

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 × 1080 pixels (though the targets were placed within
204 a grid of 1000 × 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

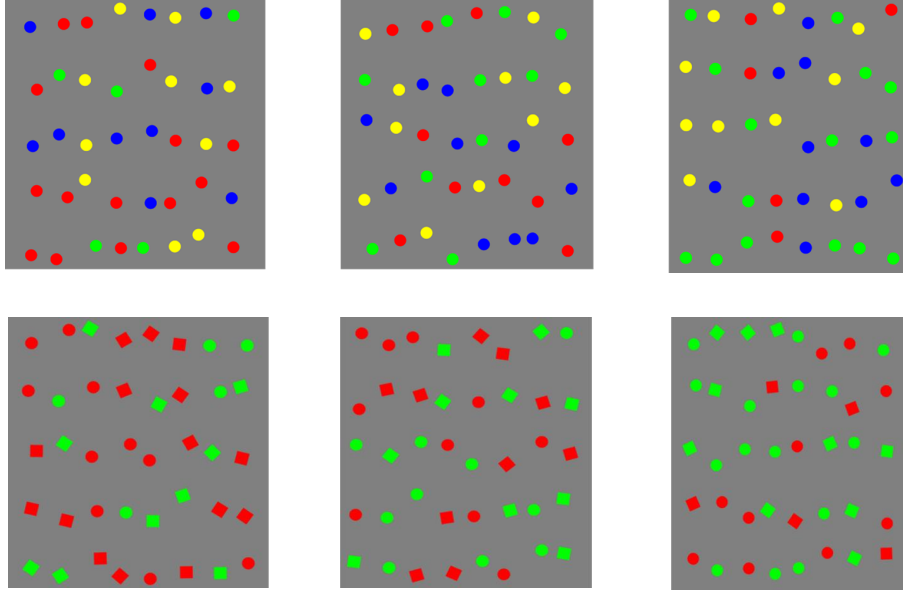


Figure 1: Example stimuli. Top row is stimuli for the feature search, bottom row is for the conjunction search. For feature, from left to right; is scarce green target condition, equal target condition, and scarce red target condition. For conjunction search, from left to right; scarce green circle condition,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

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

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

3.1 A four-parameter model of visual foraging

We model foraging as a process of weighted sampling without replacement. 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 • σ_ρ : this parameter reflects the importance of proximity when select-
 265 ing the next item. The larger σ_ρ is, the more heavily weighted selec-
 266 tion is to items that are close to the previously selected item.
- 267 • σ_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.²

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

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

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

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

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

¹The 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.

²Note 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 and have
307 been archived within a Zenodo repository.

308 3.3 Data Exclusion

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

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

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

318 4 Hypotheses

319 4.1 The Effect of Scarcity

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

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

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

326

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

327 are true, marginalising over the *feature* and *conjunction* conditions, then
 328 we can conclude in favour of our hypothesis. We also used the same pro-
 329 cedure to measure the effect of scarcity in the *feature* and *conjunction* con-
 330 ditions separately, although we had no specific hypothesis about the size
 331 or direction of potential effects.

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

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

343 4.2 Secondary Hypotheses around model fit

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

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

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

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

363 4.3 Planned exploratory analyses

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

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

374 4.4 Justification of Sample Size

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

³Please 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.

