

1 Processing of novel food reveal payoff and rank-biased social learning in a wild primate

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15

16 Abstract

17 Social learning – learning from others – is the basis for behavioural traditions. Different social
18 learning strategies (SLS), where individuals biasedly learn behaviours based on their content
19 or who demonstrates them, may increase an individual’s fitness and generate behavioural
20 traditions. While SLS have been mostly studied in isolation, their interaction and the interplay
21 between individual and social learning is less understood. We performed a field-based open
22 diffusion experiment in a wild primate. We provided two groups of vervet monkeys with a
23 novel food, unshelled peanuts, and documented how three different peanut opening
24 techniques spread within the groups. We analysed data using hierarchical Bayesian dynamic
25 learning models that explore the integration of multiple SLS with individual learning. We i)

26 report evidence of social learning compared to strictly individual learning, ii) show that
27 vervets preferentially socially learn the technique that yields the highest observed payoff and
28 iii) also bias attention toward individuals of higher rank. This shows that behavioural
29 preferences can arise when individuals integrate social information about the efficiency of a
30 behaviour alongside cues related to the rank of a demonstrator. When these preferences
31 converge to the same behaviour in a group, they may result in stable behavioural traditions.

32

33 Keywords: social learning strategy; field experiment; Experience weighted attraction models;
34 transmission; dominance bias; vervet monkeys

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36 Introduction

37

38 Organisms may learn about their environment and acquire new skills individually, by
39 trial and error, or socially, by directly observing and/or copying others' behaviour [1]. Social
40 learning has been considered adaptive since organisms may gain fitness benefits when
41 learning from others, especially in a changing environment or when individual learning is
42 costly [2]. However, social learning might also be maladaptive when social information is
43 outdated [3, 4]. Socially transmitted behaviours resulting in animal cultural traditions have
44 been described in diverse taxa and domains such as songbird vocal dialects [5], tool use in
45 crows [6], hunting techniques in whales [7], social conventions, extractive foraging
46 techniques and manipulation behaviours in numerous primates [8-11].

47 Social learning is often not random, and animals can use social learning strategies to
48 acquire behaviour. Social learning strategies are rules of thumb that permit an individual to
49 acquire behaviour rapidly or cheaply without evaluating the entire population or
50 understanding the functional significance of a behaviour. These strategies can also structure

51 within- and between-group variation in behavioural traditions. Social learning biases direct an
52 individual's attention towards a behaviour based on its content, relative frequency in a
53 population, or its association with a particular type of demonstrator. These biases are
54 typically, but not always, assumed to be shortcuts to acquiring adaptive behaviour and are
55 theoretically well explored [3, 12, 13]. Content-biases focus on characteristics of the observed
56 behaviour such as a bias towards more successful behaviours, which yield better payoffs.

57 Much theoretical work has explored the evolution of payoff-biased learning [14, 15],
58 which is useful when payoffs are stochastic or adaptive behaviour is rare. Empirical work in
59 humans show payoff-bias is used concurrently with other social learning strategies [16].
60 Researchers have recently expanded their investigation of payoff-biased learning to wild
61 animals. Wild capuchins adopted the most successful and efficient technique when processing
62 novel fruits [17]. Great tits do not use payoff-biased learning but acquire a high payoff
63 foraging technique through a combination of positive frequency-dependent learning and
64 individual learning that is highly sensitive to personal experiences in payoffs [18]. Male
65 vervet monkeys, but not females, more often used the technique displayed by male
66 demonstrators when a difference in payoff was introduced with males receiving more food
67 than females [19]. The prevalence of payoff-biased learning is likely underestimated in wild
68 populations particularly if adaptive behaviour is common, easy to innovate, or if there is a
69 single optimal solution [17].

