

# The effect of target scarcity on visual foraging

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## Abstract

Previous studies have investigated the effect of target prevalence in combination with the effect of explicit target value on human visual foraging strategies, though the conclusions have been mixed. Some find that individuals have a bias towards high-value targets even when these targets are scarcer whilst other studies find that this bias disappears when those targets are scarcer. In this study, we tested for a bias for scarce targets using standard feature vs conjunction visual foraging tasks, without an explicit value being given. Based on the idea of commodity theory and implicit value, we hypothesised that participants would show a scarcity bias. The bias was investigated using a Bayesian statistical model which has been developed for predicting target-by-target foraging behaviours. However, we found no evidence for a scarcity bias in our experiment, suggesting that participants did not inherently find rarer targets more rewarding.

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# 1 Introduction

Humans and other animals search their environment regularly, looking both for unique items, and for items where there are multiple exemplars available (such as berries on a bush). The former situation can be conceptualised as a visual search task where an observer must find a single target type from amongst distractors. The latter is referred to as foraging, in which observers search and collect multiple targets. It is considered an important behaviour given its connection to resource gathering [Bella-Fernández et al., 2021], and has even been argued to be a key behaviour driving human cognitive evolution [Hills et al., 2015, Pretelli et al., 2022]

A number of studies have addressed the factors that influence foraging behaviour. Early work by Dawkins [1971] observed that chicks appear to peck grains in ‘runs’ of one grain type before switching to the other. More recently [Kristjánsson et al., 2014] this behaviour has been studied in humans. When human participants are tasked with collecting multiple target types by sequentially tapping on them during an iPad game, they tend to consecutively select targets of one type in a series of ‘runs’. This is especially the case in relatively difficult ‘conjunction’ searches where the targets are defined by a combination of two features, compared to ‘feature’ searches where just one feature can be used to differentiate targets and distractors. (See Figure 1 for examples of the displays.) This method appears to be more efficient compared to switching between target types [Wolfe et al., 2019].

Target value has been shown to be one of the main factors governing the deployment of visual attention [Wolfe and Horowitz, 2017], and as such, it plays an important role in foraging behaviour. Value can be thought of as either explicit or implicit. An example of explicit value influencing foraging behaviour can be seen in a study by Nityananda and Chittka [2021]. They trained bees to discriminate between artificial flowers, their foraging behaviour was influenced such that they chose the more rewarding flowers (with more sucrose) in higher proportions. In humans, we can also use points and prizes as a way to manipulate explicit value e.g. by tying participant payment to gaining a certain number of points in an experiment. By contrast, implicit value is used to describe situations in which some targets may be more attractive to a forager due to an incidental feature. For example, Nityananda and Chittka [2021] manipulated saliency in their experiments by adjusting the colour contrast

54 of targets compared to their background, and found that higher saliency  
55 targets were more likely to be selected than lower ones.

56 One interesting example of implicit value is *scarcity*, where a target  
57 type is visually less common in an environment. Brock's Commodity The-  
58 ory is a theory from social psychology that suggests that participants may  
59 value scarce targets (or other 'useful things', including messages and expe-  
60 riences as well as material objects [Brock and Brannon, 1992]) more highly  
61 than readily available targets [Brock, 1968]. Empirical evidence for this  
62 theory has been found across a range of contexts [Lynn, 1991] (although  
63 not all studies have found strong evidence for scarcity biases [e.g. Echel-  
64 barger and Gelman, 2017]). A preference for scarce objects could occur  
65 because possessing a scarce object may provide a feeling of personal dis-  
66 tinctiveness or uniqueness [Lynn, 1991], or because scarcity can be taken  
67 as a proxy for other desirable features, such as popularity. However, there  
68 may also be more 'low-level' explanations for a scarcity preference: for  
69 example, it has been argued that participants show stronger sustained at-  
70 tention to scarce resources, leading to more intense evaluation of the item  
71 [Sehnert et al., 2014], and therefore perhaps changing behaviour.

72 Both explicit target value and scarcity have been manipulated in the  
73 context of foraging studies. For example, Wiegand and Wolfe [2021] ma-  
74 nipulated explicit target value and prevalence (which can be considered  
75 equivalent to scarcity) and found that participants preferentially selected  
76 targets of higher value. However, this effect was modulated by target  
77 prevalence: participants no longer showed a preference for the higher-  
78 value targets when they had a much lower prevalence than the lower-  
79 value targets. In another study, Tagu and Kristjánsson [2022] had partici-  
80 pants collect a certain number of points by collecting targets, and the high  
81 value targets were rarer than lower-value ones. In contrast to Wiegand  
82 and Wolfe [2021], participants tended to select high-value targets earlier  
83 than low-value targets, even though the high-value targets were scarcer.  
84 Wolfe et al. [2018] investigated the effect of target prevalence in a hybrid  
85 foraging task where all four possible targets had equal value, and found  
86 that participants picked the more common targets at a higher rate than the  
87 less common ones, an effect they attributed to priming. Thus, there have  
88 been mixed results in the human foraging literature on the effect of target  
89 scarcity on human foraging. It is worth noting that all the studies to date  
90 did explicitly assign targets a value (even if equal) and therefore do not  
91 necessarily tell us about the implicit value that participants may assign to

92 targets.

93 There have been a number of visual search studies that have investi-  
94 gated scarcity, focusing on the context of scarce or abundant distractors  
95 rather than studying the effect of scarce targets. In one study, where par-  
96 ticipants searched for a target amongst two types of distractor, the distrac-  
97 tor ratio strongly affected behaviour, with participants responding more  
98 quickly when one distractor was rarer than the other [Shen et al., 2000].  
99 Similarly, people have been shown to be able to search relatively efficiently  
100 for a conjunction target within the smaller group of distractors when one  
101 type of distractor is more numerous than the other [Sobel and Cave, 2002].  
102 Attention is therefore directed to the rarer elements of the display, in a  
103 manner that might share cognitive similarities to a ‘scarcity bias’, although  
104 the authors themselves argued that this behaviour was observed because  
105 it is faster to start search in a smaller group compared to a larger one.

106 In previous studies of foraging behaviour, differences between condi-  
107 tions have been studied using aggregate statistics, such as the number of  
108 ‘runs’ of a particular target type (i.e. the number of times that target is  
109 selected in a row) or the total number of targets found in the longest run.  
110 However, these measures have limitations. For example, they can be bi-  
111 ased by the spatial layout of the display. They also do not allow us to  
112 distinguish between the case where a participant sticks with a particular  
113 target because of a preference for that specific target type, compared to the  
114 case where they simply like to stay searching for the same target template,  
115 regardless of what the target is. Similarly, with these aggregate statistics  
116 methods, it is not necessarily intuitive to account for imbalances in target  
117 numbers in a display, and how we can conclude whether a ‘scarcer’ target  
118 is selected more or less often than would be expected by chance: for exam-  
119 ple, if there are fewer of target A compared to target B, a reduced number  
120 of switches between target types compared to the case where the targets  
121 are equal in number may simply reflect the fact that fewer switches are  
122 possible.

