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PREDICTION ERROR AND WORD LEARNING

1 Prediction error boosts retention of novel words in adults but not in children.

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Abstract

How do we update our linguistic knowledge? In seven experiments, we asked whether error-driven learning can explain under what circumstances adults and children are more likely to store and retain a new word meaning. Participants were exposed to novel object labels in the context of more or less constraining sentences or visual contexts. Both two-to-four-year-olds ( $M_{\text{age}} = 38$  months) and adults were strongly affected by expectations based on sentence constraint when choosing the referent of a new label. In addition, adults formed stronger memory traces for novel words that violated a stronger prior expectation. However, preschoolers' memory was unaffected by the strength of their prior expectations. We conclude that the encoding of new word-object associations in memory is affected by prediction error in adults, but not in preschoolers.

Keywords: prediction error; mutual exclusivity; disconfirmed predictions; memory retention; word learning.

## PREDICTION ERROR AND WORD LEARNING

60 Prediction error boosts retention of novel words in adults but not in children.

61 Children learn new words at a staggering rate (Fenson et al., 1994), demonstrating a  
62 remarkable ability not only to determine what a new word means, but also to retain huge numbers  
63 of form-meaning pairs in memory (Vlach, 2019). This learning extends into adulthood and indeed is  
64 lifelong, as new terms and vocabulary enter our language, and as we move between different  
65 linguistic communities (Ameel, Malt, & Storms, 2008; Borovsky, Kutas, & Elman, 2010; Hulme,  
66 Barsky, & Rodd, 2019). In this work, we investigate what factors affect our ability to retain word  
67 meanings, and whether these are the same in children and adults. In particular, we test how the  
68 retention of novel form-meaning pairs is affected by prediction errors, following theoretical claims  
69 that the computation of prediction errors drives memory encoding (Henson & Gagnepain, 2010).

70 There is now ample evidence that our interactions with the world are guided by prediction,  
71 from the way we control our movements (Wolpert & Flanagan, 2001) to how we make sense of our  
72 perceptions (Clark, 2013; Friston, 2005; Grush, 2004). Across these different domains, we are able  
73 to generate expectations about the future state of the world and, critically, we compare these  
74 expectations to information about the actual state of the world when it reaches our senses. This  
75 process of comparison between expected and observed states generates prediction error signals,  
76 which are thought not only to drive immediate behavioral responses, but also to affect long-term  
77 encoding of information in memory (Henson & Gagnepain, 2010), and thus our learning (e.g., Den  
78 Ouden, Friston, Daw, McIntosh, & Stephan, 2008; Niv & Schoenbaum, 2008; Rescorla & Wagner,  
79 1972).

80 Importantly, prediction error is the result of a comparison between expected and observed  
81 states, and thus its magnitude depends on the strength, or precision, of both the information we  
82 receive from the outside world and of our prior expectations (Friston, 2005, 2010). Under the  
83 Predictive Interactive Multiple Memory Systems (PIMMS) framework proposed by Henson and  
84 Gagnepain (2010), larger prediction errors (i.e., greater mismatches between expected and observed  
85 states) lead to the formation of stronger memory traces. Combined with the idea that stronger (i.e.,

86 more precise) expectations generate larger prediction errors (when disconfirmed), this leads to a key  
87 hypothesis: Stronger expectations that are disconfirmed should benefit memory more than weaker  
88 expectations that are disconfirmed. While this may seem surprising and even counterintuitive (after  
89 all, incorrect expectations are akin to mistakes and making mistakes should impair memory for the  
90 correct answer), it falls out of the way prediction error is defined in these accounts – that is, as the  
91 discrepancy between expectations and input.

92 For example, Greve and colleagues showed that adults were more likely to remember the  
93 association between a scene and a new face (observed only once) if the scene had previously been  
94 repeatedly paired with another face (i.e., the same face multiple times), compared to several faces  
95 all different from the new face (Greve, Cooper, Kaula, Anderson, & Henson, 2017). Crucially,  
96 although in both instances the new face violated a previously established association (i.e., it  
97 disconfirmed an expectation), the previously-established association supported a stronger  
98 expectation when the scene was paired repeatedly with the same face. Thus, this finding confirms a  
99 key hypothesis derived from accounts of memory based on the computation of prediction error.

100 But does prediction error also affect our memory for word meanings? Surprisingly, despite a  
101 lot of recent interest in adults' and children's ability to predict upcoming language (Huettig, 2015;  
102 Kuperberg & Jaeger, 2016; Pickering & Gambi, 2018; Pickering & Garrod, 2013; Rabagliati,  
103 Gambi, & Pickering, 2016), the answer to this question is still unclear. While much evidence  
104 demonstrates that adults and young children are capable of generating expectations at multiple  
105 linguistic levels (Pickering & Gambi, 2018; Rabagliati et al., 2016), including meaning (Altmann &  
106 Kamide, 1999; Borovsky, Elman, & Fernald, 2012; Lindsay, Gambi, & Rabagliati, 2019; Mani,  
107 Daum, & Huettig, 2016; Mani & Huettig, 2012), structure (Gambi, Pickering, & Rabagliati, 2016;  
108 Havron, de Carvalho, Fiévet, & Christophe, 2019; Lukyanenko & Fisher, 2016; Wicha, Moreno, &  
109 Kutas, 2004), and perhaps form (Dikker, Rabagliati, Farmer, & Pylkkänen, 2010; Ylinen et al.,  
110 2014; but see Gambi, Gorrie, Pickering, & Rabagliati, 2018), comparatively little work has  
111 examined the consequences of disconfirmed expectations on memory for novel word meanings.

112

**113 Prediction Error and Language Learning**

114 The idea that prediction errors influence language learning is not new, and indeed a number of  
115 historically important models have made the claim that prediction errors play a critical role in  
116 children's language development. In these models, prediction error typically acts as a guide for  
117 learning; it offers a signal for when the learner should (or should not) revise their linguistic  
118 knowledge. For instance, Elman (1990; see also St. John & McClelland, 1990) introduced the idea  
119 that prediction error-driven learning could help a simple recurrent connectionist network acquire  
120 approximate linguistic representations: The network was trained to predict the next word in a large  
121 corpus of text and, when an encountered word mismatched its prediction, the model's internal  
122 representations were revised through backpropagation of error (Rumelhart, Hinton, & Williams,  
123 1986). These ideas have also been highly influential for newer models of grammatical development  
124 (e.g., Chang, Dell, & Bock, 2006; Dell & Chang, 2014) and word learning (Plaut and Kello (1999).  
125 In addition, related ideas about error-driven learning can be seen in models that use theories of  
126 reinforcement learning to explain language development. For instance, Ramscar, Yarlett, Dye,  
127 Denny, and Thorpe (2010) argued that a model based on the Rescorla-Wagner learning rule  
128 (Rescorla & Wagner, 1972) can capture how children acquire word meanings under conditions of  
129 referential uncertainty, because the computation of prediction errors allows the child to discriminate  
130 between the situations in which a word can or cannot be used (see also Ramscar, Dye, & McCauley,  
131 2013b). Thus, across all of these models, prediction errors guide children in forming linguistic  
132 representations that can accurately predict the linguistic input that they are likely to encounter.

133 In the PIMMS framework (described above), prediction errors also guide learning, but they  
134 do so by indexing how robustly the learner should encode a piece of encountered information into  
135 memory. Specifically, unexpected information (i.e., information that generates a larger prediction  
136 error) is encoded more strongly and thus can be retrieved more easily in the future. For the task of  
137 learning a word, this framework highlights that prediction errors could influence how learners

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138 remember and retain word meanings over longer periods of time. While this is not fundamentally  
139 different from the models reviewed above, in those models the focus is on how learners discover the  
140 meanings of words through experience (for examples see Ramscar et al., 2010; Grimmick,  
141 Gureckis, & Kachergis, 2019; Stevens, Gleitman, Trueswell, & Yang, 2017): Prediction errors  
142 generated by current input guide changes in linguistic representations and ensure that the system  
143 can accurately predict future input. The PIMMS framework instead focuses on prediction error's  
144 influence on retention of novel information in memory, which is the topic we address here, in both  
145 adults and children.

146         At least since Carey and Bartlett (1978), it has been recognised that young children can  
147 accurately retain word meanings in long-term memory, though exactly how much they are able to  
148 retain and under what conditions has been debated (e.g., Horst & Samuelson, 2008; Spiegel &  
149 Halberda, 2011; Vlach & Sandhofer, 2012; see Samuelson & McMurray, 2017, for review). In any  
150 case, to the extent that children do retain word meanings, this long-term retention appears to rely on  
151 domain-general memory mechanisms (Markson & Bloom, 1997, Vlach, 2019; Vlach & DeBrock,  
152 2017). For instance, children's ability to retain word meanings up to one month is roughly matched  
153 to their ability to retain non-linguistic factual information over the same length of time (Markson &  
154 Bloom, 1997; Vlach & Sandhofer, 2012), and their memory for word meanings is affected by  
155 factors that are known to influence memory for non-linguistic information, such as repetition and  
156 spacing (e.g., Sandhofer & Vlach, 2011) and sleep (e.g., Henderson, Weighall, Brown, & Gaskell,  
157 2012). While adults' retention rates for novel word meanings can be higher than children's, they are  
158 similarly matched to their retention rates for novel non-linguistic information (Markson & Bloom,  
159 1997; Sandhofer & Vlach, 2012).

160         Given these considerations, and the findings that prediction errors influence memory for  
161 non-linguistic information in adults, we might expect prediction error should also affect the  
162 retention of word meanings over time, such that retention accuracy is greater for words that are

163 learned in unexpected contexts. However, the prior evidence for this is actually somewhat unclear,  
164 as we review below.

165         **Adults.** We are not aware of any study that has tested how prediction error affects retention  
166 of newly-learnt word meanings in adults. However, a small number of studies do provide indirect  
167 evidence for a role of prediction error in adult word learning. Fitneva and Christiansen showed that  
168 adults perform better in a learning task when they encounter a greater proportion of word-referent  
169 mappings that are unexpected (Fitneva & Christiansen, 2011, 2017). Using a cross-situational  
170 learning paradigm, where novel words are repeatedly presented under situations of referential  
171 ambiguity (i.e., with multiple potential referents for each word; Yu & Smith, 2007), they exposed  
172 learners to word-referent mappings that were unexpected because they differed from those trained  
173 during an initial familiarization phase. Other mappings were instead expected, as they did not differ  
174 from those established during the familiarization phase. Strikingly, when the proportion of  
175 unexpected to expected mappings was higher, adult learners actually learned more compared to  
176 when the proportion of unexpected mappings was lower.

