

# 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 the proposed study, we will test 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, it is hypothesised that participants will show a scarcity bias. The bias will be investigated using a Bayesian statistical model which has been developed for predicting target-by-target foraging behaviours.

## 1 Introduction

Humans and other animals search their environment regularly, looking both for unique items, and for items where there are multiple exemplars

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17 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  
18 target type from amongst distractors. The latter is referred to as foraging,  
19 in which observers search and collect multiple targets. It is considered  
20 an important behaviour given its connection to resource gathering [Bella-  
21 Fernández et al., 2021], and has even been argued to be a key behaviour  
22 driving human cognitive evolution [Hills et al., 2015, Pretelli et al., 2022]  
23

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

37 Target value has been shown to be one of the main factors governing  
38 the deployment of visual attention [Wolfe and Horowitz, 2017], and  
39 as such, it plays an important role in foraging behaviour. Value can be  
40 thought of as either explicit or implicit. An example of explicit value influencing  
41 foraging behaviour can be seen in a study by Nityananda and Chittka [2021].  
42 They trained bees to discriminate between artificial flowers, their foraging  
43 behaviour was influenced such that they chose the more rewarding flowers  
44 (with more sucrose) in higher proportions. In humans, we can also use points  
45 and prizes as a way to manipulate explicit value e.g. by tying participant  
46 payment to gaining a certain number of points in an experiment. By contrast,  
47 implicit value is used to describe situations in which some targets may be  
48 more attractive to a forager due to an incidental feature. For example, Nityananda  
49 and Chittka [2021] manipulated saliency in their experiments by adjusting the  
50 colour contrast of targets compared to their background, and found that higher  
51 saliency targets were more likely to be selected than lower ones.  
52

53 One interesting example of implicit value is *scarcity*, where a target  
54 type is visually less common in an environment. Brock’s Commodity The-

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

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

90 There have been a number of visual search studies that have investi-  
91 gated scarcity, focusing on the context of scarce or abundant distractors  
92 rather than studying the effect of scarce targets. In one study, where par-

123 participants searched for a target amongst two types of distractor, the distrac-  
124 tor ratio strongly affected behaviour, with participants responding more  
125 quickly when one distractor was rarer than the other [Shen et al., 2000].  
126 Similarly, people have been shown to be able to search relatively efficiently  
127 for a conjunction target within the smaller group of distractors when one  
128 type of distractor is more numerous than the other [Sobel and Cave, 2002].  
129 Attention is therefore directed to the rarer elements of the display, in a  
130 manner that might share cognitive similarities to a ‘scarcity bias’, although  
the authors themselves argued that this behaviour was observed because  
it is faster to start search in a smaller group compared to a larger one.

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

To be able to more precisely track participant behaviour in these types  
of foraging tasks, we have developed a generative Bayesian model based  
on a sampling without replacement procedure. The benefit of this model  
is that it is able to break down behaviour into a series of cognitive biases,  
such as a preference for sticking with the same target type, or a preference  
for selecting a nearby target type, thus overcoming some of the limita-  
tions inherent to analyses based on aggregate statistics. We have success-  
fully demonstrated that our model can account for average patterns of be-  
haviour in a range of human foraging experiments [Clarke et al., 2022b].  
In addition, it can make relatively accurate predictions of the next target  
a given individual will select on a trial [Clarke et al., 2022a]. We therefore

131 think that our model is a powerful tool for studying and understanding  
132 the processes underlying human foraging behaviour.