123 To be able to more precisely track participant behaviour in these types  
124 of foraging tasks, we have developed a generative Bayesian model based  
125 on a sampling without replacement procedure. The benefit of this model  
126 is that it is able to break down behaviour into a series of cognitive biases,  
127 such as a preference for sticking with the same target type, or a preference  
128 for selecting a nearby target type, thus overcoming some of the limita-  
129 tions inherent to analyses based on aggregate statistics. We have success-

130 fully demonstrated that our model can account for average patterns of be-  
131 haviour in a range of human foraging experiments [Clarke et al., 2022b].  
132 In addition, it can make relatively accurate predictions of the next target  
133 a given individual will select on a trial [Clarke et al., 2022a]. We therefore  
134 think that our model is a powerful tool for studying and understanding  
135 the processes underlying human foraging behaviour.

136 In the current study, participants searched amongst coloured targets  
137 and distractors, in feature and conjunction styles of foraging like that of  
138 [Kristjánsson et al., 2014]. In the feature task, participants had to distin-  
139 guish between targets and distractors based on colour. In the conjunc-  
140 tion task, both shape and colour had to be considered in order to differ-  
141 entiate targets and distractors. Participants took part in some conditions  
142 where there were equal numbers of each target types, and other conditions  
143 where one target type was more numerous than the other. We had two key  
144 aims. Firstly, we tested whether scarcity affects how participants forage.  
145 If participants implicitly value the scarcer target more highly, as Brock’s  
146 Commodity Theory [Brock, 1968] suggests they would, we expected par-  
147 ticipants to show a preference for the scarcer target, as measured by the  
148 bias parameter in the generative foraging model. As a secondary aim, we  
149 tested the extent to which the results of [Clarke et al., 2022b] generalise to  
150 a novel set of data. To date, we have used only secondary data sets, and  
151 therefore we used the registered report format to pre-register specific hy-  
152 potheses relating to the parameters in our model to test how generalisable  
153 previous findings are.

## 154 2 Methods

### 155 2.1 Participants

156 We collected data from 36 participants, recruited from the University of Es-  
157 sex participant pool. This sample size is justified below in Section 4.4. In-  
158 formed consent was collected at the beginning of the study and the partici-  
159 pants were debriefed as to the nature of the study afterwards. Participants  
160 confirmed (via self-report) that they had normal or corrected-to-normal vi-  
161 sion. Ethical approval for the experiment was granted by the University of  
162 Essex Research Ethics Sub-committee 1 (ETH2223-1093). The experiment  
163 took around 30 minutes to complete, and participants were compensated

164 £5 for their time.

## 165 2.2 Design

166 A 2x3 within-subjects design was used. The first independent variable  
167 was the difficulty of the task, with two levels: *feature* and *conjunction* (de-  
168 tails of the stimulus manipulation given below). The second independent  
169 variable was the ratio of targets of class *A* to *B*, with three levels: target  
170 class *A* is *scarce* (5 *A* to 15 *B*); class *B* is *scarce* (15 *A* to 5 *B*) and an *even*  
171 ratio (10 *A* to 10 *B*).

172 Each participant participated in all six conditions. Within each condi-  
173 tion, there were ten trials, meaning that they completed 60 trials. Each  
174 condition was completed as one block, and the order of blocks was coun-  
175 terbalanced across participants (half the participants completed the three  
176 feature blocks first, in a random order, and half completed the three con-  
177 junction blocks first, in a random order).

178 Before beginning the experiment, each participant completed a practice  
179 trial to familiarise themselves with the procedure: this was similar to a  
180 *feature* trial with an *even* ratio of targets, but using different colours (black  
181 and white for the targets, and 'old lace' and 'thistle' for the distractors:  
182 all colour names refer to the RGB hex colours) and shapes (all targets and  
183 distractors were triangles, approximately 1 unit of visual angle wide). All  
184 other features otherwise exactly resembled the main experimental trials.

## 185 2.3 Stimuli

186 The experiment was created in PsychoPy-2022.2.4 software, and code is  
187 available in our GitHub repository. Each trial consisted of 40 items on a  
188 grey background. These items were organised in a grid but their place-  
189 ment was slightly jittered to create some irregularity, following previous  
190 studies [Kristjánsson et al., 2014, Clarke et al., 2022c]. Each trial included  
191 20 targets and 20 distractors, and their position was randomised. In the  
192 feature task, blue and yellow circles were the distractors whilst green ('lime'  
193 was used as the green colour in all cases) and red circles were the targets.  
194 In the conjunction task, red circles and green squares were the distractors  
195 whilst red squares and green circles were the targets. Circle targets and  
196 distractors had a radius of 25 pixels (approximately 1 unit of visual angle),

197 and square targets and distractors had a width and height of 25 pixels (as  
198 before, approximately 1 unit of visual angle). Examples of the stimuli can  
199 be seen in Figure 1.

## 200 **2.4 Procedure**

201 Participants completed the experiment in a quiet room with normal illumi-  
202 nation. The experiment was conducted on a Dell Optiplex 7050 computer,  
203 with screen size 1920 x 1080 pixels (though the targets were placed within  
204 a grid of 1000 x 1000 pixels in the centre of the screen). Participants sat  
205 with their head stabilised using a chin rest at a distance of 60cm from the  
206 screen. Participants began each block by reading instructions telling them  
207 which items were the targets for that block. In each trial, they ‘collected’  
208 items by clicking on them using a computer mouse. Once a target item  
209 was clicked, it immediately disappeared from the screen. If a participant  
210 clicked on a distractor, the trial immediately ended and it was restarted  
211 (up to a maximum of 5 attempts per trial): this was done to follow the  
212 procedure used in previous studies [Kristjánsson et al., 2014, Clarke et al.,  
213 2022c]. Trials ended when the participant had clicked on all targets, again  
214 following previous work [Kristjánsson et al., 2014, Clarke et al., 2022c].  
215 Participants had to complete five valid trials with no mistakes in each con-  
216 dition.

217 Participants had their eyes tracked for the duration of the experiment  
218 using an SR EyeLink 1000 Plus eyetracker. This data is available for future  
219 exploratory analysis, but is not used in the current registered report.