177         But while this finding may suggest that prediction error plays a role in adult word learning,  
178 it is unclear whether this interpretation is correct. According to a prediction error account,  
179 participants generated expectations about the words they were going to hear based on the mappings  
180 established during the familiarization phase and, the more often these expectations were then  
181 disconfirmed (because many mappings had changed), the more the resulting error signals benefitted  
182 learning of new word-referent pairings. But if this advantage stems from prediction errors, then it  
183 should be specific to the unexpected mappings – because it is only for these items that the learner  
184 should generate incorrect expectations. In contrast, Fitneva and Christiansen (2011, 2017) found  
185 that both unexpected and expected mappings were learned better when the proportion of unexpected  
186 mappings was higher, suggesting a very different explanation: The larger number of errors may  
187 have prompted participants to allocate more attentional resources to the task, and thus process all  
188 words and referents more deeply. However, since a recent study instead found that learning was



189 enhanced specifically for unexpected mappings (Grimmick et al., 2019), it remains possible that  
 190 prediction errors do play a role in adult word learning.

191 **Children.** More child studies are relevant to our question, but the picture that emerges from  
 192 them is also mixed. Two strands of work suggest that, far from driving learning, generating  
 193 incorrect expectations may hinder children’s processing of new information, with negative  
 194 consequences for their ability to learn this information. First, when Fitneva and Christansen (2017)  
 195 asked whether 4-year-olds’ word learning would benefit from encountering high proportions of  
 196 unexpected mappings (as in adults), they instead found that 4-year-olds learn better when the  
 197 proportion of unexpected mappings is lower. But since it is unclear whether the findings in adults  
 198 demonstrate a role for prediction error, it is also unclear whether the findings in children provide  
 199 evidence against it, for the same reason: The expectancy-driven effects were not item-specific.

200 Second, Benitez and colleagues showed that infants (Benitez & Smith, 2012) and 2-year-  
 201 olds (Benitez & Saffran, 2018) learn novel word-referent associations better when the associations  
 202 are demonstrated in predictable contexts, compared to unpredictable contexts. While this seems to  
 203 go against the idea that prediction error boosts learning, in this task predictability was manipulated  
 204 by having the referents appear in predictable or unpredictable spatial locations, but the association  
 205 between the words and their referents were not themselves more or less predictable. Therefore, the  
 206 prediction error signal may have enhanced memory, but for the location of the stimuli (which was  
 207 not tested), rather than for the word-referent association.

208 In contrast, other evidence suggests that disconfirmed expectations boost children’s  
 209 memory. First, Stahl and Feigenson (2017) showed that 3-to-6-year-olds are more likely to  
 210 remember a novel action word if the action it refers to is unexpected due to violations of physical  
 211 “core knowledge” (e.g., a bag “magically” changing the color of objects that are put inside it).  
 212 However, in the control condition where no expectation was violated (i.e., the object behaved  
 213 “normally”), children did not learn the novel word at all (they performed at chance), likely because  
 214 in this condition there was no salient action, and the very use of a novel word was thus

215 pragmatically infelicitous. This finding suggests that perhaps the unexpected action did not boost  
216 memory because it violated an expectation, but rather because it created the pragmatic conditions  
217 for use of a novel word. Moreover, actions that violate core knowledge are not just unexpected, but  
218 outright impossible, so this conclusion may not generalize to word learning in the wild.

219         Second, potential evidence that children learn from disconfirmed expectations comes from  
220 Reuter, Borovsky, and Lew-Williams's (2019) eye-tracking study. Three-to-five-year-olds heard  
221 novel words while observing two potential referents, one of which was a familiar object whose  
222 name was likely known to the child, while the other was a novel (and thus nameless) object. Infants  
223 as young as 16 months (Halberda, 2003; Horst & Samuelson, 2008) reliably map a novel word unto  
224 the novel object at first exposure under these conditions, following the so-called mutual exclusivity  
225 constraint. Crucially, Reuter and colleagues embedded the novel words within sentences, and  
226 manipulated the degree of semantic constraint of such sentences, so that they would provide either a  
227 strong expectation for the name of the familiar object (high constraint) or no strong expectation  
228 (low constraint). For example, a child looking at pictures of a spoon and a novel object should  
229 generate a strong expectation of *spoon* following *Yummy! Let's eat soup. I'll stir it with a...*,  
230 whereas following *Neat! Look over there. Take a look at the...*, no strong expectation for either  
231 object should be generated.

232         The child then heard a novel word (e.g., ...*cheem*) at the end of both high and low constraint  
233 sentences. As a result of the expectation-strength manipulation, the novel word disconfirmed a  
234 stronger prior expectation in the high than in the low constraint condition, thereby generating a  
235 larger prediction error signal in the former than the latter condition. Reuter and colleagues  
236 hypothesized that novel words associated with larger prediction errors should be better learnt, and  
237 used a preferential looking task to test this: They presented children with each novel word and two  
238 novel referents (the target, and a distractor that was the correct referent for a different novel word),  
239 and measured whether the child looked more at the correct referent than the distractor. Surprisingly,  
240 children's performance was at chance with words encountered after high-constraint sentence

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241 contexts (and instead above chance in the low constraint condition). This finding is difficult to  
242 reconcile with prediction error being the driver of children’s memory: If it were, children should  
243 have been more likely to gaze at the correct referent in the high than the low constraint condition,  
244 because novel words disconfirmed a stronger prior expectation in the former than the latter  
245 condition.

246         Nevertheless, Reuter et al. (2019) suggested that their findings support error-driven accounts  
247 of novel word learning because they also found a positive correlation between each child’s ability to  
248 revise following a disconfirmed prediction and their performance at test. Specifically, they  
249 computed a “predict-and-revise” looking measure, which was larger the more the child looked at  
250 the familiar object before hearing the novel word (i.e., the stronger their prior expectation) *and* the  
251 more they looked towards the novel object upon hearing the novel word (i.e., the faster they revised  
252 their prior expectation). They argued that a positive correlation between children’s “predict-and-  
253 revise” looking pattern during learning and the extent to which they preferentially looked at the  
254 target referent for the novel word at test was evidence that the revision of incorrect expectations  
255 was driving learning. But while this correlation was specific to novel words that were embedded in  
256 high-constraint sentences (i.e., no correlation was present for items that were presented at the end of  
257 low-constraint sentences), this interpretation is at odds with the lack of an overall memory  
258 advantage for words presented in the high-constraint condition.

259         Thus, we suggest an alternative interpretation is more likely: High-constraint sentences may  
260 have hampered memory by shifting attention away from the novel object, and only those children  
261 who were able to recover from this attentional shift would have learned the correct referent for the  
262 novel word. In contrast, low-constraint sentences did not reduce children’s preference for looking at  
263 the novel object, thus supporting memory regardless of individual differences in sentence  
264 processing ability. Importantly, under this interpretation, the relation between individual children’s  
265 learning and their sentence processing ability could be entirely explained by a common underlying

266 factor, such as processing speed, rather than being explained by a specific ability to predict-and-  
267 revise.

268         In sum, we do not know whether a prediction-error mechanism underlies the formation and  
269 consolidation of novel word-object associations: Theories of memory based on prediction error  
270 predict that adults and children should form stronger memory representations following the  
271 disconfirmation of stronger expectations, but the empirical evidence is inconclusive. There is  
272 evidence that children have weaker memories for novel words when they are encountered in  
273 unexpected contexts (Benitez & Smith, 2012; Benitez & Saffran, 2018), but also some suggestive  
274 evidence that strong but incorrect expectations may in fact be beneficial (Stahl & Feigenson, 2017;  
275 Reuter et al., 2019). In adults, no study has contrasted memory following a stronger than a weaker  
276 disconfirmed expectation.

277         Thus, our first question is whether adults acquire stronger memories for new word-object  
278 associations, if they are observed in the context of a violation of a stronger linguistic expectation.  
279 Since word learning is a lifelong process, our second question is whether the underlying  
280 mechanisms remain similar across the lifespan or whether they themselves develop, and therefore  
281 we also compare adult performance to that of 2-to-4-year-olds on the same learning task. If we find  
282 evidence that this effect emerges early in development, this would suggest that the computation of  
283 prediction errors plays a role in word learning from the early stages of language acquisition.

#### 284 **The current study**

285         Using a task similar to Reuter et al. (2019), we asked whether expectation strength affects  
286 the strength of memory representations for the mapping between a novel word and its referent.  
287 Importantly, we did so both for children (2-to-4-year-olds) and young adults (university students),  
288 so we could directly observe any developmental changes in the mechanisms used for word learning  
289 (unlike Reuter et al., who tested only children). While we disagree with Reuter et al.'s interpretation  
290 of their findings, note that we do not take issue with their design, and in fact we adopt a very similar  
291 design.

292 Reuter et al.'s (2019) design has two key strengths. First, it allows for a comparison between  
293 disconfirmed expectations that differ in strength (of the a priori expectation): This is an ideal  
294 comparison for testing the effect of prediction errors on subsequent memory (see Greve et al.,  
295 2017). In contrast, most previous studies (Stahl & Feigenson, 2017; Benitez & Smith, 2012; Benitez  
296 & Saffran, 2018) compared confirmed to disconfirmed predictions, which is problematic because  
297 these conditions do not just differ in the magnitude of the prediction error: When a prediction is  
298 disconfirmed, the predicted but not encountered word may linger in memory (Rommers &  
299 Federmeier, 2018), and potentially counteract the benefits of a larger prediction error on memory, if  
300 it interferes with encoding of observed word. Second, expectations strength is manipulated using  
301 sentence contexts (rather than artificially, by changing word-referent mappings mid-way through  
302 the experiment, as in Fitneva & Christiansen, 2011, 2017), thus providing a more ecologically valid  
303 test. We retained both of these aspects of Reuter et al.'s (2019) study, but our procedure did differ  
304 from theirs in some important respects, which we highlight below.

305 Like Reuter et al. (2019), we manipulated contextual constraint in order to vary expectation  
306 strength: Adult and child learners encountered novel words (e.g., *cheem*) embedded within  
307 sentences that were either more constraining (*Now, Peppa will eat the cheem*) or less constraining  
308 (*Now, Peppa will get the cheem*) with respect to the visual context. The visual context always  
309 consisted of two objects: a familiar object that fit the more constraining verb (e.g., an apple for *eat*)  
310 and an unfamiliar object (e.g., the jelly-like object in Figure 1). Since the younger children we  
311 tested were 2-year-olds (vs. 3-year-olds in Reuter et al., 2019), we took our constraining verbs from  
312 Mani and Huettig (2012), who showed evidence for prediction in 24-month-olds.

313 Based on the vast literature on linguistic prediction in adults and children, we expected  
314 listeners to generate a strong expectation that the familiar object would be mentioned following an  
315 High Constraint context – because Peppa is much more likely to eat the apple than the jelly-like  
316 object in Figure 1 (as we confirmed in a post-test; see Methods below). In contrast, following the  
317 Low Constraint context, listeners could generate only a weaker expectation (or no expectation at

318 all), because “Now, Peppa will get the...” is not as strongly predictive of “apple” as “Now, Peppa  
319 will eat the...” is.

320 In order to disconfirm listeners’ expectations, we relied on the presence of the unfamiliar  
321 object in the display (similarly to Reuter et al., 2019). Since even very young children prefer to map  
322 novel words onto unfamiliar (and thus nameless) objects when the alternative is a familiar object  
323 with a known name (i.e., they follow the mutual exclusivity constraint; Halberda, 2003), both  
324 children and adults should be biased to revise their expectations, and select the unfamiliar object as  
325 the referent of the novel word. This bias may not operate on 100% of trials, so sometimes  
326 participants may select the familiar object as a referent for the novel word. In such cases, it may be  
327 that participants noticed the novel word but chose to interpret it as a novel name for the familiar  
328 object (e.g., the name of a novel variety of apple), or it may be that they failed to notice the novel  
329 word (e.g., because they followed their expectations).