70 Context biases focus on other cues such as their frequency in a population (e.g.
71 preferentially use the most common behaviour or the one exhibited by the majority of
72 individuals: conformity bias) or particular traits of models (e.g. preferentially use the
73 behaviour displayed by familiar, prestigious, related, or similarly aged individuals: [20]).
74 Such biases have been reported in various animal species. "Moss sponging" by chimpanzees
75 [21] and "sponging" by dolphins [22] were both transmitted within matrilineal groups; "shelling",

76 another foraging technique, spread non-vertically among associated dolphins [23]. Younger
77 female guppies socially learned the mate choice of older females [24]. Capuchins and
78 chimpanzees used the foraging method displayed by older individuals [17, 25]. In female-
79 philopatric vervet monkeys, females were preferentially chosen over males as demonstrators
80 [26], but demonstrators were all of high-rank. The techniques used by higher-ranked
81 individuals were preferentially chosen by chimpanzees [27] and vervet monkeys [28] when
82 researchers simultaneously tested for several biases. Animals also conform to the most
83 frequently observed behaviour: in vervet monkeys, dispersing males conformed to the local
84 foraging norm, abandoning their natal preference [29]. Great tits and chimpanzees
85 disproportionately adopted the most frequent local foraging technique [30, 31 but see 32].
86 Nine-spined sticklebacks preferentially chose the feeder favoured by the majority of
87 individuals, even when this feeder was less rewarding than an alternative [33]. Fruit flies
88 chose their mating partner according to the preference of the majority of copulating
89 conspecifics [34]. All these findings suggest that different contextual characteristics strongly
90 influence social learning patterns. However, relatively little research has investigated how
91 organisms jointly integrate multiple social learning strategies with individual experience. This
92 integration is important as combining social and individual learning is more adaptive than
93 solely relying on one or the other [35].

94 Open diffusion experiments with experimentally trained demonstrators in the wild
95 have been well utilized [18, 29, 30], and show what social learning strategies animals are
96 capable of in a well-defined experimental context. However, open diffusion experiments
97 without experimentally trained demonstrators may better show how traditions endogenously
98 arise in the wild in more realistic social settings; yet they are rare [17, 28].

99 Recently developed dynamic statistical models including Network Based Diffusion
100 Analysis (hereafter NBDA: [36, 37] and Experience-weighted Attraction models (hereafter

101 EWA: [15, 17, 38]) are powerful statistical modelling approaches to identify evidence for
102 social learning and the pathways of social transmission. NBDA is useful to identify evidence
103 for social learning and the typical pathways of social transmission, but it only analyses the
104 initial spread of a new behaviour, i.e. the origin of a cultural tradition. It cannot thus evaluate
105 what social learning strategies individuals use to inform behavioural choice once they have
106 learned multiple options [37]. Nor can NBDA examine how individuals uniquely combine
107 individual and social information – the combination of which makes social learning adaptive.
108 EWA models analyse the entire unique behavioural sequence chosen by each individual and
109 investigate how this is influenced over time by both personal experience and observation of
110 others, i.e. the origin and maintenance of a cultural tradition [15, 17]. EWA models permit
111 extant theoretical models of social learning strategies to be turned into statistical models to
112 examine which strategy, combination of strategies, or individual learning alone best predict an
113 individual's behaviour. These predictions are conditional upon an individual's unique
114 personal experiences and opportunities for observing social information, thus linking
115 individual variation in behaviour to population-level cultural dynamics.

116 This study aims to determine which content and/or context biased social learning
117 strategies are responsible for the transmission of novel food processing techniques - peanut
118 shelling - in wild vervet monkeys (*Chlorocebus pygerythrus*). We tested for payoff-biased
119 learning as content-biased strategy and for frequency-dependent and model-based learning
120 (sex, kin and rank) as context-biased strategies. Here, we offered a novel food – unshelled
121 peanuts – to two groups of wild vervet monkeys: Noha (hereafter 'NH') and Kubu (hereafter
122 'KB') during four months of field experiments. We recorded the exact time of each peanut
123 consumption event and the identity of observers at each time to construct a dynamic
124 observation network. We described the three different peanut extraction techniques used by
125 monkeys: crack with the hand (hereafter 'CH'; Movie S1: <https://youtu.be/BkiTJyxp3gQ>);

126 crack with the mouth from the side of the peanut (hereafter ‘CMS’; Movie S2:
127 <https://youtu.be/3JOAH4khnjik>) and crack with the mouth from the top of the peanut
128 (hereafter ‘CMT’; Movie S3: : <https://youtu.be/RaFoQpBadG8>). We then analysed data from
129 this experiment with EWA models. We predict, in accordance with another study focusing on
130 context biases [28], that higher-ranked vervet monkeys are more influential demonstrators
131 than others. We hypothesize that other context biases such as frequency-dependence or
132 content biases such as payoff-bias (i.e. the most successful technique), would also be possible.
133 The major interest of this study is to assess whether vervets rely purely on individual learning,
134 or integrate individual learning with social learning strategies, by fitting multiple hierarchical
135 EWA models to data collected in an open diffusion field experiment with no trained
136 demonstrator.