## 220 **3 Data Analysis**

221 We used the four-parameter generative foraging model proposed by [Clarke  
222 et al., 2022b] to analyse the data. The model allows for target-by-target  
223 prediction of behaviour during visual foraging [Clarke et al., 2022a] and a  
224 benefit of this approach is that it enables us to parameterise the factors that  
225 may affect the forager’s choice of targets, such as proximity or a preference  
226 for foraging in ‘runs’ of a single target type [Kristjánsson et al., 2014]. The  
227 model also contains a ‘class bias’ parameter which detects a preference for  
228 one target type over another type. If item scarcity does make some targets

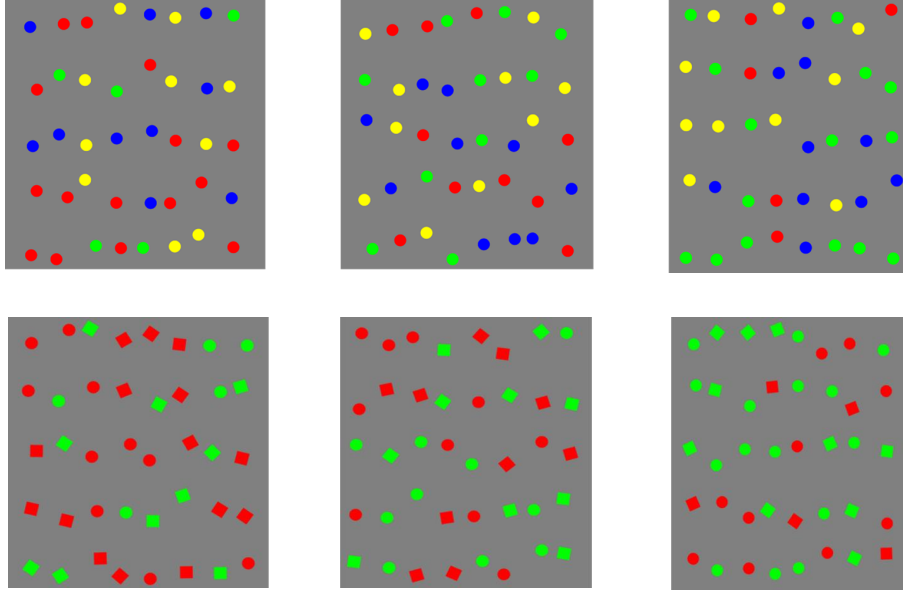


Figure 1: Example stimuli. Top row is stimuli for the feature search, bottom row is for the conjunction search. For feature, from left to right; is scarce green target condition, equal target condition, and scarce red target condition. For conjunction search, from left to right; scarce green circle condition, equal targets condition, and scarce red squares condition.

229 more attractive than others, we should be able to see a difference in this  
 230 parameter between the *scarce* and *even* conditions.

231 We have previously shown that the model can detect differences in this  
 232 parameter between value and no-value conditions of previously collected  
 233 data [Clarke et al., 2022b, Tagu and Kristjánsson, 2022], and provide jus-  
 234 tification below (in Section 4.4) that we believe that we can detect small  
 235 differences in target preference in our experimental design.

### 236 3.1 A four-parameter model of visual foraging

237 We model foraging as a process of weighted sampling without replace-  
 238 ment. We assume that target items belong to one of two classes ( $A$  and  $B$ )



239 and details of any distractor items are neglected. In the experiment pre-  
 240 sented in this manuscript,  $A$  and  $B$  are red and green circles respectively  
 241 for the feature task, then red squares and green circles for the conjunction  
 242 task.

243 The probabilities of each remaining targets item are updated after each  
 244 selection depending on four parameters defined as follows:

- 245 •  $b_A = \text{logit}(p_A)$ : the logarithm of the odds of  $p_A$ .  $p_A$  can be thought of  
 246 as the probability of selecting an item of class  $A$  compared to class  $B$ ,  
 247 all else being equal. Similarly,  $b_B = \text{logit}(p_B)$  is the logarithm of the  
 248 odds of relative attractiveness of  $B$  over  $A$ . This attractiveness could  
 249 be due to properties such as low-level salience or reward and value.  
 250 A value of  $b_A = 0$  ( $p_A = 0.5$ ) corresponds to a situation in which items  
 251 from both classes are equally likely to be selected next. The further  
 252 away this parameter is from zero, the stronger the preference for  $A$   
 253 over  $B$  is. In this experiment, we predicted that  $b_A$  would be more  
 254 strongly positive in the case where  $A$  is the scarce target category,  
 255 and would be more strongly negative when  $B$  is the scarce target  
 256 category.
- 257 •  $b_S = \text{logit}(p_S)$ : the logarithm of the odds of  $p_S$ , the preference for  
 258 selecting an item of the same class as the previously selected item.  
 259 High values of this parameter lead to 'sticky' behaviour with long  
 260 runs of the same item class, while low values lead to switching be-  
 261 haviour in which participants alternate which item class they select.  
 262  $b_S \approx 0$  indicates that the class of the previously selected item has  
 263 little effect on which item will be selected next.
- 264 •  $\sigma_\rho$ : this parameter reflects the importance of proximity when select-  
 265 ing the next item. The larger  $\sigma_\rho$  is, the more heavily weighted selec-  
 266 tion is to items that are close to the previously selected item.
- 267 •  $\sigma_d$ : measures relative direction. The larger this parameter is, the  
 268 larger the preference there is for selecting items that are 'ahead' of  
 269 the previously selected item. As this parameter becomes more nega-  
 270 tive, this behaviour flips and there is a preference for selecting items  
 271 'behind'.

272 These four parameters are fit to the data for each experimental condi-  
 273 tion:  $b_A(k)$ ,  $b_S(k)$ ,  $\sigma_\rho(k)$  and  $\sigma_d(k)$  where  $k$  is one of  $K$  experimental con-

ditions. Further details of the model implementation can be found in the Supplementary Materials.

### 3.2 Implementation Details

The model fitting procedure was the same as Clarke et al. [2022b] with three changes. Firstly, while a multi-level framework was used to account for the differences between participants, we did not model the correlations between random effects. This is because we previously found relatively weak correlations when modelling similar experiments in Clarke et al. [2022b], and this modification significantly reduces computational time. Secondly, we adjusted the manner in which relative distances are calculated in order to account for the fact that the stimulus display is not necessarily square (although we used a square display in this experiment).

The following weakly informative priors were used.<sup>2</sup>

$$b_A, b_B \sim \mathcal{N}(0, 1) \quad (1)$$

$$b_S \sim \mathcal{N}(0, 1) \quad (2)$$

$$\sigma_p \sim \mathcal{N}(15, 5) \quad (3)$$

$$\sigma_\rho \sim \mathcal{N}(0, 1) \quad (4)$$

Each prior was a normal distribution with a specified mean and standard deviation, and the values chosen were based on applying the model to data from previous related experiments [Clarke et al., 2022b]. Importantly, we used the same set of priors for both the *equal* and *scarce* experimental conditions.