133 In the current study, participants will search amongst coloured targets  
134 and distractors, in feature and conjunction styles of foraging like that of  
135 [Kristjánsson et al., 2014]. In the feature task, participants have to distin-  
136 guish between targets and distractors based on colour. In the conjunction  
137 task, both shape and colour will need to be considered in order to differen-  
138 tiate targets and distractors. Participants will take part in some conditions  
139 where there are equal numbers of each target types, and other conditions  
140 where one target type is more numerous than the other. We have two key  
141 aims. Firstly, we will test whether scarcity affects how participants forage.  
142 If participants implicitly value the scarcer target more highly, as Brock’s  
143 Commodity Theory [Brock, 1968] suggests they would, we expect partici-  
144 pants to show a preference for the scarcer target, as measured by the bias  
145 parameter in the generative foraging model. As a secondary aim, we will  
146 test the extent to which the results of [Clarke et al., 2022b] generalise to  
147 a novel set of data. To date, we have used only secondary data sets, and  
148 therefore we will use the registered report format to pre-register specific  
149 hypotheses relating to the parameters in our model to test how generalis-  
150 able previous findings are.

## 151 2 Planned methods

### 152 2.1 Participants

153 We will collect data from 36 participants, recruited from the University of  
154 Essex participant pool. This sample size is justified below in Section 4.4.  
155 Informed consent will be collected at the beginning of the study and the  
156 participants will be debriefed as to the nature of the study afterwards. Par-  
157 ticipants will confirm (via self-report) that they have normal or corrected-  
158 to-normal vision. Ethical approval for the experiment has been granted by  
159 the University of Essex Research Ethics Sub-committee 1 (ETH2223-1093).  
160 We anticipate the experiment will take around 30 minutes to complete,  
161 and participants will be compensated £5 for their time.

## 162 2.2 Design

163 A 2x3 within-subjects design will be used. The first independent variable  
164 is the difficulty of the task, with two levels: *feature* and *conjunction* (details  
165 of the stimulus manipulation given below). The second independent vari-  
166 able is the ratio of targets of class *A* to *B*, with three levels: target class *A*  
167 is *scarce* (5 *A* to 15 *B*); class *B* is *scarce* (15 *A* to 5 *B*) and an *even* ratio (10 *A*  
168 to 10 *B*).

169 Each participant will participate in all six conditions. Within each con-  
170 dition, there will be ten trials, meaning that they will complete 60 trials.  
171 Each condition is completed as one block, and the order of blocks will be  
172 counterbalanced across participants (half the participants will complete  
173 the three feature blocks first, in a random order, and half will complete the  
174 three conjunction blocks first, in a random order).

175 Before beginning the experiment, each participant will complete a prac-  
176 tice trial to familiarise themselves with the procedure: this will be similar  
177 to a *feature* trial with an *even* ratio of targets, but using different colours  
178 (black and white for the targets, and 'old lace' and 'thistle' for the dis-  
179 tractors: all colour names refer to the RGB hex colours) and shapes (all  
180 targets and distractors will be triangles, approximately 1 unit of visual  
181 angle wide). All other feature will otherwise exactly resemble the main  
182 experimental trials.

## 183 2.3 Stimuli

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

197 stimuli can be seen in Figure 1.

## 198 2.4 Procedure

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

215 Participants will have their eyes tracked for the duration of the exper-  
216 iment using an SR EyeLink 1000 Plus eyetracker. This data will be made  
217 available for exploratory analysis in the future, but will not be used in the  
218 current registered report.

## 219 3 Data Analysis

220 We will use the four-parameter generative foraging model proposed by  
221 [Clarke et al., 2022b] to analyse the data. The model allows for target-by-  
222 target prediction of behaviour during visual foraging [Clarke et al., 2022a]  
223 and a benefit of this approach is that it enables us to parameterise the fac-  
224 tors that may affect the forager’s choice of targets, such as proximity or a  
225 preference for foraging in ‘runs’ of a single target type [Kristjánsson et al.,  
226 2014]. The model also contains a ‘class bias’ parameter which detects a  
227 preference for one target type over another type. If item scarcity does  
228 make some targets more attractive than others, we should be able to see a  
229 difference in this parameter between the *scarce* and *even* conditions.