330 Because it is hard to discriminate between these two options, we conducted analyses that  
331 exclude such cases, and are restricted to instances in which participants selected the unfamiliar  
332 object explicitly, as in these cases we can be certain that they mapped the novel word onto the  
333 unfamiliar object. Crucially, while the occurrence of the novel word should disconfirm participants’  
334 expectations following both more and less constraining contexts, the magnitude of the resulting  
335 prediction error should be larger following more constraining contexts, where the strength of the  
336 prior expectation was higher. Compare Figures 1a and 1b for a graphical illustration of the  
337 processes at play during high and low constraint learning trials.

338 To test how memory depends upon processing during learning, we asked participants to  
339 select a referent for each novel word at test to probe retention of the novel mappings. Note that this  
340 task differs from the preferential looking measure used by Reuter et al. (2019), and it is a more  
341 explicit measure of memory. We chose this explicit measure because it is the one used in much  
342 research on the mutual exclusivity constraint. Studies that have tested 2-year-olds on similar tasks  
343 have shown that, even though children correctly map the novel word *cheem* to the unfamiliar object

344 on the fly, they often fail to retain the mapping established via mutual exclusivity in memory when  
345 tested at short (i.e., on the order of 5-10 minutes) retention intervals (e.g., Horst & Samuelson,  
346 2008; see Samuelson & McMurray, 2017 for review; but cf. Spiegel & Halberda, 2011). While this  
347 means we were expecting the youngest children to perform well below ceiling overall in our  
348 explicit memory test, it also provides an additional motivation for our study: If children initially  
349 encode novel words only weakly in memory after a first encounter, is it possible to strengthen such  
350 memory traces by encouraging them to generate linguistic expectations that will be later  
351 disconfirmed?

352         To summarize, we hypothesize that both adults and young children should be more likely to  
353 remember novel words that violate stronger, as opposed to weaker expectations. We test this  
354 hypothesis in 7 experiments (see Table 1 for an overview).

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369 Table 1. Overview of experiments. Please refer to the text for an explanation of the  
 370 differences between experiments.

Experiment	Participants	Aim	Manipulation	Testing modality / task during break	Context repetitions
1	40 adults	Power calculation	Verb constraint	Experimenter present / tapping, conversation with experimenter	1
2	40 adults	Power calculation	Verb constraint	Online / video + comprehension questions	2
3	58 adults	Replication of Exp. 1-2	Verb constraint	Online / video + comprehension questions	1
4	58 adults	Control experiment	Object distractor	Online / video + comprehension questions	1
5	65 adults	Replication of Exp. 4	Object distractor	Online / video + comprehension questions	1
6	80 children	Child version of Exp. 1-3	Verb constraint	Experimenter present / tapping	1
7	86 children	Child version of Exp. 4-5	Object distractor	Experimenter present / tapping	1

371

372 **Experiments 1-3: Verb-constrained prediction errors in adults**

373 While the paradigm was designed with children in mind, we first tested it on adult participants to  
 374 assess the robustness of the effect. We established this in three experiments, which differed  
 375 minimally in procedure. These differences are described below (and summarized in Table 1), but  
 376 since findings were consistent across experiments, here we present combined results. All materials,  
 377 data, and analyses scripts, including separate analyses and graphs for each experiment are available



378 at [https://osf.io/zvn6u/?view\\_only=ce8cc8f5432e41019498a98a2687982b](https://osf.io/zvn6u/?view_only=ce8cc8f5432e41019498a98a2687982b), see Additional analyses  
379 in the *analysis\_scripts* folder, section 1).

### 380 **Methods.**

381 **Participants.** Experiments 1 and 2 tested 40 adults each; this sample size was a rough estimate, and  
382 it was expected to yield around 80% power only with a large effect size ( $d=0.8$ ; Westfall, Kenny, &  
383 Judd, 2014). We then used a simulation approach to compute sample size (N) for subsequent  
384 studies. We did this through a bootstrapping approach: we repeatedly (1000 times) randomly  
385 sampled N adult participants, analyzed retention accuracy as reported below (Data Analysis), and  
386 extracted the z statistics associated with the effect of interest (i.e., the effect of sentence constraint).  
387 We defined power as the percentage of samples that yielded z equal to or greater than 1.645 - i.e.,  
388 the threshold for significance of a one-tailed test, as our prediction is directional: High Constraint  
389 contexts should lead to better memory than Low Constraint contexts. When this procedure was  
390 applied to data from Experiments 1 and 2, it indicated that 58 participants would achieve 95%  
391 power, so we recruited that many participants for a replication (Experiment 3). In total, 138  
392 University of Edinburgh students (32 male, age range: 17 to 31; 40 participants did not provide age  
393 information) took part across the three experiments, either for course credit or £2; 16 reported to be  
394 native speakers of a language other than English, but since this did not affect the results (see  
395 Additional analyses in the *analysis\_scripts* folder on the OSF, section 4), the analyses below  
396 disregard language status. The study received ethical approval from the University of Edinburgh.

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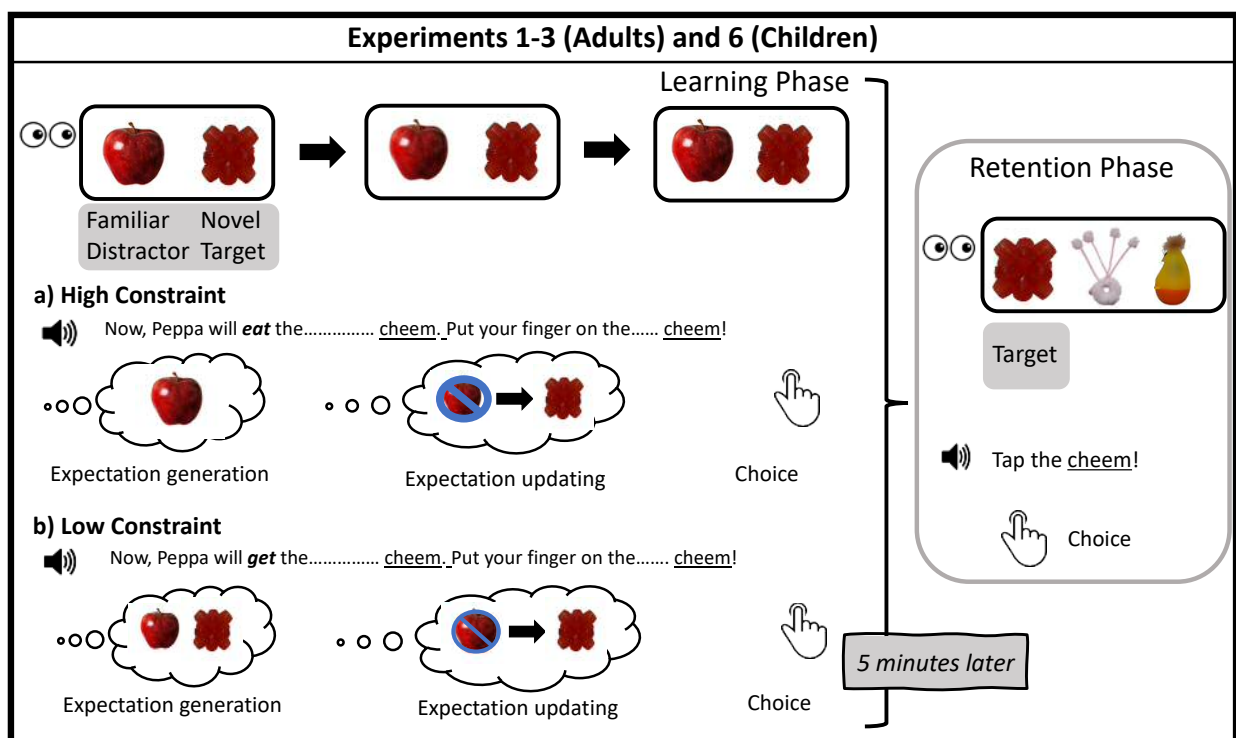
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PREDICTION ERROR AND WORD LEARNING

403 Figure 1. Schematic depiction of the experimental design in Experiments 1-3 and 6, including a  
 404 graphical illustration of the processes at play during different types of learning trials: a) High  
 405 Constraint trials, b) Low Constraint trials. Note that in (a) we conservatively assume no expectation  
 406 that the novel object will be named before the participant hears the novel word – this is because the  
 407 novel objects only had a loose fit with the constraining verb (e.g., the spiky red object in the figure  
 408 had a jelly-like consistency). We depict only learning trials on which participants choose the novel  
 409 object as the referent of the novel word.



410

411 **Materials and Procedure.** The experiments consisted of two phases (see Figure 1). In the learning  
 412 phase (top), participants completed 14 trials: Following two practice trials, 8 experimental trials  
 413 were randomly interspersed with 4 filler trials. All learning trials had the same structure.

414 Participants saw a picture of the cartoon character Peppa Pig centered on the top half of the screen.  
 415 On the bottom half of the screen, they saw photographs of a familiar and an unfamiliar object.

416 Participants began a trial by clicking or tapping on the picture of Peppa Pig, which triggered  
 417 a pre-recorded sentence. To test whether repetition helps participants revise a disconfirmed  
 418 expectation, in Experiment 2 adults heard two sentences, so the target word was always presented at

## PREDICTION ERROR AND WORD LEARNING

419 least twice. However, adults' performance in Experiment 2 did not differ from Experiment 1, where  
420 only one sentence was used. Thus, Experiment 3 and all other experiments reported here used only  
421 one sentence. Participants could listen to the sentence as many times as they wished by tapping on  
422 the top picture again.

423 Filler sentences were always high constraint and mentioned the predictable, familiar object  
424 (e.g., *Now, Peppa will rock the baby*) in order to encourage participants to predict familiar words.  
425 Crucially, on half the experimental trials participants listened to a High Constraint sentence (e.g.,  
426 *Now, Peppa will eat the*, when the familiar object was an apple), but on the other half they listened  
427 to a Low Constraint sentence (e.g., *Now, Peppa will get the*). This way we manipulated the degree  
428 to which participants expected to hear the name of the familiar object. Constraint was manipulated  
429 within participants and items, counterbalanced across two lists.