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

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

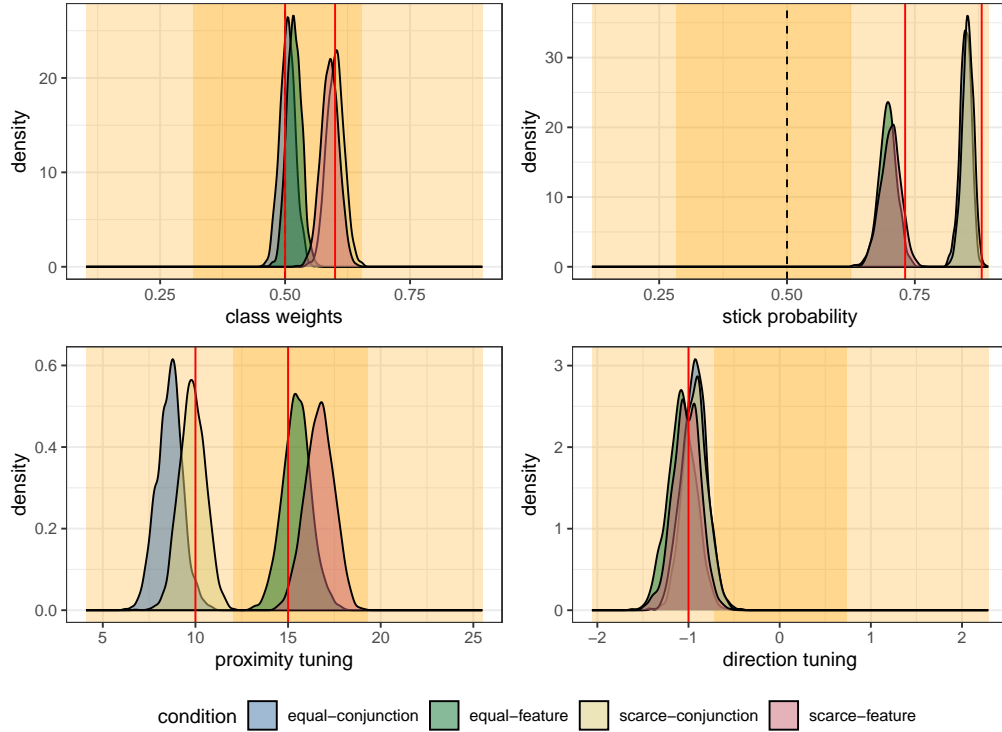


Figure 2: Posterior probabilities after fitting the model to the simulated data. The yellow-shaded background areas represent the prior distribution (53% and 97% HPDIs). Red lines indicate the parameter values used in the simulation.

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.

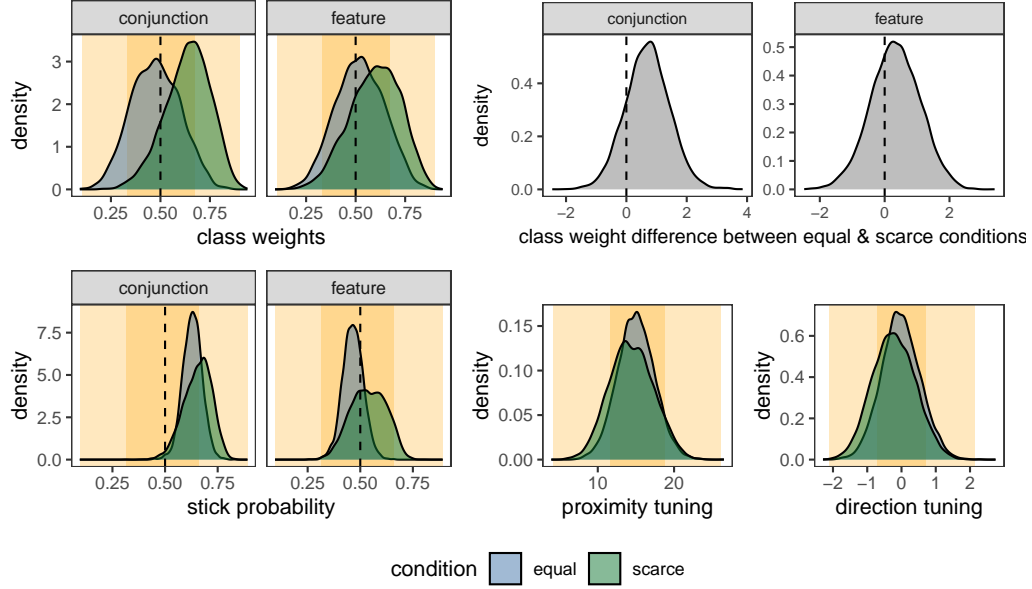


Figure 3: Posterior probabilities after fitting the model to the pilot data. The orange shaded background areas represent the prior distribution (53% and 97% HPDIs). (top left) Posterior distribution for p_A . (top right) Posterior distributions for the difference between the *scarce* and *equal* conditions.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

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

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

5.2 The Effect of Scarcity

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

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

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

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

459 instead finding 67% for condition AB subtracted from condition A, and
 460 82% for condition B subtracted from condition AB.