Models were fit using R [R Core Team, 2021] and Stan [Stan Development Team, 2020] (full details of the software environment are included

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<sup>1</sup>The original Stage 1 report also included the statement: ‘Finally, we have incorporated the initial selection bias described in Clarke et al. [2022a] into the full model: this allows us to take into account a person’s preference for starting each trial in a particular region of the screen (e.g. the centre, or the top left hand corner).’ This turned out to be more difficult to model than anticipated, and was not critical for testing our hypotheses, so we decided not to include this feature in the models presented in the paper, but we leave this statement here for full transparency.

<sup>2</sup>Note that we made some minor adjustments in the SD values for these priors compared to the Stage 1 registered report in order to facilitate model fitting.

298 in supplementary materials). The model fit was checked to ensure that  
299  $\hat{r} < 1.01$  and the traceplots were visually inspected to check convergence.

300 Applying sophisticated modelling to new data can sometimes lead to  
301 unexpected problems. Such issues can sometimes be easily solved by us-  
302 ing a different set of priors, or some other change to how the model is im-  
303 plemented. We have aimed to transparently document all changes from  
304 our original plan by adding footnotes into the main manuscript where rel-  
305 evant.

306 Analysis materials are available on our GitHub repository.

### 307 3.3 Data Exclusion

308 The following criteria were used for data inclusion/exclusion:

- 309 • Data from terminated trials (due to selecting a distractor) were not  
310 analysed.
- 311 • Any trial containing an inter-target selection time of more than five  
312 seconds was removed.

313 We only analysed data from participants who had at least five trials of  
314 data for each condition after the above criteria were applied. We collected  
315 enough data to ensure we had 36 participants for the final analyses after  
316 data exclusion criteria were applied.

## 317 4 Hypotheses

### 318 4.1 The Effect of Scarcity

319 Our main hypothesis [H1] was that participants will show a preference  
320 for selecting scarce targets. As preferences to select one target class over  
321 another may also differ due to visual salience, we took  $b_A(equal)$  as our  
322 baseline condition and compared this to  $b_A(scarce_A)$  and  $b_A(scarce_B)$ .

323 We tested this hypothesis by examining the posterior distributions (given  
324 the data  $D$ ) for the difference between these parameters: if both

$$Pr(b_A(scarce_A) - b_A(equal) > 0 | D) > 0.99 \quad (5)$$

$$Pr(b_A(equal) - b_A(scarce_B) > 0 | D) > 0.99 \quad (6)$$

are true, marginalising over the *feature* and *conjunction* conditions, then we can conclude in favour of our hypothesis. We also used the same procedure to measure the effect of scarcity in the *feature* and *conjunction* conditions separately, although we had no specific hypothesis about the size or direction of potential effects.

In Stage 1, we indicated that if we did not find strong evidence in favour of our hypothesis, we would carry out exploratory analysis to a) investigate if one of the counterbalanced conditions showed a scarcity effect but not the other and/or b) investigate the extent to which it holds in a subset of participants. If there was a range of scarcity effects across different participants, we said we would explore whether these were correlated with the other parameters in our model.

We also said that in the unlikely event that we were unable to achieve a good model fit using the full four parameter model, we would fit a simpler ‘sampling without replacement’ model which ignores the spatial components of the model [Clarke et al., 2022b]. However, this was not necessary.

## 4.2 Secondary Hypotheses around model fit

We also tested a number of secondary hypotheses to test the extent to which the results of [Clarke et al., 2022b] generalise to a novel set of data:

H2 : If our *feature* vs. *conjunction* manipulation showed a similar effect as that seen in [Kristjánsson et al., 2014] and [Clarke et al., 2022c], we expected to see a larger value for  $b_S$  in the *conjunction* condition compared to the *feature* condition. This was investigated by examining the posterior distribution for a difference between feature and conjunction conditions using the same procedure as above.

H3 : We predicted there will be a large ( $\sigma_\rho > 10$ ) proximity bias in both conditions. Previous work has shown values of around  $\sigma_\rho = 20$  are typical. We expected the effect of proximity to be larger in the *feature* condition, based on findings from [Kristjánsson et al., 2014] and [Clarke et al., 2022c] (as analysed in [Clarke et al., 2022b]). This was investigated in a similar manner to [H2].

357 H4 : We predicted we will see a negative effect of relative direction, al-  
358 though we predicted this effect would likely be weak (around -1)  
359 with considerable variation between individuals. In order to test this  
360 hypothesis, we calculated whether 99% of the posterior distribution  
361 for the relative direction parameter was negative.

### 362 4.3 Planned exploratory analyses

363 A new version of our model was released by the time we collected our  
364 data, so we also present results using this (in supplementary material).  
365 This model does use include the full random effects correlation structure.  
366 An LKJ prior was used for the random effect structure [Lewandowski  
367 et al., 2009].<sup>3</sup>

368 We also present (in supplementary material) the standard aggregate  
369 descriptive statistics used in foraging research (maximum run length and  
370 total number of runs). We do not use these in our analyses, but they pro-  
371 vide a useful reference point for comparisons with previous research in  
372 the field.

### 373 4.4 Justification of Sample Size

374 We used a simulation approach to justify our sample size. In short, we  
375 used our generative model of visual foraging to simulate data for a given  
376 set of parameters. Based on the results from [Clarke et al., 2022b] we set  
377  $b_S = 1$  (i.e.,  $p_S = 0.73$ ) for the feature condition with  $\sigma_\rho = 15$  and  $\sigma_d = -1$ .  
378 For the conjunction condition, we set  $b_S = 2$ ,  $\sigma_\rho = 10$  and  $\sigma_d = -1$ . For the  
379 *equal* condition (in both the feature and conjunction cases), we made both  
380 target types equally likely ( $b_A = 0$ ), while in the *scarce* condition (again,  
381 for both feature and conjunction) we assumed a small preference for the  
382 less common target type of  $p_A = 0.6$  (i.e.,  $b_A = 0.405$ ). This effect was  
383 chosen so that it was somewhat smaller than the effect of explicit value  
384 found in data from [Tagu and Kristjánsson, 2022] of 0.75. It is also similar  
385 to the target preference seen in [Clarke et al., 2022c]: in this experiment,  
386 there was no specific experimental manipulation or hypothesis regarding

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<sup>3</sup>Please note that in Stage 1, this sentence was mistakenly included in Section 3.2, but in the main model presented in this paper, we do not measure the correlation between random effects, and so this prior is not relevant in that case.