430 While filler sentences always ended with the name of the familiar object, experimental  
431 sentences ended with one of 8 novel pseudowords (*cheem, dite, doop, fode, foo, pabe, roke* and  
432 *yok*), mostly drawn from Horst and Samuelson (2008). After the sentence, learners heard an  
433 instruction (e.g., *Put your finger on the cheem!*) asking them to select the object corresponding to  
434 the final word in the sentence. Unfamiliar objects were selected from Horst and Hout's (2016)  
435 NOUN database; familiarity and nameability were kept as low as possible, but such that the novel  
436 objects would always match the constraint of the verb in High Constraint sentences (e.g., the object  
437 paired with *eat* had to look edible). A post-test with 20 adults (7 males, 22 to 61 years of age)  
438 recruited from the online platform CloudFlower confirmed that novel objects were a better fit for  
439 the constraining verbs they were paired with ( $M = 3.08$  on a 1-to-7 Likert scale), than for another  
440 (randomly selected) constraining verb ( $M = 2.19$ ,  $t(19) = 4.12$ ,  $p < .001$ ). The same post-test showed  
441 that, unsurprisingly, familiar objects were a better fit for the constraining verbs ( $M = 6.10$ )  
442 compared to the unfamiliar objects ( $M = 3.08$ ) they were paired with ( $t(19) = 7.85$ ,  $p < .001$ ). We  
443 return to this issue below as it was part of the motivation for conducting Experiments 4 and 5.

## PREDICTION ERROR AND WORD LEARNING

444           Following completion of the learning phase, participants took a short (approximately 5-  
445 minute-long) break. What happened during the break depended on whether the experiment was  
446 conducted in the lab or online. Participants in Experiment 1 were tested in the lab and, during the  
447 break, they first tapped on a series of cartoon characters (this task was designed for children, and is  
448 described in more detail below, as it was also used in Experiments 6 and 7); since they completed  
449 this task quite quickly, for the remaining time they engaged in a conversation with the experimenter  
450 about their studies. Participants in Experiments 2 and 3 completed the study online and, during the  
451 break, they were asked to watch a short video from an episode of Peppa Pig and answer four  
452 comprehension questions (to ensure they were paying attention).

453           Immediately after the break, all participants completed 8 trials in the retention phase (bottom  
454 of Figure 1). On each retention trial, they again tapped on the picture of the cartoon character Peppa  
455 Pig (top of the screen) and then heard an instruction to select the object corresponding to one of the  
456 novel words (e.g., *Tap the cheem!*), while they observed three randomly-ordered pictures at the  
457 bottom of the screen: the unfamiliar target object (the one that had appeared on the learning trial the  
458 novel word was used on) and two other unfamiliar objects, which served as distractors. Of these,  
459 one was a target object from a different trial, while the other had been also encountered by  
460 participants in the learning phase, but on a filler trial, and had therefore not been named (see  
461 Additional analyses in the *analysis\_scripts* folder on the OSF, section 5, for a breakdown of  
462 participants' errors by distractor type). Across retention trials, each unfamiliar target object  
463 appeared twice (once as target, once as distractor) and each unfamiliar filler object also appeared  
464 twice (always as a distractor, but paired with two different target words). Participants never  
465 received any feedback about the accuracy of their choices. When pairing target objects with  
466 distractors, we made sure that the average pairwise dissimilarity of the three objects was  
467 comparable across trials (Mean = 0.8173, SD = 0.098, range [0.6490, 0.9624]; ratings from Horst  
468 and Hout, 2016).

469 All spoken instructions were recorded by a female native speaker of Scottish English with  
470 child-directed prosody. Target words were recorded separately and combined with the spoken  
471 contexts online, so that we could fully randomize object-word pairings for each participant. Trial  
472 order was also randomized separately for each participant and each phase of the experiment.  
473 Participants first completed the learning phase for all items and then completed the retention phase  
474 (i.e., learning and retention were fully blocked, with no interleaving) The task was custom-coded in  
475 HTML and Javascript. An OSF link to the code is available upon request: Since some of the visual  
476 stimuli are protected by copyright, we are unfortunately unable to make all materials publicly  
477 available.

478 **Data Analysis and Results.**

479 **Data analysis.** We analyzed participants' choices on learning trials (i.e., choosing the novel vs.  
480 familiar object) and their accuracy on retention trials as a function of Constraint. For the retention  
481 trials, accuracy was coded in terms of whether participants were able to retain the pairing of the  
482 novel label with the novel object, regardless of whether they had chosen the novel object or the  
483 familiar distractor during the learning phase. Additional analyses of retention accuracy controlled  
484 for the choice made on the corresponding learning trial (Choice-at-learning) and were followed up  
485 with separate analyses of retention trials for which the novel object had been chosen (Novel) on the  
486 corresponding learning trial, and retention trials for which the familiar object had been chosen  
487 during learning (Familiar) to check how previous referential choices affected retention. Fixed  
488 effects were contrast coded and centered.

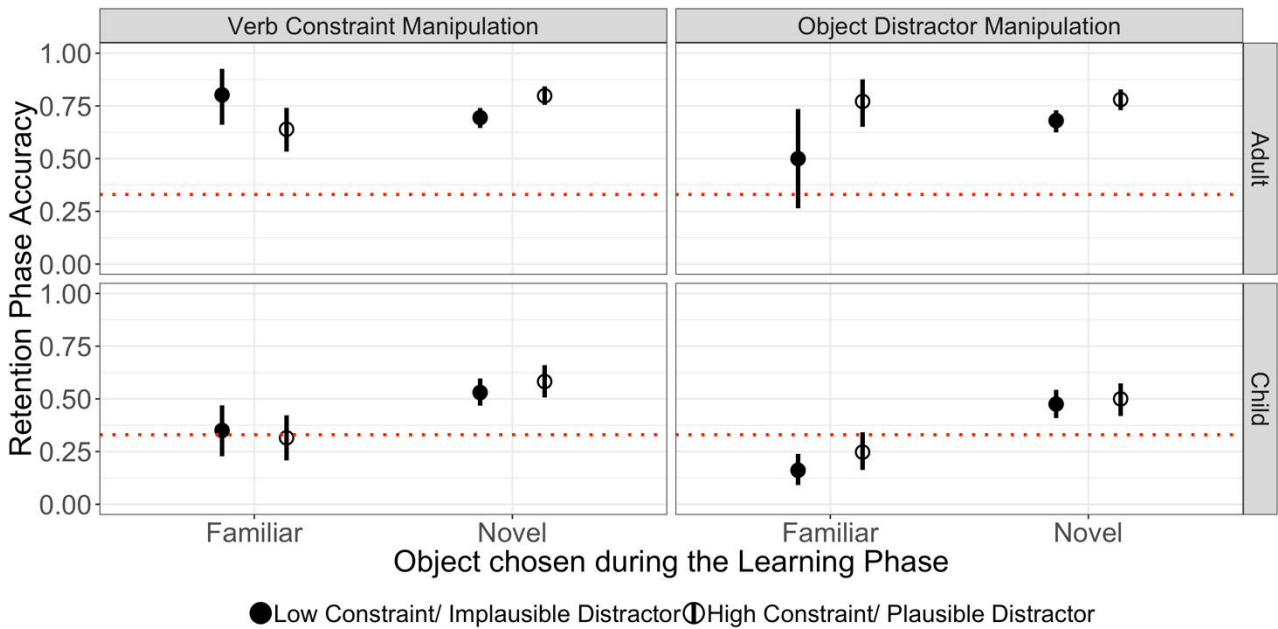
489 Since we combined data for three experiments, Experiment was added as an additional  
490 factor with three levels and contrast coded; the first contrast compared performance in Experiment  
491 1, which took place in the lab, to performance in the two online experiments (2 and 3), while the  
492 second contrast compared performance in Experiment 2 to Experiment 3. The models included  
493 interactions between these two contrasts and the fixed effect of interest (Constraint); for analyses of  
494 retention accuracy, we initially also included interactions between the Experiment contrasts and

495 Choice-at-learning, but these more complex models did not converge. All analyses used generalized  
496 linear mixed effects models with a logistic link function (function *glmer* from the *lme4* package;  
497 Bates, Maechler, Bolker, & Walker, 2015) in R (R, Version 3.5.1). Random effects structure was  
498 kept maximal, unless (1) correlations between random effects and/or (2) higher-order random  
499 slopes had to be dropped to aid convergence (full model specifications available in the Analysis  
500 Summary within the *analysis\_scripts* folder, section 1, at the OSF link). Instead of *p* values, we  
501 report 95% confidence intervals for model estimates from the *confint* function (method="Wald").  
502 **Results.** To maximize power, we report a combined analysis of data from all three adult  
503 experiments, but findings were highly consistent across all experiments (see Additional analyses in  
504 the *analysis\_scripts* folder, section 1, on the OSF for separate analyses for Experiments 1, 2 and 3),  
505 and there were no significant differences between Experiments (either as main effects or  
506 interactions with Constraint) in any of the analyses reported below (see Analysis Summary in the  
507 *analysis\_scripts* folder, section 1, on the OSF). Importantly, the planned replication (Experiment 3)  
508 was successful ( $z = 1.65$ ). Descriptive statistics for these and subsequent experiments are provided  
509 in Table 2.

510 Accuracy on filler trials was 100%. During learning, adults were more likely to (correctly)  
511 select the novel object on low constraint (92%) than high constraint trials (81%); this difference was  
512 significant: log-odds  $B = -1.59$ ,  $SE = 0.26$ ,  $z = -6.23$ ,  $CI = [-2.53, -1.09]$ . Conversely, on retention  
513 trials, adults were more accurate for novel word-object pairs they had encountered on High  
514 Constraint trials during the learning phase (76%) than on those they had encountered on Low  
515 Constraint trials (69%); log-odds  $B = 0.39$ ,  $SE = 0.15$ ,  $z = 2.65$ ,  $CI = [0.10, 0.67]$ ; see Figure 2, top  
516 left. This pattern was qualified by an interaction between Constraint and Choice-at-learning (log-  
517 odds  $B = 1.38$ ,  $SE = 0.49$ ,  $z = 2.81$ ,  $CI = [0.42, 2.33]$ ), which indicated that it was driven by novel  
518 (i.e., "correct") learning trials; log-odds  $B = 0.66$ ,  $SE = 0.17$ ,  $z = 3.98$ ,  $CI = [0.34, 0.98]$ . In contrast,  
519 retention of familiar (i.e., "inaccurate") learning trials tended to be worse for High Constraint items,  
520 but this pattern was not reliable;  $CI = [-1.68, 0.07]$ .

PREDICTION ERROR AND WORD LEARNING

521 Figure 2. Retention accuracy (%) as a function of Verb Constraint (left) or type of Object Distractor  
 522 (right) and of the referent chosen during learning (Familiar vs. Novel). The top panels report data  
 523 from the adult experiments (Verb Constraint: Experiments 1-3; Object Distractor: Experiments 4-  
 524 5), while the bottom panels report the child data (Verb Constraint: Experiment 6; Object Distractor:  
 525 Experiment 7). Conditions where weaker expectations were violated are represented by a filled  
 526 circle, while conditions where stronger expectations were violated are represented by an empty  
 527 circle. The error bars represent 95% bootstrap CI's (1000 samples) over subjects. The dashed  
 528 horizontal lines represent chance performance (33%).



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539 Table 2. Descriptive statistics for all experiments.

