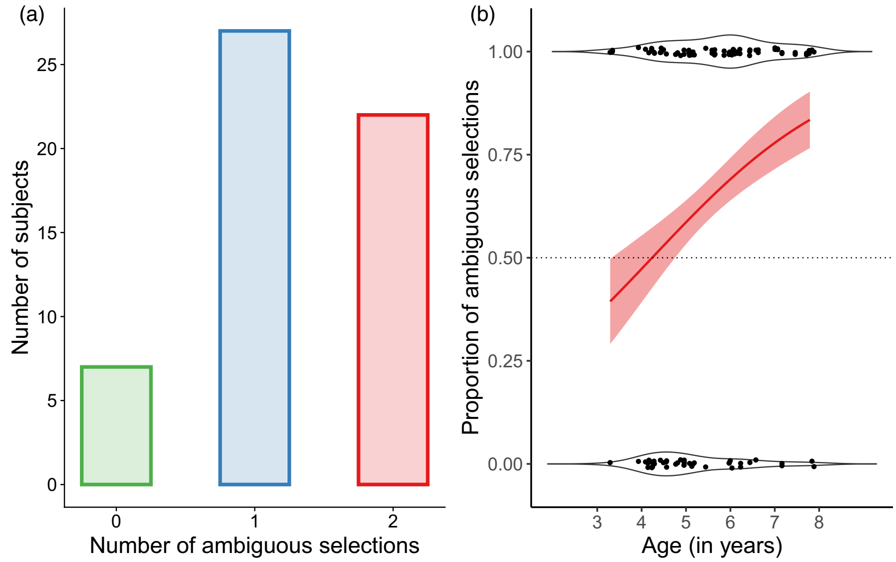

FIGURE 6 Distribution of ambiguous item selections in Experiment 3 overall (a) and across age (b). Error bands are +1/−1 SEs based on model estimates.

4.2.2 | Test performance

We fit logistic mixed-effects models analogously to Experiments 1 and 2 (including the identical random effects structure). Overall, participants showed significant learning of the object-label pairs, choosing the correct object to go with a label at above-chance levels (chance selection of novel object = 0.25), M = 57.6%, 95% CI = [48.4%, 66.8%], z = 5.08, p < 0.001. Accuracy for mutual exclusivity items (M = 61.6%, 95% CI=[52.8%, 70.4%]) and for the ambiguous items (M = 53.6%, 95% CI = [44.8%, 62.4%]) was not significantly different, b = −0.44, Wald 95% CI = [−1.15, 0.27], z = −1.22, p = 0.22 (see supplementary material S4.1 for a graphical representation of the data).

4.2.3 | Relationship between sampling selections and test performance

As in Experiment 2, we investigated the relationship between children's selections during the Sampling Phase and their subsequent accuracy on sampled (vs. non-sampled) items. We fit the same logistic mixed-effects model predicting children's test accuracy from Item Type (centered; ambiguous = 0.5; mutual exclusivity = −0.5), sampling choice, i.e. whether or not the item was chosen by a participant during the Sampling Phase (centered; sampled=0.5; not sampled = −0.5), and their interaction, including by-participant and by-item random intercepts, and a by-participant random slope for Item Type. There were no significant effects of sampling choice (p = 0.33) or item type (p = 0.15), and no significant interaction between the two (p = 0.77) (see S4.2. in the supplementary materials for further information). In addition, children's tendency to sample items from the ambiguous set was not related to test accuracy (r(54) = 0.07, 95% CI = [−0.20, .32], p = 0.62).

4.3 | Discussion

When given the opportunity to select which object-label pairs they wanted to learn more about, 3–8-year-olds preferentially selected object-label pairs that remained ambiguous during training over object-label pairs that could be disambiguated through mutual exclusivity. These findings demonstrate that – at least in some word learning situations – children preferentially select learning events that aid in reducing referential uncertainty. The tendency to make ambiguity-reducing selections began to emerge around 5 years of age in our sample.

While children's tendency to sample ambiguity-reducing items has the potential to be a powerful driver in word learning (Hidaka et al., 2017; Keijser et al., 2019), the impact of this sampling strategy on learning outcomes remains open in the current work. Children learned the ambiguous and the mutual exclusivity items at similar rates, consistent with the fact that children used the sampling phase to aid in disentangling the reference of novel words. However, there was no evidence that children performed more accurately during the test on label-object pairs that they had previously selected during the Sampling Phase. Since the experiment was principally designed to answer questions about sampling strategy, we had limited power to trace the impact of children's selections on subsequent learning. In particular, the small number of sampling trials provided to children (n = 2) limits our ability to measure correlations between sampling preference and learning. Future work will delve deeper into questions concerning the impact of children's sampling preferences by systematically manipulating the input children select and receive prior to test (e.g., Kachergis et al., 2013; Markant & Gureckis, 2014) and by increasing power to measure stable individual differences in children's sampling strategies.