387 a bias for one target or another, so we would expect this to be a reasonable  
388 minimal effect size of interest.

389 We simulated 36 participants, each completing five trials per condition  
390 (this was a highly conservative estimate: in most cases, we expected that  
391 each participant will complete ten trials per condition). While five trials  
392 may seem a relatively small amount, we have shown previously that good  
393 parameter estimates can be recovered with as little as one trial of data in  
394 a similar task [Clarke et al., 2022b]. The parameters for the random ef-  
395 fect structure were again based on results from [Clarke et al., 2022b] (see  
396 Supplementary Materials for full details and code). We then fit the four-  
397 parameter foraging model to these simulated data, the results of which  
398 can be seen in Figure 2. We can clearly detect the bias towards the less  
399 common target type in the scarce conditions. We can also see clear differ-  
400 ences between the feature and conjunction conditions in stick probability  
401 and proximity tuning, demonstrating that we should have been able to  
402 detect these effects if they were present in the data.

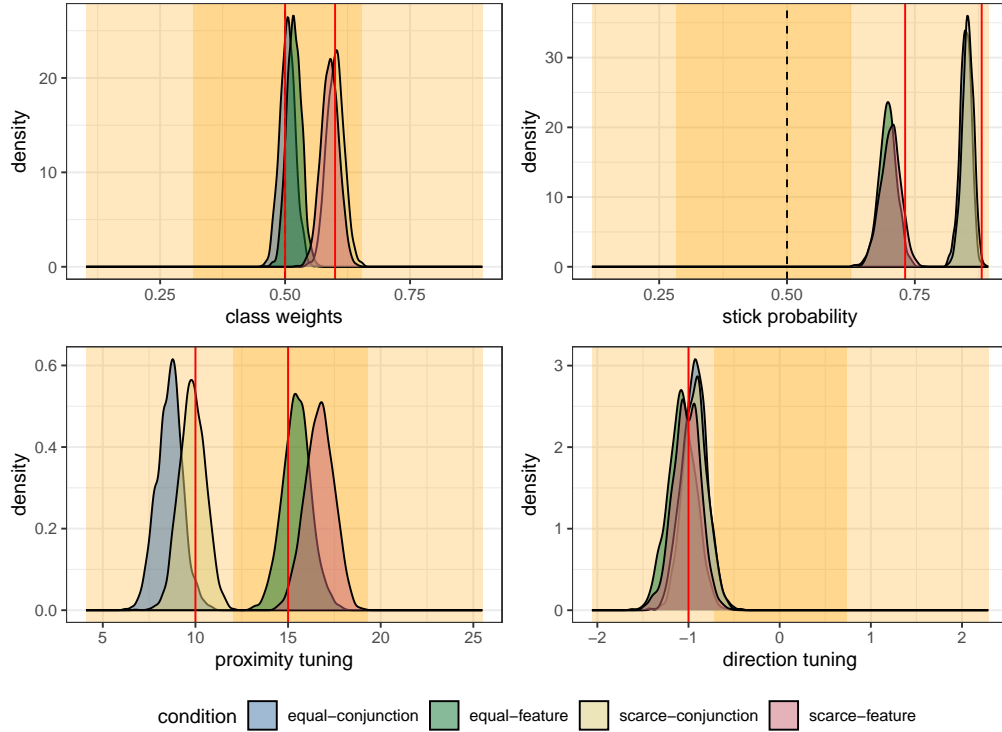


Figure 2: Posterior probabilities after fitting the model to the simulated data. The yellow-shaded background areas represent the prior distribution (53% and 97% HPDIs). Red lines indicate the parameter values used in the simulation.

## 4.5 Pilot Results

Pilot data was taken from 3 female participants, each performing 5 trials in all 6 conditions. When applying [Clarke et al., 2022b]’s model, we see in the  $p_S$  parameter a replication of [Kristjánsson et al., 2014]’s findings; participants tended to stick to one target type more in the conjunction tasks compared to the feature tasks. In the  $p_A$  parameter, there is a slight preference for scarce targets in the conjunction task (see Figure 3). We can also see a proximity bias of approximately the expected size, although no real suggestion of a directional bias (although previously we have found this is a rather small effect). Overall, the pilot data showed that in a small

number of participants, the effects seen were generally in line with our hypotheses.

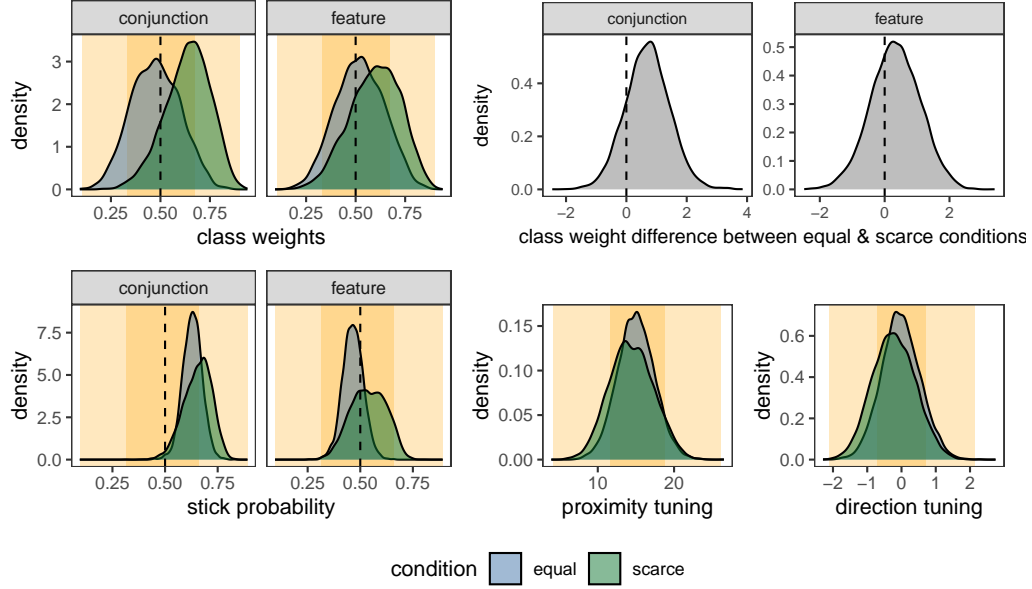


Figure 3: Posterior probabilities after fitting the model to the pilot data. The orange shaded background areas represent the prior distribution (53% and 97% HPDIs). (top left) Posterior distribution for  $p_A$ . (top right) Posterior distributions for the difference between the *scarce* and *equal* conditions. (bottom) Posterior distributions for the other model parameters.