137

138

139 Results

140

141 Effects of group, rank, sex and age on success, manipulation and observation

142 In NH, 25 individuals (9 adults; 12 juveniles; 4 infants) succeeded in opening 2104
143 peanuts and attempted to open a further 1401 peanuts. In KB, 9 individuals (5 juveniles; 4
144 infants) succeeded in opening 45 peanuts and 10 individuals (6 juveniles; 4 infants) attempted
145 to open 102 peanuts (Table S1). We found an effect on rank and sex both on the rate of peanut
146 opening successes and on the rate of manipulation. Higher rankers succeeded significantly
147 more to extract peanuts (GLMs: β estimate=-2.67; standard error (SE) =0.67; t value=-4.00;
148 $P=0.0004$) and manipulated more peanuts than lower rankers ($\beta=-2.22$; SE =0.65; t value=-
149 3.56; $P=0.002$). Males succeeded significantly more to extract peanuts (18/24 males; 16/29

150 females; $\beta=1.12$; SE =0.32; t value=3.56; P=0.001) and manipulated significantly more
151 peanuts than females (19/24 males; 16/29 females; $\beta=0.93$; SE =0.32; t value=2.95; P=0.007).

152 The latency of first success ranged from 2.03 minutes to 448.1 minutes in NH
153 (mean=218.35 min; SE of the mean=25.29 min) and from 78.95 min to 393.6 min in KB
154 (mean=223.33 min; SE of the mean=38.85 min; Table S1). The innovator, in terms of
155 opening peanut, in NH was a low-ranked, newly immigrated adult male at the first exposure
156 to peanuts (Avo) while, in KB, it was an infant male (Aar) at the third exposure. We found a
157 significant effect of age on latency of first peanut opening success. Juveniles had a lower
158 latency compared to infants (GLMs: $\beta=-0.57$; SE =0.25; t value=-2.34; P=0.05), but we found
159 no significant difference between infants and adults ($\beta=0.13$; SE =0.31; t value=0.41; P=0.91)
160 nor between juveniles and adults ($\beta=-0.45$; SE =0.25; t value=-1.82; P=0.16). We found no
161 significant difference between groups ($\beta=-0.16$; SE =0.24; t value=-0.67; P=0.51), between
162 males and females ($\beta=0.12$; SE =0.21; t value=0.57; P=0.58) and no significant effect of rank
163 ($\beta=-0.11$; SE =0.42; t value=-0.26; P=0.80) on latency of first success.

164 We found no clear difference in the rate of observation of successes between groups
165 (GLMs: $\beta=2.79$; SE =1.66; t value=1.68; P=0.10), between high rankers and low rankers ($\beta=-$
166 1.64; SE =0.86; t value=-1.91; P=0.07), between adults and infants ($\beta=0.64$; SE =0.59; t
167 value=1.08; P=0.29), between adults and juveniles ($\beta=-0.007$; SE =0.42; t value=-0.017;
168 P=0.99) nor between males and females ($\beta=0.81$; SE =0.44; t value=1.85; P=0.08). We found
169 limited evidence for any difference on the rate of observation of manipulations between
170 groups ($\beta=2.42$; SE =1.36; t value=1.78; P=0.09), between high and low rankers ($\beta=-1.56$; SE
171 =0.83; t value=-1.89; P=0.07), between adults and infants ($\beta=0.57$; SE =0.58; t value=0.98;
172 P=0.33), between adults and juveniles ($\beta=-0.01$; SE =0.41; t value=-0.03; P=0.98) and
173 between males and females ($\beta=0.79$; SE =0.42; t value=1.88; P=0.07).