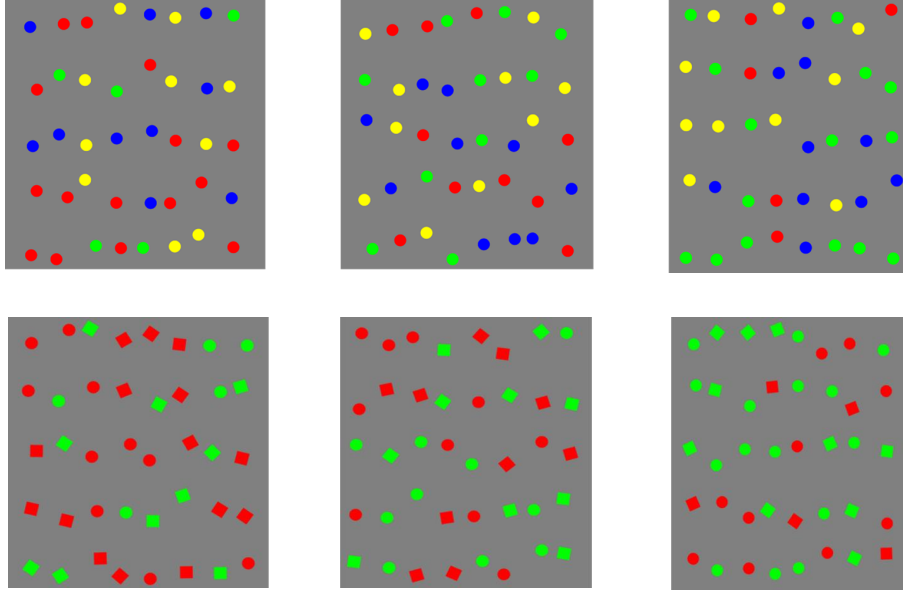


Figure 1: Example stimuli. Top row is stimuli for the feature search, bottom row is for the conjunction search. For feature, from left to right; is scarce green target condition, equal target condition, and scarce red target condition. For conjunction search, from left to right; scarce green circle condition,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

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

### 235 3.1 A four-parameter model of visual foraging

236 We model foraging as a process of weighted sampling without replace-  
 237 ment. We assume that target items belong to one of two classes ( $A$  and  $B$ )  
 238 and details of any distractor items are neglected. In the experiment pre-  
 239 sented in this manuscript,  $A$  and  $B$  are red and green circles respectively



240 for the feature task, then red squares and green circles for the conjunction  
241 task.

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

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

270 These four parameters are fit to the data for each experimental condi-  
271 tion:  $b_A(k)$ ,  $b_S(k)$ ,  $\sigma_\rho(k)$  and  $\sigma_d(k)$  where  $k$  is one of  $K$  experimental con-  
272 ditions. Further details of the model implementation can be found in the  
273 Supplementary Materials.

## 274 3.2 Implementation Details

275 The model fitting procedure will be the same as Clarke et al. [2022b] with  
276 three changes. Firstly, while a multi-level framework will be used to ac-  
277 count for the differences between participants, we will not model the cor-  
278 relations between random effects. This is because we previously found rel-  
279 atively weak correlations when modelling similar experiments in Clarke  
280 et al. [2022b], and this modification will significantly reduce computa-  
281 tional time. Secondly, we have adjusted the manner in which relative  
282 distances are calculated in order to account for the fact that the stimulus  
283 display is not necessarily square (although we intend in this experiment  
284 to use a square display). Finally, we have incorporated the initial selection  
285 bias described in Clarke et al. [2022a] into the full model: this allows us to  
286 take into account a person’s preference for starting each trial in a particular  
287 region of the screen (e.g. the centre, or the top left hand corner).