Experiment		1-3	4-5	6	7
% Filler accuracy		100	>99	>99	96
(learning phase)					
% Novel object choices	High Constraint/ Plausible	81	86	66	63
(learning phase)	Distractor trials				
	Low Constraint/Implausible	92	96	77	69
	Distractor trials				
% Retention accuracy	High Constraint/ Plausible	80	79	57	50
(novel trials)	Distractor trials				
	Low Constraint/Implausible	69	68	52	49
	Distractor trials				
% Retention accuracy	High Constraint/ Plausible	61	73	30	25
(familiar trials)	Distractor trials				
	Low Constraint/Implausible	78	48	35	20
	Distractor trials				

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541

542 **Discussion.**

543         In accord with prediction error-based theories of memory (Henson & Gagnepain, 2010),  
 544 adults were more likely to retain a newly formed association between a word and its referent when  
 545 that association disconfirmed a stronger expectation compared to a weaker one. Importantly, this is  
 546 not merely a novelty effect: Pseudowords and unfamiliar objects were equally novel for participants  
 547 across High and Low Constraint contexts. Critically, what changed was the strength of the prior  
 548 expectations generated by the verbs.



## PREDICTION ERROR AND WORD LEARNING

549           However, adults were also much more likely to disregard mutual exclusivity when the  
550 constraint was High rather than Low (e.g., picking a picture of an apple as the referent for *cheem*  
551 more often after *eat* than *get*). This may suggest that, when contextual support is strong, adult word  
552 learners may be more likely to infer that a novel word is a synonym for a highly expected familiar  
553 word (e.g., *cheem* is a synonym for *apple*, or perhaps a type of apple). While this finding is  
554 interesting in itself, and in line with previous evidence about adults' learning of novel word  
555 meanings from context (Borovsky et al., 2010), it also means that we may have underestimated the  
556 benefit of disconfirming strong expectations: Since familiar target objects were a much better fit  
557 than unfamiliar objects after High Constraint contexts, adult learners may have found it more  
558 difficult to revise their expectations following such contexts. Thus, we devised a second version of  
559 the task where new unfamiliar objects were selected to better fit the High Constraint verbs.

560           Importantly, the new version also addressed a potential confound. Given that High and Low  
561 Constraint conditions used different verbs, and that constraining verbs tend to be semantically  
562 richer, it is possible that adult learners performed better in the High Constraint condition simply  
563 because they could build richer and more distinctive representations for the word meanings,  
564 providing more cues for retrieving information from memory. In the new version we therefore kept  
565 sentential contexts constant and manipulated expectations by varying the plausibility of the familiar  
566 object distractor instead.

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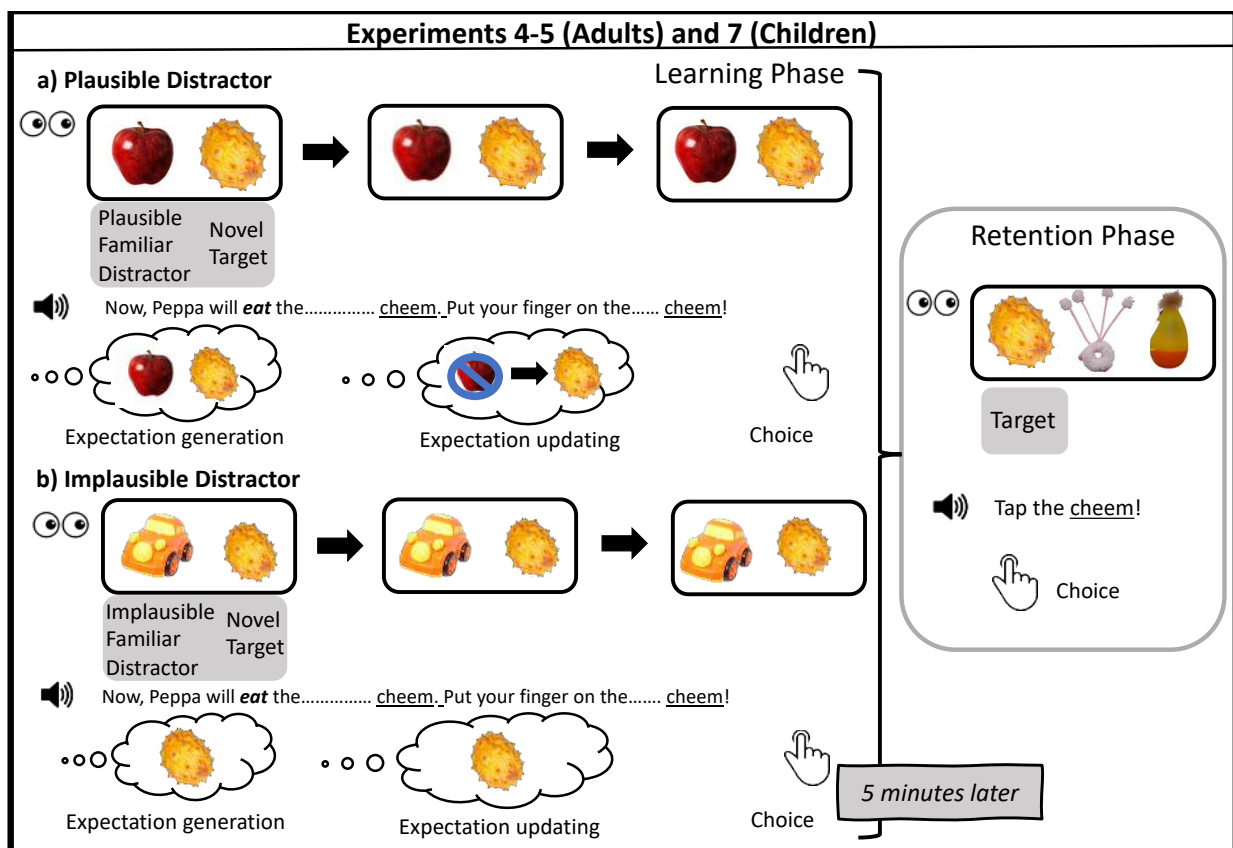
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576 Figure 3. Schematic depiction of the experimental design and graphical illustration of the processes  
 577 at play during different types of learning trials in Experiments 4-5 and 7; a) Plausible Distractor  
 578 trials, b) Implausible Distractor trials. Note that in (a) the strength of the expectation is larger for the  
 579 plausible familiar distractor (apple) than the novel object (exotic fruit), but there is some  
 580 expectation for the latter to be named – this reflects the findings from our post-test: The novel  
 581 objects used in Experiments 4-5 and 7 were less of a good fit for the constraining verbs compared to  
 582 the familiar objects, but they were also a better fit compared to the novel objects used in  
 583 Experiments 1-3 and 6 (cf. Figure 1). In (b) the expectation updating step confirms the expectation  
 584 generated initially (i.e., that the novel object will be named). We depict only learning trials on  
 585 which participants choose the novel object as the referent of the novel word.



586

587 **Experiments 4 and 5: Generating prediction errors using plausible distractor objects in adults**

588

These experiments were closely modelled on Experiments 1-3 but with two key

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modifications. First, we replaced all unfamiliar objects with objects that, while still unfamiliar,

## PREDICTION ERROR AND WORD LEARNING

590 would better fit constraining verbs. For example, the target for *eat* was now an exotic fruit (see  
591 Figure 3; a full list of materials is available in *the materials&lists* folder on the OSF). An additional  
592 20 adults (6 male, 19 to 57 years of age), who participated in a similar post-test to the one  
593 mentioned above, rated the new unfamiliar objects as more likely to undergo the actions referred to  
594 by the constraining verbs ( $M=4.91$ ), compared to the unfamiliar objects used in Experiments 1-3 ( $M$   
595  $= 3.08$ ,  $t(34.72) = 5.40$ ,  $p < .001$ ).

596 Secondly, learners were exposed only to semantically rich verbs (the constraining verbs  
597 from Experiments 1-3). Rather than manipulating expectations by varying the verb, we instead  
598 paired the same constraining verb (e.g., *eat*) either with a familiar object that fit its constraint (e.g.,  
599 apple, as in Experiments 1-3) or with a different familiar object (e.g., car), which was implausible  
600 given the verb (see Figure 3b). Thus, if semantic richness was responsible for the memory boost we  
601 observed previously, we should now find no difference in retention accuracy using this design.  
602 However, if the memory boost was driven by disconfirmed expectations, then we should find better  
603 retention accuracy for trials with plausible than implausible familiar object distractors.

604 Implausible distractors should facilitate mapping of the novel word onto the correct,  
605 unfamiliar target, even before the novel word is heard, so they should make it less likely that  
606 participants will have their expectations disconfirmed (see Figure 3b); in other words, on  
607 implausible distractor trials both the sentence context and the mutual exclusivity constraint should  
608 bias participants to map the novel word onto the unfamiliar object. In contrast, on plausible  
609 distractor trials, participants should still generate a strong expectation that the plausible familiar  
610 distractors will be named (just as on high constraint trials in Experiments 1-3); in addition, they  
611 may generate a weaker expectation that the unfamiliar object will be named (as this also fits the  
612 constraint of the verb, though not as well as the familiar object). In any case, the occurrence of the  
613 novel word should disconfirm the stronger expectation for the familiar distractor to be named,  
614 generating prediction error (see Figure 3a).

615 **Participants.**

## PREDICTION ERROR AND WORD LEARNING

616 One hundred and twenty-three adult participants took part online. Fifty-eight of these were students  
617 from the University of Edinburgh (14 male, age range: 18 to 22, one participant did not provide age  
618 information), who took part in Experiment 4. The remaining 65 participants were students from  
619 Cardiff University (11 male, age range: 19 to 22, two participants did not provide age information)  
620 and they took part in Experiment 5; two participants only completed the learning phase, so analyses  
621 of retention accuracy are based on a sample size of 63 participants. Across the two experiments,  
622 eleven participants were native speakers of a language other than English (6 in Experiment 4, 5 in  
623 Experiment 5).

### 624 **Methods.**

625 The procedure was identical to Experiment 3. The design and materials were similar except for the  
626 modifications described above: New unfamiliar target objects were chosen that provided a better fit  
627 to the constraining verbs, and only sentences with constraining verbs were used, as we instead  
628 varied the identity of the familiar distractor object, which could either be a good fit for the verb  
629 (e.g., *apple* for *eat*; Plausible Distractor) or not (e.g., *car* for *eat*; Implausible Distractor).

630 Experiment 4 and 5 were almost identical replications of each other, with only a minor  
631 variation in the assignment of items to conditions across the two experimental lists. We used two  
632 lists in order to counterbalance the assignment of items to conditions (Plausible vs. Implausible  
633 Distractor). While analyzing Experiment 4 data, we noticed that for a subset of the items, adults  
634 were particularly likely to select the incorrect (familiar) distractor as the referent for the novel word  
635 in the Plausible Distractor condition (but not in the Implausible Distractor condition), and these  
636 items happened to cluster together in the counterbalancing (i.e., they all appeared in the Plausible  
637 Distractor condition in the same list). As a result, one list led to fewer novel object selections during  
638 the learning phase on Plausible Distractor than Implausible Distractor trials (88% vs. 99% Novel  
639 choices), while the other did not (98% vs. 96% Novel choices). Since we were concerned this may  
640 affect the results, we re-distributed item versions across lists before running Experiment 5. Lists for  
641 both experiments are available in the *materials&lists* folder on the OSF.