5 | GENERAL DISCUSSION

When learning the referents of novel labels in ambiguous contexts, adult learners chose to learn more about object-label associations that remained ambiguous at the end of training (Experiment 1). Children also spontaneously sampled object-label associations that reduce ambiguity, though only when the task was simplified to emphasize referential ambiguity. When presented with a similar task as adults, children did not choose to learn about object-label associations that remained ambiguous during training (Experiment 2). However, this result is likely at least partially explained by the fact that children – contrary to our expectation - did not link novel words to their target objects more readily for disambiguated items than for ambiguous items in Experiment 2. In a simplified design that highlighted the ambiguous nature of the trials in which two referents always occurred together (Experiment 3), children chose to learn about items that reduced uncertainty about the words' referents.

The preference for selecting ambiguous items was strongly related to age, with children beginning to reliably select the ambiguous items around 5 years of age in our sample. Past work on social referencing suggests that children as young as 2 years of age (Hembacher et al., 2020) and even infants as young as 12 months are sensitive to referential uncertainty (Bazhydai et al., 2020; Vaish et al., 2011). Our studies go beyond measuring sensitivity to uncertainty by asking whether child learners choose to sample new words based on referential ambiguity. Proactively making sampling decisions based on uncertainty may require more sophisticated skills in metacognition (Ghetti et al., 2013; Lyons & Ghetti, 2011) and cognitive control (Munakata et al., 2012) that undergo substantial development during early childhood. Similar to Experiment 2, the absence of a sampling preference among younger children in Experiment 3 may also be due to younger participants being less likely to encode the learning input as providing ambiguous information for some sets of words. Limits on the extent to which younger children spontaneously make ambiguity-reducing selections raise important questions for future research on when children encode input as providing ambiguous information about word reference, the contexts in which children can effectively employ sampling strategies that reduce this ambiguity, and how children's sampling strategies develop and interact with their cognitive development more generally.

While the current experiments focused on learners' active sampling strategies, an important direction for future work will be investigating how children's active selections influence learning outcomes. In Experiments 1 and 2, we found preliminary evidence that sampling choices were associated with learning. In Experiment 1, adults who tended to select ambiguous items during the sampling phase had higher test accuracy. However, this correlation may be at least partially explained by better learners preferring to select ambiguous items, rather than ambiguous selections driving better learning alone (see S1 in the supplementary materials for further discussion). In Experiment 2, children were more accurate for test items they had selected during the sampling phase. However, we found no relationship between children's sampling selections and their subsequent test accuracy in Experiment 3.

There are several possible explanations for why we find mixed evidence for a relationship between sampling and subsequent test performance in the current experiments. First, our results highlight that information-seeking strategies and past learning are mutually dependent. What information is most relevant to the learner depends on what they have already learned. The reciprocal relationship between sampling preference and learning is clearly visible in the adult experiments – adults who preferred to sample ambiguous items were the most successful word learners, but successfully learning words during the training phase was likely a prerequisite for recognizing and subsequently sampling ambiguous object-label associations. The mutual dependence of sampling and learning highlights the need for experimental manipulations geared toward systematically manipulating sampling experiences to understand the influence of sampling selections on subsequent learning, particularly in future research with children (Markant & Gureckis, 2014; Partridge et al., 2015; Sim et al., 2015). Second, it is important to consider how different sampling strategies may be associated with trade-offs as learners encode new words, and how these may interact with developments in working memory (Vlach, 2019; Wojcik, 2013). While selecting an item for further study that has been associated with ambiguity in the past reduces referential uncertainty, it also comes at the cost of opportunities for studying other items - perhaps hampering successful maintenance of memory for items not sampled. Whether and how learners manage these trade-offs in a manner that supports overall word learning is an important question for future research, for example by comparing overall learning when children actively construct learning events and when learning events are randomly generated (e.g., Kachergis et al., 2013).

Children have considerable control over their "curriculum" as they learn new words (Mani & Ackermann, 2018; Smith et al., 2018), with potentially immense consequences for the difficulty of the learning problems they face (Hidaka et al., 2017). While children are confronted with substantial referential uncertainty, active sampling strategies have the potential to structure and simplify the complex problem of linking words with their meanings in ambiguous contexts (Keijser et al., 2019; Yu & Smith, 2012). The present results demonstrate that, at least in some circumstances, children preferentially sample new words that reduce referential ambiguity. These studies contribute to a growing literature demonstrating that children are curious learners who actively contribute to their own language development.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in a publicly accessible repository on the Open Science Framework (OSF) at https://osf.io/udmvh/ and on GitHub at https://github.com/mzettersten/crossAct.

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ENDNOTE

[1]The original target age range for the study was 4.0 years-8.0 years. Three 3-year-olds were recruited and run in the experiment. Given that all three children completed the experiment without issue, we opted for an inclusive data policy and included these participants in the analyses. All analytic results and conclusions are qualitatively similar if these three participants are excluded.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section.

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