288 The following weakly informative priors will be used.

$$289 \quad b_A, b_B \sim \mathcal{N}(0, 1) \quad (1)$$

$$290 \quad b_S \sim \mathcal{N}(0, 1) \quad (2)$$

$$291 \quad \sigma_p \sim \mathcal{N}(15, 4) \quad (3)$$

$$\sigma_\rho \sim \mathcal{N}(0, 3) \quad (4)$$

292 Each prior is a normal distribution with a specified mean and standard  
293 deviation, and the values chosen are based on applying the model to data  
294 from previous related experiments [Clarke et al., 2022b]. An LKJ prior  
295 will be used for the random effect structure [Lewandowski et al., 2009].  
296 Importantly, we use the same set of priors for both the *equal* and *scarce*  
297 experimental conditions.

298 Models will be fit using R [R Core Team, 2021] and Stan [Stan Devel-  
299 opment Team, 2020] (full details of the software environment will be in-  
300 cluded in supplementary materials). The model fit will be checked to en-  
301 sure that  $\hat{r} < 1.01$  and the traceplots will be visually inspected to check  
302 convergence.

303 Applying sophisticated modelling to new data can sometimes lead to  
304 unexpected problems. Such issues can sometimes be easily solved by us-  
305 ing a different set of priors, or some other change to how the model is  
306 implemented. If we find ourselves in this situation, we will transparently

307 document all changes from our original plan in our supplementary mate-  
308 rials.

309 Proposed analysis materials are available on our GitHub repository.

### 310 3.3 Data Exclusion

311 The following criteria will be used for data inclusion/exclusion:

- 312 • Data from terminated trials (due to selecting a distractor) will not be  
313 analysed.
- 314 • Any trial containing an inter-target selection time of more than five  
315 seconds will be removed.

316 We will only analyse data from participants who have at least five trials  
317 of data for each condition after the above criteria are applied. We will  
318 collect enough data to ensure we have 36 participants for the final analyses  
319 after data exclusion criteria are applied.

## 320 4 Hypotheses

### 321 4.1 The Effect of Scarcity

322 Our main hypothesis [H1] is that participants will show a preference for  
323 selecting scarce targets. As preferences to select one target class over an-  
324 other may also differ due to visual salience, we will take  $b_A(equal)$  as our  
325 baseline condition and compare this to  $b_A(scarce_A)$  and  $b_A(scarce_B)$ .

326 We will test this hypothesis by examining the posterior distributions  
327 (given the data  $D$ ) for the difference between these parameters: if both

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

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

329 are true, marginalising over the *feature* and *conjunction* conditions, then  
330 we will conclude in favour of our hypothesis. We will also use the same  
331 procedure to measure the effect of scarcity in the *feature* and *conjunction*  
332 conditions separately, although we have no specific hypothesis about the  
333 size or direction of potential effects.

334 If we do not find strong evidence in favour of our hypothesis, we will  
335 carry out exploratory analysis to a) investigate if one of the counterbal-  
336 anced conditions shows a scarcity effect but not the other and/or b) in-  
337 vestigate the extent to which it holds in a subset of participants. If there  
338 is a range of scarcity effects across different participants, we will explore  
339 whether these are correlated with the other parameters in our model.

340 In the unlikely event that we are unable to achieve a good model fit us-  
341 ing the full four parameter model, we will fit a simpler ‘sampling without  
342 replacement’ model which ignores the spatial components of the model  
343 [Clarke et al., 2022b].

## 344 4.2 Secondary Hypotheses around model fit

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

347 H2 : If our *feature* vs. *conjunction* manipulation shows a similar effect as  
348 that seen in [Kristjánsson et al., 2014] and [Clarke et al., 2022c], we  
349 expect to see a larger value for  $b_S$  in the *conjunction* condition com-  
350 pared to the *feature* condition. This will be investigated by examining  
351 the posterior distribution for a difference between feature and con-  
352 junction conditions using the same procedure as above.

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

359 H4 : We predict we will see a negative effect of relative direction, al-  
360 though this effect will likely be weak (around -1) with considerable  
361 variation between individuals. In order to test this hypothesis, we  
362 will calculate whether 99% of the posterior distribution for the rela-  
363 tive direction parameter is negative.