## 5 Results

### 5.1 Data Preparation and Demographics

We collected data from 43 participants, but following removal of participants where there were technical faults or the experiment was not completed (see supplementary materials for full details) we used data from 36 participants in our final analyses. We applied the data exclusion criteria outlined above, and removed 55 trials which contained an inter-target selection time of more than 5s, but all participants continued to have at least



423 five trials per condition. Participants had a mean age of 23.9 (SD = 4.2) and  
424 26 of our participants identified as female.

425 All data and digital materials/code can be found in our GitHub repos-  
426 itory. Note that each participant data file contains a date stamp, and we  
427 save the experimental parameters (e.g. conditions and blocks run) with  
428 each set of participant data, to act as a lab log. The approved Stage 1 proto-  
429 col is available on OSF. The experiment was executed and analysed in the  
430 manner originally approved: any unforeseen changes in those approved  
431 methods and analyses have been noted below.

## 432 5.2 The Effect of Scarcity

433 We fit the model as described in Section 3.2. Model checking procedures  
434 are detailed in the supplementary materials, but we assessed the model fit  
435 to be good based on standard procedures (e.g. checking traceplots visu-  
436 ally for convergence). The posterior density distributions are illustrated in  
437 Figure 4. Overall, we can see that many parameters have been estimated  
438 by the model to be very similar across the different conditions of the ex-  
439 periment (the posterior distributions overlap in many cases).

440 We hypothesised that participants will show a preference for scarce  
441 targets across both *feature* and *conjunction* conditions. The top left panel  
442 of Figure 4 shows the posterior distributions for  $p_A$  i.e. the relative at-  
443 tractiveness of target A over target B. A posterior distribution shifted to  
444 the right of 0.5 indicates that target A was relatively preferred; a posterior  
445 distribution shifted towards the left of 0.5 indicates that target A was not  
446 preferred, and instead participants preferred target B.

447 In the *feature* condition, scarcity condition A (where target type A was  
448 less common) is slightly shifted to the right, and scarcity condition B (where  
449 target type B was less common) is slightly shifted to the left, as predicted.  
450 However, these are not very strong shifts. A similar pattern is seen in the  
451 *conjunction* condition, although there is a shift even for the AB condition  
452 (where the number of each target type was equal). This indicates that that  
453 target type A was preferred generally, for a reason other than scarcity.

454 Despite the slight trends seen in the graph, we did not find evidence  
455 for an effect of scarcity according to our pre-registered criteria: we did  
456 not find that 99% of the difference between the posterior distributions for  
457 the  $b_A$  parameter was greater than zero for the two relevant comparisons,

458 instead finding 67% for condition AB subtracted from condition A, and  
 459 82% for condition B subtracted from condition AB.

460 We also measured the effects of scarcity separately in the *feature* and  
 461 *conjunction* conditions separately. Again, we did not find evidence for a  
 462 scarcity effect based on the 99% criterion (see supplementary materials for  
 463 full details).

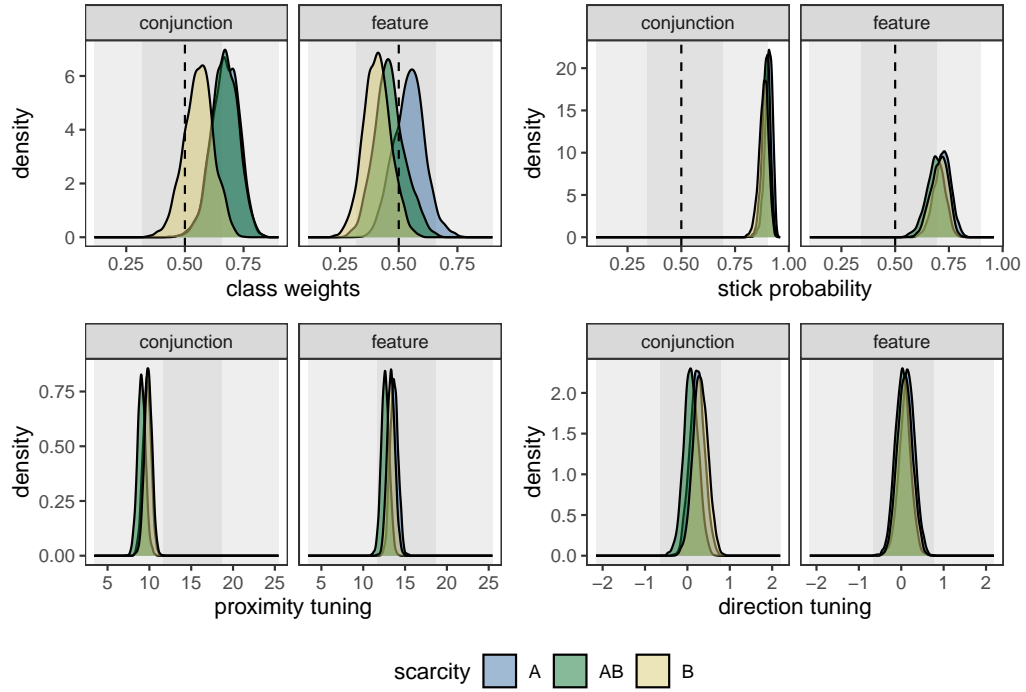


Figure 4: Posterior probabilities after fitting the model to the real data. The grey shaded background areas represent the prior distribution (53% and 97% HPDIs). (top left) Posterior distribution for  $p_A$ . (top right) Posterior distributions for the stick probability  $p_S$ . (bottom left) Posterior distributions for the proximity tuning parameter  $\sigma_\rho$ . (bottom right) Posterior distributions for the direction tuning parameter.

### 464 5.2.1 Exploratory analyses for scarcity

465 Given that we did not find strong evidence in favour of our hypothesis, we  
 466 carried out exploratory analyses. Firstly, we investigated whether one of

467 the counterbalanced conditions showed a scarcity effect but not the other  
468 (some participants completed *feature* conditions first, whereas others com-  
469 pleted *conjunction* conditions first <sup>4</sup>). There was no evidence for this sug-  
470 gestion, with neither group showing a scarcity effect (see supplementary  
471 material for full details).

472 Secondly, we investigated whether there was a subgroup of partici-  
473 pants who showed a scarcity effect. From Figure 5, we can see that partici-  
474 pants tended to be fairly similar in their behaviour in the *feature* condition,  
475 while there were a wider variety of strategies evident in the *conjunction*  
476 condition. Marginalising across both *feature* and *conjunction* conditions, we  
477 did not see any individuals with a scarcity bias. However, if we consider  
478 just the conjunction condition, participant 6 shows evidence for a scarcity  
479 bias, and three other participants (10, 24 and 25) are close to meeting the  
480 evidence threshold. However, there is also one person (participant 1) who  
481 shows an anti-scarcity bias, being more likely to pick the most common  
482 target in each condition. It therefore seems likely that participants pick id-  
483 iosyncratic strategies to complete the task in the *conjunction* condition: in  
484 some cases, this can look like a scarcity bias, but other strategies are also  
485 possible.