**642 Results and Discussion.**

643 Since the two experiments yielded comparable findings, here we report combined analyses to  
644 maximize power. Again, Experiment (contrast coded) and its interactions with the predictors of  
645 interest (Distractor and Choice-at-Learning) were added to all models, and again there were no  
646 significant differences between experiments, and there were no interactions modulating any of the  
647 effects reported below. For separate analyses for each experiment, see Additional analyses in the  
648 *analysis\_scripts* folder, section 2, on the OSF. Accuracy on filler trials was higher than 99%.  
649 During learning, adults were more likely to (correctly) select the target when the familiar distractor  
650 was implausible (96%) compared to when it was a good fit (86%), though this difference was only  
651 marginal; log-odds  $B = -1.84$ ,  $SE = 1.10$ ,  $z = -1.68$ ,  $CI = [-3.99, 0.31]$ .

652 Most importantly, adult learners performed better at retention when their expectations had  
653 been disconfirmed during learning (78%) than when they had not (67%); log-odds  $B = 0.61$ ,  $SE =$   
654  $0.19$ ,  $z = 3.43$ ,  $CI = [0.26, 0.96]$  (and this pattern did not depend on their choice during learning;  $CI$   
655  $= [-2.22, 0.49]$ ); see Figure 2, top right. Thus, disconfirmed expectations can enhance memory for  
656 novel words, and it is unlikely that the findings from Experiments 1-3 were only due to differences  
657 in semantic richness between verbs.

**658 Experiments 6-7: Children**

659 Having established that adults' memory for novel word-object associations is boosted by larger  
660 prediction errors, we tested whether children would show similar effects using both the original  
661 design (i.e., manipulating verb constraint as in Experiments 1-3) and the modified design (i.e.,  
662 manipulating the distractor object as in Experiments 4-5).

**663 Methods.**

664 **Participants.** A refined power calculation based on data from Experiment 1-3 (total  $N = 138$ )  
665 suggested that we may have overestimated the size of the effect in adults. This refined power  
666 analysis indicated that a sample size of  $N=80$  would achieve 83% power, so we aimed to recruit at

667 least 80 children per experiment. The final sample sizes were 80 in Experiment 6 and 86 in  
668 Experiment 7.

669 We had originally planned to test 2- and 3-year-olds because this age range sits at the  
670 intersection between research on mutual exclusivity (e.g., Horst & Samuelson, 2008) and on  
671 linguistic prediction (Borovsky et al., 2012; Mani & Huettig, 2012), but a few 4-year-olds were  
672 included (10 in Experiment 6, 13 in Experiment 7) due to recruitment constraints; additional  
673 analyses including the child's age in months did not reveal any age-related differences (see  
674 Additional analyses in the analysis-scripts folder, section 3, on the OSF), so below we report  
675 analyses that collapse across all ages. Children in Experiment 6 ( $M_{\text{age}} = 38$  months, range = 25-56  
676 months; 45 males, 35 females) were recruited from nurseries in the Edinburgh area, Edinburgh Zoo,  
677 a local library, and from a database of families interested in research; children in Experiment 7  
678 ( $M_{\text{age}} = 38$  months, range = 24-59 months; 43 males, 43 females) were recruited from nurseries in  
679 and around Cardiff, Techniquet (a science museum in Cardiff), from a database of families  
680 interested in research, or through personal contacts. Written informed consent was obtained from all  
681 caregivers and verbal assent from all children. All participants were exposed to English as one of  
682 their home languages or at nursery, and some were exposed to at least one additional language (15  
683 in Experiment 6, 16 in Experiment 7). Children who grow up bilingual may follow the mutual  
684 exclusivity principle to a lesser extent than monolingual children (Byers-Heinlein & Werker, 2009),  
685 so we added language background as a covariate in preliminary analyses. Since no differences were  
686 found in these preliminary analyses, below we report analyses collapsing across number of  
687 languages; note that in Byers-Heinlein and Werker (2009) the largest differences were observed  
688 between monolingual and trilingual children and there were only two trilingual children in our  
689 sample.

690 **Procedure.** The procedure was as similar as possible to the adult one. Children completed the task  
691 on a touch-screen tablet. Although they were allowed to pace the task for themselves, the  
692 experimenter monitored them closely to make sure they were paying attention to the spoken

693 instructions and, in case they appeared distracted, encouraged them to listen to the instructions  
694 again. During the break between the learning phase and the retention phase of the experiment,  
695 children completed a series of three tapping games involving known cartoon characters (as in  
696 Experiment 1); in each game, their task was to find the character named by the experimenter and  
697 “turn it” into a green tick mark by tapping on it with their finger. Experiment 6 used the same lists  
698 as Experiments 1-3 and Experiment 7 used the same lists as Experiment 4.

### 699 **Results.**

700 Children’s accuracy on filler trials was high (Exp. 6: >99%, Exp. 7: 96%). Like adults,  
701 children were more likely to (correctly) select the novel object on Low Constraint than High  
702 Constraint trials; Exp. 6: 77% vs. 66%); log-odds  $B = -0.59$ ,  $SE = 0.25$ ,  $z = -2.33$ ,  $CI = [-1.08,-$   
703  $0.09]$ . Numerically, they were also more likely to select the novel object when the familiar  
704 distractor was implausible; Exp. 7: 69% vs. 63%), but this difference was not reliable;  $CI = [-$   
705  $0.67,0.10]$ .

706 In contrast to the adult findings, children’s retention of the novel word-object mappings was  
707 unaffected by the expectations they had generated during learning (see Figure 2, bottom panels). In  
708 Experiment 6, they were as accurate for pairs they had encountered on High (48%) or Low  
709 Constraint (48%) trials;  $CI = [-0.35,0.30]$ . In Experiment 7, they were similarly accurate regardless  
710 of whether the familiar distractor fit the verb well (41%) or was implausible (40%);  $CI = [-$   
711  $0.26,0.36]$ . These findings held even when we restricted the analysis to items for which children had  
712 chosen the novel referent during the learning phase (Experiment 6:  $CI = [-0.18,0.60]$ , Experiment 7:  
713  $CI = [-0.32,0.45]$ ).

714 Retention accuracy was much higher when children had (correctly) selected the novel object  
715 during learning, than when they had not (Exp. 6: 55% vs. 32%; Exp. 7: 50% vs. 23%); Experiment  
716 6: log-odds  $B = 1.10$ ,  $SE = 0.27$ ,  $z = 4.01$ ,  $CI = [0.56,1.63]$ ; Experiment 7: log-odds  $B = 1.33$ ,  $SE =$   
717  $0.21$ ,  $z = 6.44$ ,  $CI = [0.92,1.73]$ . However, choice at learning did not interact with our  
718 manipulations.

## PREDICTION ERROR AND WORD LEARNING

719 While we set our sample size for each study using power analyses, these were based on adult  
720 data, which are likely less variable than children's. However, combined analyses of data from both  
721 Experiment 6 and 7 found no evidence for an effect of expectation strength on retention accuracy  
722 (log-odds  $B = 0.10$ ,  $SE = 0.13$ ,  $z = 0.79$ ,  $CI = [-0.15, 0.35]$ ), despite their increased power. There  
723 was also no indication that performance improved within the age range tested (log-odds  $B = -0.001$ ,  
724  $SE = 0.007$ ,  $z = -0.09$ ,  $CI = [-0.015, 0.014]$ ), nor that the size of the expectation strength effect was  
725 larger for older children (log-odds  $B = 0.01$ ,  $SE = 0.02$ ,  $z = 0.99$ ,  $CI = [-0.01, 0.04]$ ; see Additional  
726 analyses in the *analysis\_scripts* folder, section 3, on the OSF).

727 Follow-up analyses combining data from all 7 experiments showed that, overall, adults'  
728 choices at learning were affected by the strength prior expectations more than children's (log-odds  
729  $B = -0.94$ ,  $SE = 0.23$ ,  $z = -4.04$ ,  $CI = [-1.40, -0.48]$ ). Importantly, these analyses also confirmed that  
730 adults' retention performance was affected by the strength prior expectations more than children's  
731 (log-odds  $B = 0.39$ ,  $SE = 0.18$ ,  $z = 2.18$ ,  $CI = [0.04, 0.75]$ ).

732

### 733 Discussion

734 Unlike for adults, prediction errors did not enhance children's memory for word-referent  
735 associations. This was despite clear evidence that children can generate expectations based on the  
736 constraint of verbs even at age 2 (Mani & Huettig, 2012; recall that all of our constraining verbs  
737 were English translations of stimuli in Mani and Huettig's German study). Moreover, children  
738 clearly demonstrated sensitivity to the constraint manipulation in Experiment 6: Like adults, they  
739 were much more likely to disregard mutual exclusivity when constraint was High (i.e., picking the  
740 apple as the referent more often after *eat* than *get*), though their choices at learning were less  
741 sensitive than adults' to the strength of prior expectations. Finally, although children's memory  
742 performance was (unsurprisingly) lower than adults', it was still above chance, which suggests that,  
743 although the task was difficult, children still encoded significant amounts of information during the



744 learning phase. Thus, our results cannot be explained by a floor effect. They suggest that prediction  
 745 errors play a surprisingly small role in how children encode word meanings.

746 Moreover, as we discuss below, other aspects of these data may be informative for models  
 747 of children’s word learning. Children were strongly affected by their choices during learning: In  
 748 fact, while their retention was above chance-level (33% in this task) for words they had (correctly)  
 749 mapped onto the novel referent during learning, it was at chance for words they had instead mapped  
 750 onto the familiar referent. This suggests that children had only tracked one potential word-referent  
 751 mapping during this task (Stevens et al., 2017; Trueswell, Medina, Hafri, & Gleitman, 2013). We  
 752 return to this point in the General Discussion. Finally, while Horst and Samuelson (2008) found no  
 753 evidence for retention in 24-month-olds, we showed that children aged between 2 and 4 years were  
 754 able to retain the new word-referent mappings at above-chance levels over at least a 5-minute  
 755 period. This could suggest that children’s retention abilities improve dramatically during the second  
 756 year of life, but note another important difference between our design and Horst and Samuelson’s:  
 757 We presented the novel words in informationally rich, high constraint sentential contexts (e.g. ...*eat*  
 758 *the cheem*), which may have facilitated more robust encoding of the word-referent mappings,  
 759 whereas they used only low constraint contexts (e.g., *get the cheem!*).

760

### 761 **General Discussion**

762 Can a prediction-error mechanism explain how adults and children encode associations  
 763 between novel word forms and their meanings? The evidence around this important question is  
 764 surprisingly mixed and, despite considerable evidence that both adults and children can process  
 765 language predictively, the role of prediction in the creation of new linguistic representations  
 766 remains poorly understood. In the introduction, we argued that a key hypothesis of error-driven  
 767 accounts of memory formation is that the disconfirmation of expectations should enhance memory  
 768 for the unexpected information and, importantly, the more so the stronger the initial expectation. In  
 769 this study, we tested this prediction in both 2-to-4-year-olds (2 experiments, combined N = 166)

770 and young adults (5 experiments, combined N = 259). Below, we summarize our findings and then  
771 discuss their implications for our understanding of the mechanisms that support word learning and  
772 their development.