### 364 4.3 Planned exploratory analyses

365 If a new version of our model has been released by the time we have col-  
366 lected our data, we will also present results using this (in supplementary  
367 material).

368 We will also present (in supplementary material) the standard aggre-  
369 gate descriptive statistics used in foraging research (maximum run length  
370 and total number of runs). We do not intend to use these in our analy-  
371 ses, but they will provide a useful reference point for comparisons with  
372 previous research in the field.

373 We would also be willing to test alternative models proposed by other  
374 researchers if appropriate.

### 375 4.4 Justification of Sample Size

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

391 We simulated 36 participants, each completing five trials per condition  
392 (this is a highly conservative estimate: in most cases, we expect that each  
393 participant will complete ten trials per condition). While five trials may  
394 seem a relatively small amount, we have shown previously that good pa-  
395 rameter estimates can be recovered with as little as one trial of data in  
396 a similar task [Clarke et al., 2022b]. The parameters for the random ef-  
397 fect structure were again based on results from [Clarke et al., 2022b] (see  
398 Supplementary Materials for full details and code). We then fit the four-

parameter foraging model to these simulated data, the results of which can be seen in Figure 2. We can clearly detect the bias towards the less common target type in the scarce conditions. We can also see clear differences between the feature and conjunction conditions in stick probability and proximity tuning, demonstrating that we should be able to detect these effects if they are present in the data.

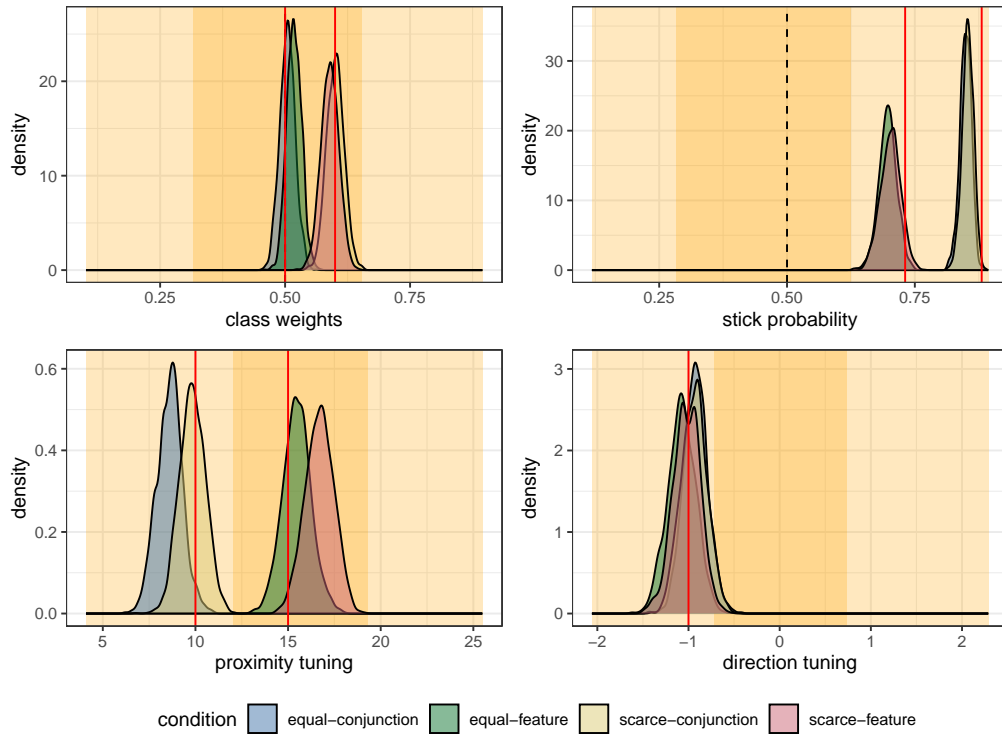


Figure 2: Posterior probabilities after fitting the model to the simulated data. The yellow-shaded background areas represent the prior distribution (53% and 97% HPDIs). Red lines indicate the parameter values used in the simulation.