486 While there are a range of scarcity effects across different participants,  
487 we did not find good evidence that these are correlated with other param-  
488 eters in our model (see supplementary materials for full details).

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<sup>4</sup>Note that due to a minor coding error and uneven data exclusion, we did not have exactly equal numbers in each condition: 14 participants completed the feature condition first, and 22 participants completed the conjunction condition first.

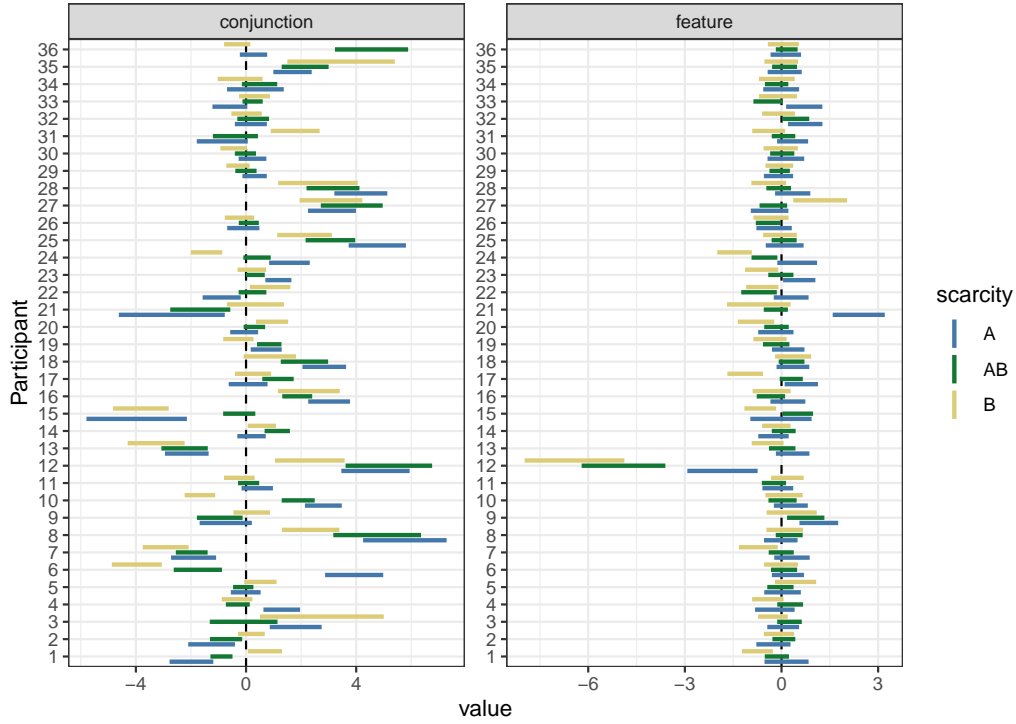


Figure 5: The random effects  $u_A$  for each participant, for all scarcity and difficulty (feature vs. conjunction) conditions.

### 5.3 Secondary Hypotheses around model fit

H2 : We found a larger value for  $b_S$  in the *conjunction* condition compared to the *feature* condition, as predicted (see Figure 4, top right).

H3 : We found a larger proximity bias in the *feature* condition compared to the conjunction condition, as predicted (see Figure 4, bottom left), supporting H3. In both cases, the proximity bias was relatively large, although our original prediction that  $(\sigma_\rho > 10)$  was only true for the *feature* condition.

H4 : We did not find that 99% of the posterior distribution for the relative direction parameter was negative (see 4, bottom right). Therefore our data does not support H4, where we predicted we would see a negative effect of relative direction.

## 5.4 Planned exploratory analyses

In the supplementary material, we present the standard aggregate descriptive statistics used in foraging research (maximum run length and total number of runs). In keeping with previous findings, we see that the *conjunction* conditions have a greater maximum run length and a smaller number of runs compared to the *feature* conditions. The model’s random effect parameters for each person for sticking with the same target type correlate well with their total number of switches, confirming that this parameter in our model maps well on to this traditional measure.

We also present results (in the supplementary material) using a more recent version of our foraging model, which is mathematically equivalent to the main version used in this paper, but with a tidier code base. The basic findings remained identical to those presented in Figure 4.

## 5.5 Further exploratory analyses

During the review process, a reviewer suggested that one reason for the lack of scarcity effects is that participants may need time to learn which target is scarcer, and therefore we might only see strong effects in later trials. We tested this by analysing the first half of trials separately from the second half (see supplementary material for full details), but we did not see any difference in the results in the first half vs. the second half, and in both cases, there was no evidence for a scarcity bias.

## 6 Discussion

In the current study, we tested whether target scarcity affects how people forage. We predicted that participants would implicitly value the scarcer target in a display more highly, as suggested by Brock’s Commodity Theory [Brock, 1968]. However, our analyses suggested that there was no strong evidence for an effect of scarcity, either for group-level analysis or at the level of individual participants.

These results are perhaps surprising in the context of previous findings [Brock and Brannon, 1992, Lynn, 1991] that have suggested that scarcity effects can be found across a wide variety of contexts. However, it is worth noting that these studies predominantly relate to ‘higher-level’ reasoning

533 tasks rather than low level perceptual ones: for example, in one study,  
534 participants were asked whether they preferred a scarce or available art  
535 print [Lynn, 1989]. Our findings therefore perhaps support the idea that  
536 if people do have a preference for scarce objects, this may be a ‘cognitive’  
537 bias that reflects high-level desirable factors, such as believing that items  
538 are scarce because they are popular, rather than a ‘low-level’ bias where  
539 people show stronger sustained attention to less common items [Sehn-  
540 ert et al., 2014]. Interestingly, a previous study showed that children and  
541 adults care more about variety than scarcity when selecting novel items,  
542 but were more likely to select scarce items for themselves when they were  
543 in a context with multiple recipients [Echelbarger and Gelman, 2017]. This  
544 perhaps strengthens the argument that the social context may be key to  
545 triggering scarcity effects.