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

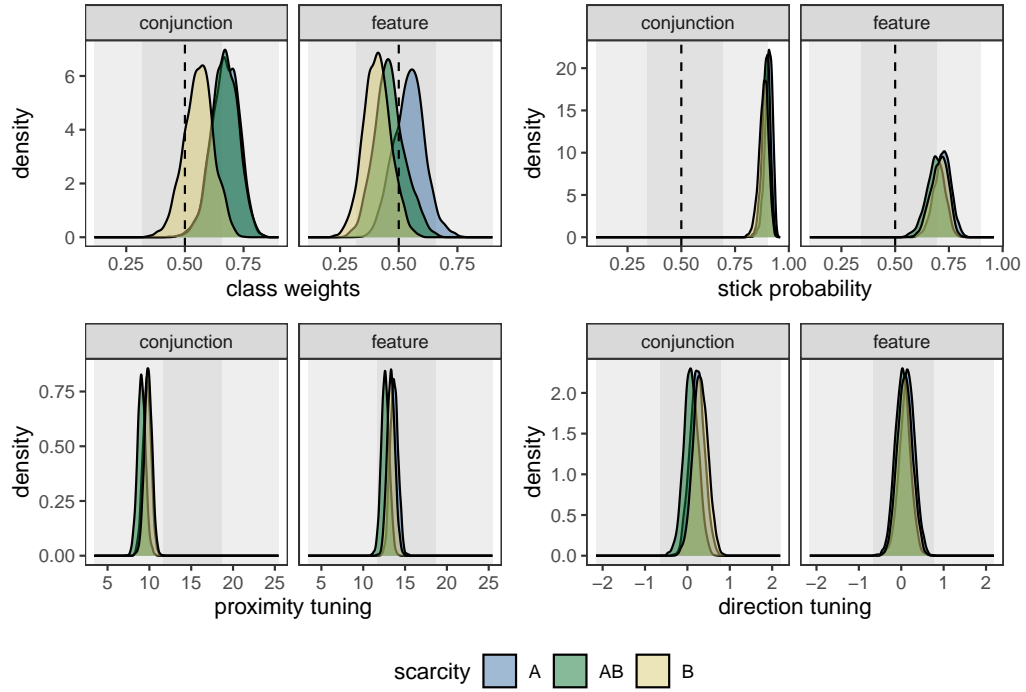


Figure 4: Posterior probabilities after fitting the model to the real data. The grey shaded background areas represent the prior distribution (53% and 97% HPDIs). (top left) Posterior distribution for p_A . (top right) Posterior distributions for the stick probability p_S . (bottom left) Posterior distributions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

465 5.2.1 Exploratory analyses for scarcity

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

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

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

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

⁴Note 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.

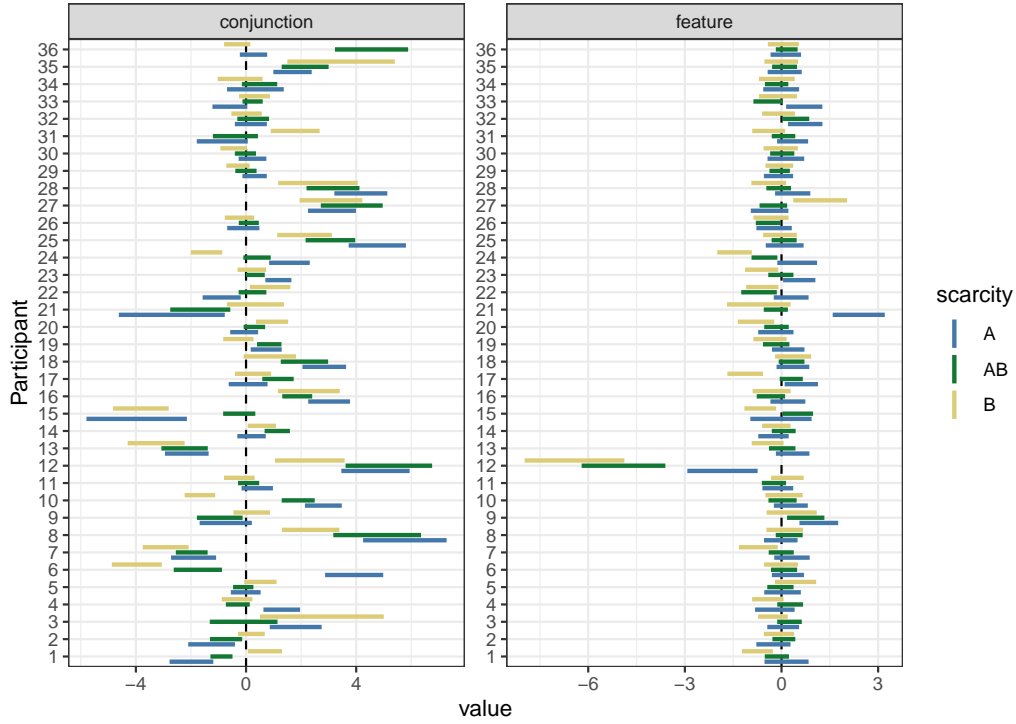


Figure 5: The random effects u_A for each participant, for all scarcity and difficulty (feature vs. conjunction) conditions.

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

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

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

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

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

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

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

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

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

642 7 Conclusion

643 Overall, we find no evidence that target scarcity affects participant’s be-
644 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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