## 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 shows that in a small number of participants, the effects seen are generally in line with our hypotheses.

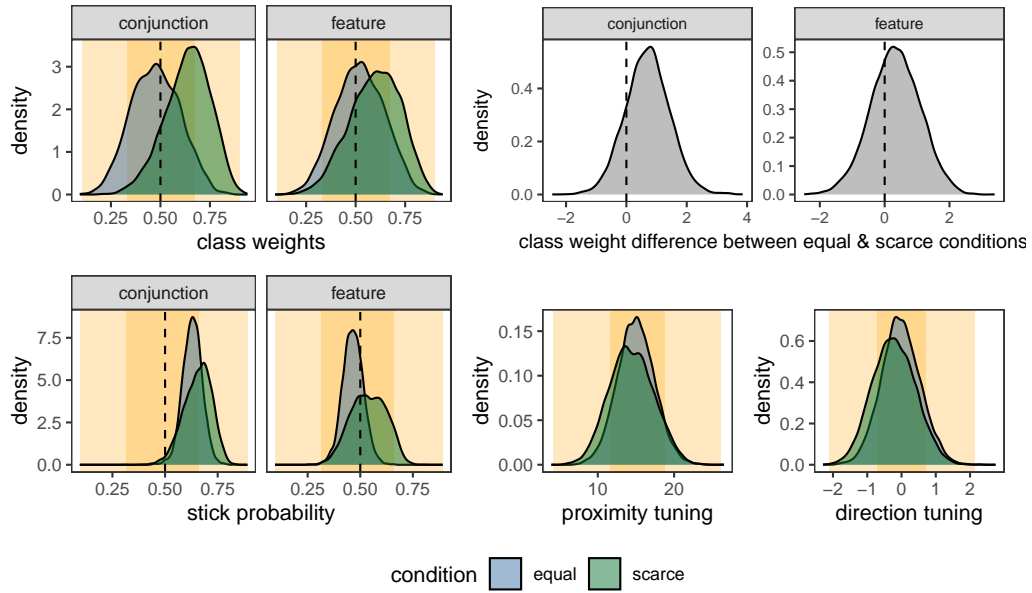


Figure 3: Posterior probabilities after fitting the model to the pilot data. The grey shaded background areas represent the prior distribution (53% and 97% HPDIs). (top left) Posterior distribution for  $p_A$ . (top right) Posterior distributions for the difference between the *scarce* and *equal* conditions.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

## 5 Results

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## 418 6 Discussion

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## 423 References

- 424 M. Bella-Fernández, M. Suero Suñé, and B. Gil-Gómez de Liaño. Foraging  
425 behavior in visual search: A review of theoretical and mathematical  
426 models in humans and animals. *Psychological research*, pages 1–19, 2021.
- 427 T. C. Brock. Implications of commodity theory for value change. In  
428 *Psychological foundations of attitudes*, pages 243–275. Elsevier, 1968.
- 429 T. C. Brock and L. A. Brannon. Liberalization of commodity theory. *Basic*  
430 *and Applied Social Psychology*, 13(1):135–144, 1992.
- 431 A. D. Clarke, A. R. Hunt, and A. E. Hughes. A bayesian statistical model  
432 is able to predict target-by-target selection behaviour in a human  
433 foraging task. *Vision*, 6(4):66, 2022a.
- 434 A. D. Clarke, A. R. Hunt, and A. E. Hughes. Foraging as sampling  
435 without replacement: A bayesian statistical model for estimating biases  
436 in target selection. *PLOS Computational Biology*, 18(1):e1009813, 2022b.
- 437 A. D. Clarke, J. L. Irons, W. James, A. B. Leber, and A. R. Hunt. Stable  
438 individual differences in strategies within, but not between, visual  
439 search tasks. *Quarterly Journal of Experimental Psychology*, 75(2):289–296,  
440 2022c.
- 441 M. Dawkins. Shifts of ‘attention’ in chicks during feeding. *Animal*  
442 *Behaviour*, 19(3):575–582, 1971.
- 443 M. Echelbarger and S. A. Gelman. The value of variety and scarcity across  
444 development. *Journal of experimental child psychology*, 156:43–61, 2017.