174 We found effects of rank, age and sex on the rate of being observed when
175 manipulating and successfully opening peanuts. High-rankers were observed significantly
176 more than low-rankers when succeeding (GLMs: $\beta=-3.61$; SE =0.65; t value=-5.57; $P<0.001$)
177 and manipulating ($\beta=-3.31$; SE =0.65; t value=-5.08; $P<0.001$). Adults were observed
178 significantly more than juveniles when succeeding ($\beta=-0.91$; SE =0.29; t value=-3.12;
179 $P=0.004$) and manipulating ($\beta=-0.73$; SE =0.29; t value=-2.56; $P=0.02$). Males were observed
180 significantly more than females when successfully opening ($\beta=1.15$; SE =0.27; t value=4.20;
181 $P<0.001$) and manipulating peanuts ($\beta=1.02$; SE =0.28; t value=3.63; $P=0.001$).

182

183 EWA model interpretations

184 For most individuals, and at the population level, we found that CMS was the most
185 successful technique, and CMS became the most common technique in the population. CMS
186 was successful on 46.8% occasions in NH and 24.8% in KB over all manipulations. This was
187 followed by CMT (8.1% in NH, 5.4% success in KB) and CH (5.1% in NH, 0.7% in KB).
188 From WAIC values and inspecting model predictions against raw data, we found that the
189 global model best predicts our data compared to any model representing a single social
190 learning strategy (Table 2) and successfully predicts the frequency of each technique used at
191 the population-level (Fig. 1) and across all individuals (Fig. 2; Fig. S1). Although the global
192 model has the lowest WAIC score and predicts data best across all individuals in the
193 population, there is more to learn from comparing predictions and parameter estimates from
194 all models as it helps us better understand the importance of different cues and their
195 corresponding learning strategies. Model predictions show that the highest-payoff behaviour
196 became the most common for nearly all individuals in the population (Fig. 2; Fig. 3 and Fig.
197 S1). The parameters' magnitudes and certainties in the global model, as well as WAIC score

198 and parameter estimates in individual models, suggest that payoff-bias, followed by rank-bias,
199 were the two singular most important learning strategies (Table 2; Table 3).

200 Figure 3 shows predictions for the seven evaluated models for a single individual
201 ('Gran' in NH). In this case, all EWA models allow the highest payoff behaviour (CMS;
202 displayed in purple) to become the most common in the population. However, their dynamics
203 and ability to accurately predict the behavioural sequence differ. The global model tends to
204 show more uncertainty around any particular prediction, whereas models evaluating single
205 learning strategies tend to be overconfident in their estimates, less accurate across the
206 behavioural trajectory, or do not predict well for all individuals in the population. Payoff-
207 biased and rank-biased learning models perform well, but do not adequately predict the
208 frequency of all three behaviours across the entire time series, whereas frequency-dependent
209 learning over-predicts the frequency of the most common, high-payoff behaviour. The
210 individual learning model is the one having the least support from WAIC values (Table 2) and
211 visual inspection of model predictions, strongly suggesting that individual learning alone does
212 not explain techniques' spread. The individual learning model's predictions are overconfident,
213 tend to drift around, and underestimate the frequency of CMS, particularly at the beginning of
214 the time series. Reproducible code to plot these predictions from all models for all individuals
215 in the population is found in the online repository given in the Method section.

216 We found little support that individuals preferentially used the technique displayed by
217 females or individuals of the same sex (Table 2). Kin-biased learning might be important for a
218 few, but not most individuals. We encourage readers to examine Figure S1, which shows
219 global model predictions of behavioural choice for each individual vervet, as we believe it is
220 the most informative about model fit compared to real data and is informative about
221 individual variation. Figures S2-S11 show dot plots of parameter predictions of the global
222 model for age category, sex, group, and individual.

223

224 Variation between individuals and groups in parameters

225 We see considerable variation between the two groups and among individuals for
226 many varying effects parameters in these models, this occurred for several reasons. In KB,
227 fewer individuals participated in the experiment and they had fewer foraging bouts. This
228 generated more uncertain estimates as reflected by width of the HPDIs of parameter
229 prediction for KB compared to NH, visualized in green in Figures S2-S11. They were also
230 less likely to observe social information, based on the 20-minute time windows we selected in
231 this analysis. For these reasons, many of the individual-level parameter estimates of varying
232 effects have tighter 89% HPDIs than the population mean estimates.