773         There are two key findings. First, young adults are more likely to remember a novel word-  
774 object association that has disconfirmed a stronger, compared to a weaker, expectation. We  
775 established this finding (Experiments 1 and 2), directly replicated it (Experiment 3), and showed  
776 that it still held when we modulated expectation strength through visual rather than linguistic  
777 context (Experiments 4 and 5). Second, and in contrast to the adult findings, 2-to-4-year-olds'  
778 memory was not enhanced by violations of stronger, compared to weaker expectations  
779 (Experiments 6 and 7). This was despite the fact that children clearly generated linguistic  
780 expectations: These expectations were strong enough to affect their referential choices (i.e.,  
781 choosing the familiar object more often when it was more expected). Moreover, these expectations  
782 also had an indirect effect on memory: When children failed to revise during the learning phrase,  
783 they retained nothing about the novel objects and associated labels for the test phase. But when  
784 words were mapped to novel objects during learning, expectation strength did not affect children's  
785 retention.

786

787 **Prediction error shapes the encoding of linguistic information in adult memory: Implications**  
788 **for models of word learning.**

789         Our adult findings clearly show that linguistic expectations shape the encoding of the link  
790 between novel words and their meanings in memory, and can thus be viewed as an extension of the  
791 PIMMS framework for memory (Henson & Gagnepain, 2010; Greve et al., 2017) to *linguistic*  
792 representations. Importantly, these findings also have far-reaching consequences for computational  
793 models of word learning. Such models have implemented a variety of different mechanisms, from  
794 associative (i.e., Hebbian) learning (e.g., Kachergis, Yu, & Shiffrin, 2012; McMurray, Horst, &  
795 Samuelson, 2012; Yu, Smith, Klein, & Shiffrin, 2007) to Bayesian inference (e.g., Xu &

796 Tenenbaum, 2007; Frank, Goodman, & Tenenbaum, 2009), from hypothesis testing (e.g., Stevens et  
797 al., 2017; Trueswell et al., 2013; Yu et al., 2007) to the application to semantic-interpretation rules  
798 (e.g., Siskind, 1996). However, with a few exceptions (Plaut & Kello, 1999; Ramsar et al. 2010;  
799 Grimmick et al., 2019; Stevens et al., 2017), such mechanisms have not included error-driven  
800 learning.

801         An error-driven learning mechanism is one that updates the current state of the model based  
802 on the discrepancy between expected and observed inputs. By doing so, it can account for the role  
803 played by prior expectations in learning: In our study, generating a stronger, but incorrect, prior  
804 expectation led to the creation of a stronger memory trace for the correct word picture-mapping  
805 (once the initial expectation was revised), suggesting that the generation of incorrect expectations  
806 may benefit word learning. It is useful to contrast this with associative (Hebbian) learning: In its  
807 simplest form, an associative word learner tracks the co-occurrences between words and referents,  
808 augmenting the strength of the association between a word and a referent every time they co-occur  
809 (e.g., Yu et al., 2007). More sophisticated associative models include parameters that let the  
810 strength of associations decay over time, and can also model attention – that is, the fact that not all  
811 possible word-referent associations are processed and stored equally (e.g., Kachergis et al., 2012).

812         However, associative models cannot straightforwardly account for the fact that association  
813 strength depends on prior expectations. Recall that Grimmick et al. (2019) recently showed that  
814 training adults on one set of word-referent mappings in a cross-situational learning paradigm, and  
815 then changing the mappings, led to better memory performance for the items that had been changed  
816 (i.e., initially incorrect items) than for those that had not. We argued that Grimmick et al.’s finding  
817 also supports the hypothesis that prediction error is implicated in adult word learning and, indeed, in  
818 order to reproduce their human data, Grimmick et al. augmented an associative word learning  
819 model (Kachergis et al., 2012) with a prediction-error mechanism; the associative model by itself  
820 could not reproduce their finding. Similarly, our findings suggest that adult word learning makes  
821 use of a prediction-error mechanism.

822 Our findings can also be explained in terms of McMurray et al.'s (2012) competition-based  
823 model of word learning. This model assumes that potential referents for a heard word compete with  
824 each other, and that this process of "in-the-moment" competition during linguistic processing can  
825 affect long-term learning (i.e., leading to changes in the weights representing the strength of  
826 associations between words and their referents). In our study, competition levels were likely higher  
827 on high-constraint and plausible distractor trials (compared to low constraint and implausible  
828 distractor trials, respectively), and thus the novel target referent had to reach a higher level of  
829 activation in order to be selected. If this higher activation translates into stronger association  
830 weights, McMurray et al.'s model could explain the higher memory performance displayed by  
831 adults for items encountered on those trials.

832 Note that other types of models can also be augmented with prediction-error mechanisms.  
833 Recent years have seen the emergence of so-called hypothesis-testing models of word learning  
834 (e.g., Trueswell et al., 2013). In these models, when learners hear a novel word, they generate a  
835 single hypothesis about its referent, rather than tracking all possible associations between the word  
836 and every co-occurring referent. If this hypothesis is confirmed on the next encounter, the  
837 hypothesized word-referent mapping is retained, but if it happens to be disconfirmed, then the  
838 learner needs to start afresh, as they have not retained any information from previous encounters;  
839 see Berens, Horst, and Bird (2018) for evidence supporting this model using fMRI activation  
840 patterns in the hippocampus during cross-situational word learning.

841 While the original hypothesis-testing model (Trueswell et al., 2013) includes processes of  
842 expectation generation and error computation, it does not incorporate a prediction-error mechanism  
843 because its learning following a disconfirmed expectation is *not* proportional to the strength of that  
844 expectation. However, a recent modification of the original model, called PURSUIT, augments it  
845 with a prediction-error mechanism where the amount of learning is proportional to expectation  
846 strength (Stevens et al., 2017). We suggest that our findings are more compatible with this  
847 augmented model than with the original hypothesis-testing model.

848           While an error-based learning mechanism straightforwardly explains our findings, we note  
849 that they could also be accommodated within a Bayesian framework. Expectation generation would  
850 be akin to positing a prior probability distribution, and expectations would then be updated based on  
851 how surprising the data are given the prior, to derive a posterior probability distribution. On a high  
852 constraint trial, most of the prior probability mass is placed on the expectation that the familiar  
853 object will be mentioned next, while on a low constraint trial, it is distributed more evenly between  
854 the familiar and unfamiliar object (see Figure 1). Thus, the very same data (i.e., the occurrence of  
855 the novel word) will lead to a larger updating on a high constraint than low constraint trials, because  
856 the novel word increases the probability that the unfamiliar object will be mentioned. However,  
857 existing Bayesian models of word learning (Xu & Tenenbaum, 2007; Frank, et al., 2009) do not  
858 include memory parameters, so it is unclear how they would account for the finding that larger  
859 updating leads to enhanced retention. In contrast, this finding highlights the importance of building  
860 models of word learning that account for the nature of memory.

861           More speculatively, our findings may also help link computational models of word learning  
862 with the cognitive neuroscience of word learning. A large body of evidence implicates the  
863 hippocampus in the initial stages of word learning in adults (Davis & Gaskell, 2009; Tagarelli,  
864 Shattuck, Turkeltaub, & Ullman, 2019; Berens et al., 2018). According to the complementary  
865 systems account of word learning (Lindsay & Gaskell, 2010), the hippocampus supports rapid,  
866 initial acquisition of novel words, whereas the neocortex is responsible for slower consolidation,  
867 typically following periods of sleep (see McClelland, McNaughton, & O'Reilly, 1995 for detailed  
868 theoretical arguments in support of the complementary systems account of learning and memory).  
869 Strong evidence for this account comes from the inability of patients with hippocampal lesions to  
870 learn new words (see Cooper, Greve, & Henson, 2019, for a recent review and discussion).

871           Interestingly, the hippocampus is sensitive to novelty and unexpected events (e.g., Kumaran  
872 & Maguire, 2006), and it is thought to encode not just episodic memories but also predictions about  
873 future outcomes (e.g., Shohamy & Adcock, 2010). Our finding that prediction errors affect word

874 learning in adults, therefore, is consistent with a key role for the hippocampus in this process. Given  
875 we did not find evidence for a role of prediction error in children word learning, an interesting  
876 question for future research is whether there are significant developmental changes in the reliance  
877 of word learning processes on the hippocampus (similarly to what has been shown for other areas of  
878 cognitive development; Qin et al., 2014). It may also be that children only show sensitivity to  
879 prediction error after a period of sleep consolidation (which was not included in our study).

880

881 **Do the mechanisms of word learning change across the lifespan?**

882         A key contribution of our study is to highlight a potential developmental discontinuity in the  
883 mechanisms of word learning: While adult memory for novel word-referent mappings was affected  
884 by the strength of prior expectations, we found no evidence that 2-to-4-year-olds' memory was  
885 similarly affected. This raises the possibility that the above-described models of word learning,  
886 which have often been evaluated based on adult data, may not automatically generalize to explain  
887 children's behavior.

888         Our study is not the first to highlight differences between adults' and children's word  
889 learning mechanisms. We have already mentioned Fitneva and Christiansen's (2017) work,  
890 showing that 4-year-olds learn more when their expectations are confirmed, but adults learn more  
891 when they are exposed to a higher proportion of unexpected word-referent mappings. But while  
892 their findings suggest that children should benefit from generating correct expectations (see also  
893 Benitez & Saffran, 2012, 2018), we found no difference in memory performance between trials on  
894 which generating an incorrect expectation was more likely (high constraint) and those in which it  
895 was less likely (low constraint).

896         Can Fitneva and Christiansen's (2017) findings be reconciled with ours? Incorrect  
897 expectations may both hinder selection of the correct novel referent and benefit memory for it, if it  
898 is selected. However, when we excluded all trials on which children (incorrectly) selected the  
899 familiar referent, we still found no evidence for a difference in children's memory performance

900 between strong and weak expectation trials. Thus, it seems more likely that children at this age are  
901 yet to develop the mechanism that makes memory sensitive to expectation strength.

902         Further, our results seem incompatible with Ramscar, Dye, and Klein (2013a), who argued  
903 that children's word learning is more likely than adults' to be driven by an error-based mechanism  
904 (rather than *less* likely, as our findings suggest). They devised a word learning task in which a  
905 learner driven only by prediction error (Rescorla & Wagner, 1972; Ramscar et al., 2010) would  
906 behave differently from one who additionally makes use of explicit inferences (e.g., reasoning by  
907 exclusion). Participants were first exposed to three novel objects and two novel words. Two of the  
908 objects co-occurred with only one of the words each, while the third object co-occurred with both of  
909 the words. When children were presented with a third novel word at test (here, *wug*), they were less  
910 likely to select this third object as a referent for *wug*. While none of the objects had co-occurred  
911 with *wug* during the learning phase, the object that had co-occurred with two other words was the  
912 least predictive of *wug*, and so it should be the least preferred choice of an error-driven learner  
913 (Ramscar et al., 2010). In contrast, adults were more likely to select the third object than either of  
914 the other objects, suggesting that they were more likely to explicitly reason by exclusion, choosing  
915 the third object because they had already mapped each of the other two objects onto the word it had  
916 co-occurred with.