- 445 T. T. Hills, P. M. Todd, D. Lazer, A. D. Redish, and I. D. Couzin.  
446 Exploration versus exploitation in space, mind, and society. *Trends in*  
447 *cognitive sciences*, 19(1):46–54, 2015.
- 448 Á. Kristjánsson, Ó. I. Jóhannesson, and I. M. Thornton. Common  
449 attentional constraints in visual foraging. *PloS one*, 9(6):e100752, 2014.
- 450 D. Lewandowski, D. Kurowicka, and H. Joe. Generating random  
451 correlation matrices based on vines and extended onion method.  
452 *Journal of Multivariate Analysis*, 100(9):1989–2001, 2009. ISSN 0047-259X.  
453 doi: <https://doi.org/10.1016/j.jmva.2009.04.008>. URL  
454 [https://www.sciencedirect.com/science/article/pii/](https://www.sciencedirect.com/science/article/pii/S0047259X09000876)  
455 [S0047259X09000876](https://www.sciencedirect.com/science/article/pii/S0047259X09000876).
- 456 M. Lynn. Scarcity effects on value: A quantitative review of the  
457 commodity theory literature. *Psychology & Marketing*, 8(1):43–57, 1991.
- 458 V. Nityananda and L. Chittka. Different effects of reward value and  
459 saliency during bumblebee visual search for multiple rewarding  
460 targets. *Animal Cognition*, 24(4):803–814, 2021.
- 461 I. Pretelli, E. Ringen, and S. Lew-Levy. Foraging complexity and the  
462 evolution of childhood. *Science Advances*, 8(41):eabn9889, 2022.
- 463 R Core Team. *R: A Language and Environment for Statistical Computing*. R  
464 Foundation for Statistical Computing, Vienna, Austria, 2021. URL  
465 <https://www.R-project.org/>.
- 466 S. Sehnert, B. Franks, A. J. Yap, and E. T. Higgins. Scarcity, engagement,  
467 and value. *Motivation and Emotion*, 38:823–831, 2014.
- 468 J. Shen, E. M. Reingold, and M. Pomplun. Distractor ratio influences  
469 patterns of eye movements during visual search. *Perception*, 29(2):  
470 241–250, 2000.
- 471 K. V. Sobel and K. R. Cave. Roles of salience and strategy in conjunction  
472 search. *Journal of Experimental Psychology: Human Perception and*  
473 *Performance*, 28(5):1055, 2002.
- 474 Stan Development Team. RStan: the R interface to Stan, 2020. URL  
475 <http://mc-stan.org/>. R package version 2.21.2.

- 476 J. Tagu and Á. Kristjánsson. The selection balance: Contrasting value,  
477 proximity and priming in a multitarget foraging task. *Cognition*, 218:  
478 104935, 2022.
- 479 I. Wiegand and J. M. Wolfe. Target value and prevalence influence visual  
480 foraging in younger and older age. *Vision research*, 186:87–102, 2021.
- 481 J. M. Wolfe and T. S. Horowitz. Five factors that guide attention in visual  
482 search. *Nature Human Behaviour*, 1(3):0058, 2017.
- 483 J. M. Wolfe, M. S. Cain, and A. Alaoui-Soce. Hybrid value foraging: How  
484 the value of targets shapes human foraging behavior. *Attention,*  
485 *Perception, & Psychophysics*, 80:609–621, 2018.
- 486 J. M. Wolfe, M. S. Cain, and A. M. Aizenman. Guidance and selection  
487 history in hybrid foraging visual search. *Attention, Perception, &*  
488 *Psychophysics*, 81:637–653, 2019.