546 A related, but distinct, idea is that the instructions given to the partic-  
547 ipants in the experiment may be important. In many previous social psy-  
548 chology studies on scarcity, the participants are explicitly told by the ex-  
549 perimenter that one type of target is scarce, and another is more common,  
550 as in the example of the art print given above [Lynn, 1989]. This is dis-  
551 tinct from the current experiment, where participants are not told which  
552 stimulus is scarcer. However, prevalence studies in visual search have  
553 shown that these different scenarios may have different effects on search  
554 behaviour, with top-down instructions potentially altering low-level at-  
555 tentional biases [Horowitz, 2017]. This could suggest that while the scarcity  
556 effects may need a ‘top-down’ input that was not present in our experi-  
557 ment, they could still act via ‘low level’ biases. An interesting avenue for  
558 future exploration could be to run an experiment where participants are  
559 specifically instructed that certain targets are more prevalent than others,  
560 and to see if this alters behaviour.

561 A final explanation is that perhaps our participants did find the scarcer  
562 targets more rewarding, but there were other factors in the experimen-  
563 tal design that changed the ‘selection balance’, meaning that the partic-  
564 ipant behaviour on our task was mostly impacted by other, stronger fac-  
565 tors [Tagu and Kristjánsson, 2022]. Previous research using more cognitive  
566 tasks have found effects of target prevalence: in the most directly compa-  
567 rable study, where all targets had equal value, the effect was in the op-  
568 posite of our prediction, in that participants were more likely to choose  
569 the more common targets [Wolfe et al., 2018]. We did not find any ev-  
570 idence for this type of ‘anti-scarcity’ bias in our study either. We think

571 this may reflect some interesting methodological differences that perhaps  
572 altered the ‘selection balance’. Firstly, Wolfe et al. [2018] used a design  
573 where participants were able to move on from a ‘patch’ at any time of their  
574 choosing, rather than the exhaustive search that our participants were re-  
575 quired to complete. They also used four targets in their study, compared to  
576 our two, and targets made up a smaller proportion of the display (around  
577 20 – 30%) than in our experiment. Finally, each target collected the partic-  
578 ipant points, and therefore participants aimed to collect as many points as  
579 possible over the experiment. It therefore seems likely that a sensible strat-  
580 egy for participants to maximise their points in their experiment would be  
581 to search for the most numerous targets, as these were still relatively rare  
582 and difficult to find in the display, and then move on to the next screen  
583 rather than spending a lot of time trying to find even rarer scarce targets.  
584 In our study, participants gained no explicit benefit from finding one type  
585 of target before the other, and our results suggest that there was no implicit  
586 benefit to them prioritising either the more or less frequent target type.

587 Despite finding no evidence for scarcity biases, we did see that par-  
588 ticipants had an overall preference for target type A in the *conjunction*  
589 condition: all three scarcity conditions showed a positively skewed class  
590 weight distribution. This was not seen in the *feature* condition, where in  
591 the AB condition, people showed a similar preference for the two target  
592 types. For the *conjunction* condition, the bias for target type A (red squares)  
593 seems unlikely to relate to differences in salience of the colours chosen: the  
594 same colours (red and green) were used in the *feature* condition, and did  
595 not seem to lead to bias. We therefore speculate that this effect may re-  
596 flect a difference in shape salience, perhaps because circles were used as  
597 targets in all trials, so the square stimulus was slightly more novel and  
598 salient overall. Another possible explanation could be that the rotation of  
599 the targets matters: the square targets are more ‘unique’ compared to the  
600 circle targets, which all continue to have the same orientation when ro-  
601 tated, which may make the squares more salient. Interestingly, previous  
602 work using the same stimuli also shows a similar bias when analysed us-  
603 ing our model e.g. the datasets in Clarke et al. [2022c] and Kristjánsson  
604 et al. [2014], as re-analysed in Clarke et al. [2022b]. The design of our ex-  
605 periment means that this ‘baseline’ preference is unlikely to matter for un-  
606 derstanding the effects of scarcity, but it is worth noting that these types of  
607 underlying saliency preferences appear to be stable and repeatable across  
608 individuals and experiments, and therefore it may be interesting in future

609 work to try to understand more fully why they occur.

610 A secondary aim of this experiment was to test the generalisability of  
611 the results from Clarke et al. [2022b]. To date, we have only tested our  
612 modelling framework on secondary datasets, so we wanted to see to what  
613 extent the previous findings replicate to a novel, pre-registered set of data.  
614 In the main experiment, the findings were very similar to previous work:  
615 we find that people are more likely to stick with the same target type in  
616 the *conjunction* condition compared to the *feature* condition, as has been  
617 found in [Kristjánsson et al., 2014, Clarke et al., 2022c] and many other for-  
618 aging studies. We also find the values of  $b_S$  our model converged on for  
619 this set of experimental data were very similar to those found in [Clarke  
620 et al., 2022b]. Similarly, we found that proximity was an important pa-  
621 rameter in the model, and the effect was larger for the *feature* condition, as  
622 predicted. However, the absolute values for the effect of proximity were  
623 a little smaller than we originally predicted, particularly for the *conjunc-*  
624 *tion* condition. This may be due to slight model adjustments compared to  
625 our original paper [Clarke et al., 2022b], particularly in the way that rela-  
626 tive distance is calculated, or may reflect methodological differences. We  
627 would recommend that inferences about proximity using the model are  
628 based on differences between conditions within an experiment, as these  
629 seem to be replicable.

630 We predicted that we would see a negative effect of relative direction,  
631 with participants being slightly more likely to ‘track back’ on themselves  
632 to pick up targets behind the last selected one than to continue on in a  
633 straight line. We made this prediction because we found this effect in our  
634 re-analysis of [Clarke et al., 2022c] in Clarke et al. [2022b]. However, in the  
635 current dataset, we found no evidence for any type of direction bias, with  
636 the posterior distributions being centred on zero. One possible difference  
637 with the current experiment was that the number of targets was smaller  
638 than used in previous experiments (20 vs. 40), which may make it harder  
639 to detect differences in directional strategy. Future modelling work could  
640 carry out sensitivity analyses to investigate this further.

## 641 7 Conclusion

642 Overall, we find no evidence that target scarcity affects participant’s be-  
643 haviour in a foraging task, challenging Brock’s Commodity Theory [Brock,



1968] that suggests that participants should implicitly value scarce targets more highly. However, we are able to replicate many of the results from [Clarke et al., 2022b], suggesting that the modelling findings from that study broadly generalise to a new set of data.

We would argue that our modelling approach is a powerful method to develop our understanding of the cognitive processes that underlie human foraging behaviour. Given that many visual search tasks involve repeated sampling of the environment, even if only one final correct target is present, this modelling approach may also generalise fruitfully to a wider range of search behaviours. The modelling framework is also flexible, meaning that other relevant cognitive parameters can be easily included (e.g. memory), again broadening the scope of the questions that could be answered using this approach.

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