917         While Ramscar et al.'s (2013a) findings suggest that child word learners track co-occurrence  
918 information across multiple encounters, we note that in our study co-occurrence information was  
919 identical across high and low constraint conditions. Instead, what (likely) changed across conditions  
920 was participants' processing of the novel word and novel target object; for example, by violating a  
921 strong linguistic expectation, we may have prompted deeper processing of the novel word and  
922 object, which in turn would have led to enhanced encoding of the association between word and  
923 object in memory.

924         We thus suggest that by the age of 4 children may be capable of accumulating information  
925 using an error-driven learning rule to track which words and referents co-occur and which do not

926 (in accordance with Ramscar et al., 2013a), and form expectations about future co-occurrences. But  
 927 at this age the violation of such prior expectations does not yet lead to deeper processing and  
 928 encoding of unexpected information in memory. In sum, different mechanisms, with different  
 929 developmental trajectories, may underly our ability to track regularities in the environment (i.e.,  
 930 statistical learning; Yu & Smith, 2007) and to focus attention and cognitive resources on the  
 931 encoding of unexpected events.

932

933 **The effect of linguistic prediction on children’s word learning.**

934 Our findings suggest two conclusions about how prediction affects children’s learning. The  
 935 first conclusion is that children’s predictions affect what children learn, by guiding their attention,  
 936 but the second conclusion is that these predictions do not affect the strength of children’s memory  
 937 representations. These two conclusions may seem to contradict one another, but we propose they  
 938 can be reconciled with one another, and with findings from previous work (Reuter et al., 2019) by  
 939 carefully distinguishing the mechanisms involved.

940 First, the predictive strength of the sentence contexts affected the inferences that children  
 941 made about the likely referent of the novel word: They were more likely to choose the familiar  
 942 object (thus disregarding the mutual exclusivity constraint) when the sentence context led them to  
 943 expect a reference to this object. In turn, choosing the familiar object as the referent led to chance  
 944 performance at test, suggesting that children’s attention was focused on the selected referent, to the  
 945 extent that little information about the unselected referent was retained – a finding which,  
 946 incidentally, replicates previous studies (Aravind et al., 2018; Woodard, Gleitman, & Trueswell,  
 947 2016; but see Yurovsky & Frank, 2015) and is consistent with hypothesis-testing models of word  
 948 learning (Trueswell et al., 2013). Importantly, however, during the learning phase children still  
 949 selected the novel referent at above-chance rates, even when doing so required them to abandon a  
 950 prior expectation, and when they did select the novel referent during learning, they then  
 951 demonstrated above-chance retention of the association between the novel word and this novel



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952 referent during the test phase. Thus, children were capable of revising and updating their  
953 expectations based on the mismatch between those and the auditory input (i.e., when a novel word  
954 occurred instead of the expected familiar one) on the majority of trials.

955         Second, the predictive strength of the sentence contexts did not affect children's likelihood  
956 of retaining the association between the novel word and the novel object. Thus, while the ability to  
957 revise disconfirmed expectations may guide children to discover new linguistic information (i.e.,  
958 one aspect of learning), we suggest it is not a key driver of *retention* of this information. This  
959 interpretation allows our data to be reconciled with Reuter et al.'s (2019) finding that children who  
960 show a stronger predict-and-revise looking pattern are also better at word learning. Recall that in  
961 their study children's performance at test was no greater in the high than the low constraint  
962 condition (in fact, it was greater in the latter than the former), so they also found no evidence that  
963 stronger expectations were associated with enhanced memory, when disconfirmed. What they did  
964 find was that children who engaged less in prediction-and-revision were less likely to remember  
965 high-constraint words, which is actually in line with our findings: When children did not engage in  
966 mutual exclusivity reasoning during learning, then they had poor memory at test. Thus, Reuter et  
967 al.'s findings concur with ours in suggesting that prediction-and-revision skills help reference  
968 resolution in children, but do not affect retention, so long as reference is resolved to the object that  
969 is later tested for retention.

970         There is however one caveat to these conclusions that is worth considering. Children's  
971 choices during learning were less sensitive to the strength of prior expectations compared to adults'.  
972 This could be in part because children's choices are often noisier than adults' (e.g., due to lapses in  
973 attention). But it is also expected because studies that have compared predictive skills between  
974 children and adults have typically found stronger effects of prediction in adults (e.g., Gambi et al.,  
975 2016, 2018; Borovsky et al., 2012). Moreover, the strength of prediction effects increases  
976 throughout the pre-school years (Gambi, Jindal, Sharpe, Pickering, & Rabagliati, in press). This

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977 raises the possibility that prediction did not affect children's retention because they did not generate  
978 expectations that were strong or consistent enough (unlike adults).

979         However, we think that this possibility is unlikely, because children clearly generated quite  
980 strong expectations. As noted above, when children did follow their expectations and chose the  
981 familiar referent (which they were more likely to do than adults in the High Constraint/Plausible  
982 Distractor conditions; compare 66% novel referent selections in Experiment 6 and 63% in  
983 Experiment 7 for children with 81% in Experiments 1-3 and 86% in Experiments 4-5 for adults),  
984 this choice had a large impact on their memory performance during the retention phase. Similarly,  
985 there may be a worry that the lack of expectation strength effects on children's memory is down to  
986 the task being too difficult for children of this age, but as noted above children's performance was  
987 well above chance when they selected the novel object during learning, which they did on most  
988 trials.

989         In sum, we argue that, despite the use of different tasks during the learning phase and  
990 different measures of learning (looking-while-listening vs. referent selection), as well as a slightly  
991 different age range (3-to-5 vs. 2-to-4-year-olds), Reuter et al.'s (2019) findings are consistent with  
992 our own: Both studies suggest that children's predictions affect reference resolution but are unlikely  
993 to drive retention of new word-meaning mappings. Therefore, we disagree with Reuter et al.'s  
994 suggestion that their findings show that children's memory for novel word-object associations is  
995 supported by a prediction-error mechanism. Instead, we suggest that children who exhibited a  
996 stronger predict-and-revise pattern were better at word learning in their study because they were  
997 faster at processing sentences, and their higher processing speed allowed them to learn following  
998 high-constraint sentences even though these initially biased their attention towards the incorrect  
999 referent.

1000

1001 **Why did disconfirmed expectations not boost memory in young children?**

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1002           If pre-school aged children can generate linguistic expectations, and revise such  
1003 expectations “in-the-moment” when they are disconfirmed, then why does prediction error not  
1004 affect encoding of novel linguistic information in young children’s memory? Below we discuss two  
1005 possible answers to this question.

1006           One possibility is that the null effect follows from children’s lack of fluency at completing  
1007 the task, which follows from a recent proposal that violations of expectations only influence  
1008 memory once inhibitory control skills are well-developed (Brod, Breitwieser, Hasselhorn, & Bunge,  
1009 2019). In our task, inhibitory control skills would be important for quickly suppressing the  
1010 generated expectation once a novel word is encountered, allowing fluent mapping to the correct  
1011 referent. Brod and colleagues (2019) have proposed that this use of inhibitory control is still not  
1012 apparent even in late childhood: They found that violating expectations did not enhance memory for  
1013 new declarative knowledge in children aged 9 to 12 years, but that it did enhance memory in adults  
1014 (Brod, Hasselhorn, & Bunge, 2018).

1015           This could potentially explain children’s difficulty with our task. While our child  
1016 participants were able to inhibit selection of the strongly expected familiar object on the majority of  
1017 trials, it is likely that they took longer than adults to focus attention on the novel object, by which  
1018 time, activation of the novel word in their working memory may have already started to decay, and  
1019 this could have led to a weaker binding of the word-object association. In sum, perhaps children  
1020 were not able to re-direct their attention quickly enough to benefit from the stronger encoding of  
1021 information following a larger prediction error. If this is the case, then our findings indicate that  
1022 children may have already developed an error-based learning mechanism, but their memory for  
1023 novel word-referent mappings does not benefit from this mechanism (at least in our paradigm)  
1024 because of delays in children’s development of attentional skills.

1025           Alternatively, children may show relative insensitivity to disconfirmed expectations because  
1026 doing so is in fact adaptive for their learning. Since children’s linguistic knowledge is so limited,  
1027 their linguistic input is likely to deliver more surprises more frequently (i.e., unexpected words), at

1028 least compared to adults. Children may therefore be more likely than adults to “expect the  
1029 unexpected” (i.e., placing a higher likelihood on the eventuality of encountering unexpected words).  
1030 While this means that unexpected words may not leave a particularly strong trace in children’s  
1031 memory, it also allows attentional resources to be distributed more evenly across many mildly  
1032 surprising words. This idea is supported by evidence that children are indeed sensitive to the  
1033 predictability of the environment. For example, the so-called Goldilocks effect shows that infants  
1034 and young children prefer to attend to input that is of intermediate predictability, neither too  
1035 predictable nor too unpredictable given their current knowledge about the environment (Kidd,  
1036 Piantadosi, & Aslin, 2014), and children can also quickly learn to expect the unexpected when they  
1037 have been exposed to a speaker that talks about very unlikely events (Yurovsky, Case, & Frank,  
1038 2017).

1039         We do not know of any research that shows that children’s memory becomes more sensitive  
1040 to unpredictable information as they become more knowledgeable about the environment, but if  
1041 children’s word learning does indeed benefit from encountering unexpected information that  
1042 violates “core knowledge” (Stahl & Feigenson, 2017), this may suggest that children’s memory is  
1043 more sensitive to unpredictable information in domains that the child is more knowledgeable about  
1044 (because core knowledge is acquired very early on). Similarly, children may be more sensitive to  
1045 prediction error when there is a conflict between internally-generated expectations and strong  
1046 external cues (e.g., unambiguous referential cues, such as an adult’s pointing) compared to  
1047 situations where there is a conflict between internally-generated expectations and the child’s  
1048 preferred interpretation of a novel stimulus, as in our task. In the latter case, the error signal may be  
1049 too weak or noisy because it is based on the child’s own developing knowledge of language,  
1050 whereas strong error signals from the environment may play a much more important role in shaping  
1051 children’s error-based learning.

1052

1053 **Conclusion**

1054 In sum, we showed that prediction error drives the encoding of novel word-object  
1055 associations in adult memory, as associations were encoded more strongly when they violated a  
1056 stronger compared to a weaker prior expectation. However, we found no effect of disconfirming a  
1057 stronger versus weaker prior expectation on children's memory. The adult findings represent a clear  
1058 demonstration that at least one of the mechanisms underlying adult word learning is based on the  
1059 computation of prediction errors. Thus, they set an important constraint on models of adult word  
1060 learning. The lack of a comparable effect of prediction error on children memory was not due to  
1061 children's inability to generate linguistic expectations, nor to an inability to revise them when they  
1062 proved incorrect. Instead, we suggest that children are either too slow to inhibit disconfirmed  
1063 expectations or that they do not prioritize the processing of unexpected information as much as  
1064 adults, because the environment is overall more unpredictable to them. These findings thus  
1065 highlight an important developmental discontinuity in the mechanisms that underlie prediction's  
1066 role in language learning.

1067

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1074

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