233 Posterior estimates of group-level varying effects also differ greatly for some
234 parameters. These estimates are more precise and parameter values related to social learning
235 are higher for NH due to the greater number of individuals who participated to the
236 experiment. This can be visualized when looking at the shaded HPDIs around model
237 predictions in Figure S1 for individuals in both groups of different sample sizes. It is also
238 visualized in Figures S2-S10. Estimates of σ , the variance estimated between groups and
239 individuals for each parameter, are extracted from the variance-covariance matrix of the
240 global model are in Figure S11.

241

242 Sensitivity to attraction scores (λ)

243 Females (Posterior Mean ($\lambda_f=8.38$; [89% HPDI: 4.01-14.86]) are more sensitive than
244 males ($\lambda_m=6.27$ [3.35-10.35]) to differences in attraction scores while juveniles are more
245 sensitive than adults ($\lambda_j=10.04$ [5.45-17.07]; $\lambda_a=5.22$ [2.64-9.03]). A higher attraction score
246 typically means that individuals are more sensitive to personally-experienced differences of
247 behavioural payoffs. The direction of these effects is consistent across nearly all evaluated

248 models (Table 3). We see considerable variation in varying effects of λ at the group and
249 individual level (Fig. S2), but much of this is due to sampling differences.

250

251 Weight given to recent experiences (\square)

252 Overall, we see small values for \square , suggesting that individuals tend to weight past
253 experiences more heavily than recent experiences; memory strongly influences behaviour.

254 Adults tend to weight new experiences more heavily than juveniles ($\square_a=0.08$ [0.02-0.17];

255 $\square_j=0.04$ [0.01-0.08]). We see little support for sex differences ($\square_f =0.06$ [0.02-0.12];

256 $\square_m=0.05$ [0.01-0.11]). The direction and magnitude of these effects are consistent across all

257 evaluated models (Table 3). Groups and individuals (particularly in KB) tend to have larger

258 and more uncertain estimates of \square as a wider range of parameter values can predict the

259 observed data (Fig. S3).

260

261 Weight given to social information (γ)

262 In the global model, social information influences behaviour slightly more heavily for

263 adults than juveniles ($\gamma_a=0.23$ [0.05-0.48]; $\gamma_j=0.20$ [0.05-0.38]), and for females than males (γ

264 $_f =0.23$ [0.05-0.43]; $\gamma_m=0.20$ [0.04-0.43]). However, these patterns are not consistent across

265 all models. This is because for each individual model, one learning bias might be particularly

266 salient for a particular age or sex class. We can gain insight into this from comparing

267 predictions from the global model to models representing individual learning strategies (Fig.

268 S4). For example, the payoff-bias learning model has higher values of γ for juveniles and

269 females ($\gamma_j=0.31$ [0.13-0.50] ; $\gamma_a=0.28$ [0.11-0.49]; $\gamma_f =0.30$ [0.13-0.51]; $\gamma_m=0.28$ [0.11-0.49]),

270 while the rank-bias learning model has higher values for of γ for adults and males ($\gamma_a=0.29$

271 [0.12-0.50]; $\gamma_j=0.18$ [0.07-0.33]; $\gamma_m=0.27$ [0.11-0.47]; $\gamma_f =0.20$ [0.08-0.37]).

272

273 Payoff-bias

274 We find reliable support for payoff-biased learning, for nearly all individuals in the
275 population (Fig. S6). Of the social learning biases, we also see the most salient differences
276 between age and sex classes. Juveniles rely more on payoff-biased social learning than adults
277 ($\beta_{\text{pay}_j}=1.24$ [-0.36-2.76]; $\beta_{\text{pay}_j}=0.45$ [-1.06-1.97]), while females rely more heavily on it than
278 males ($\beta_{\text{pay}_f}=1.07$ [-0.49-2.63]; $\beta_{\text{pay}_m}=0.62$ [-0.88-2.08]). Of the EWA models representing
279 single social learning strategies, payoff-biased learning had the lowest WAIC value (Table 2)
280 and its predictions were most similar to the global model for most individuals in the
281 population. Similar differences and stronger effect sizes were estimated in the payoff-biased
282 learning model when compared to the global model (β_{pay} in Table 1).

283

284 Rank-bias

285 We also see good support for rank-biased social learning for most individuals in the
286 population, although there is more uncertainty around these predictions (Fig. S7). The global
287 model suggests that adults are more likely to learn from high-ranking individuals than
288 juveniles ($\beta_{\text{rank}_a}=1.26$ [-0.25,2.72]; $\beta_{\text{rank}_j}=0.80$ [-0.85,2.53]), and females are more likely to
289 learn from high-ranking individuals than males ($\beta_{\text{rank}_f}=1.18$ [-0.40,2.75]; $\beta_{\text{rank}_m}=0.89$ [-
290 0.60,2.48]). These differences between age and sex parameters are much smaller in the rank-
291 biased learning model (See β_{rank} in Table 3). This is likely because higher ranking
292 individuals are more successful than low ranking individuals. When including both rank and
293 payoff in the global models, differences in reliance on rank cues, instead of payoff cues,
294 emerge.

295

296 Frequency-dependence

297 On average, the population tends to be somewhere between linear and slightly
298 positive-frequency-dependent (See f^c in Table 1). We see posterior means slightly larger than
299 1 for most individuals (Fig. S5). However, boundary conditions ($f^c > 0$) often make posterior
300 point estimates misleading; nearly half of the posterior mass for many individuals and all age
301 and sex classes lies in a parameter space consistent with anti-conformity. The frequency-
302 dependent learning model estimated a stronger degree of conformist transmission, but it often
303 under-predicts the probability of an individual choosing a less common behaviour (Figure 3).

304

305 Matrilineal kin-, Female- and Same-sex biased learning

306 We see some evidence for matrilineal kin-biased learning (See β_{kin} Table 3), but this
307 might only be for some individuals in the population (i.e. Pro, Gran, Xian in Fig. S8). We see
308 little evidence for sex-biased and female-biased transmission (Table 3; Fig. S9; Fig. S10).

309

310

311 Discussion

312

313 In the present study we used a time-series model predicting each technique's
314 probability of being chosen to infer which social learning strategies were utilized in two
315 groups of wild vervet monkeys when learning to process unshelled peanuts, a novel food. The
316 best supported statistical model, and evidence from a suite of models integrating individual
317 and social learning, suggests that vervet monkeys learned the most successful, highest payoff
318 technique, and displayed by the higher ranked demonstrators. We found weak support for a
319 positive frequency-dependent conformity bias defined as 'use the most observed technique'.
320 We also found no clear evidence that they show a bias toward the technique displayed by

321 females, individuals of the same sex, or related individuals. Individual learning alone is very
322 unlikely to be responsible for the techniques' spread.

323 We reported high variation between groups and among individuals for many
324 parameters in the models (Figure S11). This group-level variation is likely due to differences
325 in data sample size between the two groups: one group (NH) with many more participants
326 eating peanuts than the other (KB). Consequently, estimates of parameters for individuals in
327 KB were more uncertain and often had larger posterior means. These larger point estimates
328 for lambda, phi, gamma, and fc are likely not due to group-level differences but likely arise
329 because they are near a boundary condition of zero, and uncertainty drives mean estimates
330 upward. It is thus important to evaluate the full shape of posterior and be cautious before
331 drawing conclusions from point estimates of parameter differences between groups and
332 individual with unequal sampling. Finally, we reported effects of age, sex and rank on
333 individual and social learning which are discussed in the remainder of the discussion.

334 Note that we avoided using the term “copying” across the manuscript which is
335 strongly associated to “imitation” by some scholars [39, 40], although not by all [11, 41].
336 Here, we do not make any assumption and conclusion regarding the social learning
337 mechanisms (action form copying versus non-form copying/socially mediated individual
338 learning: [40]) implied in the acquisition of the peanuts processing techniques. We
339 acknowledge that the three peanuts processing techniques we describe are within the Zone of
340 Latent Solution of vervet monkeys [40] and we do not claim for form copying, i.e. that vervet
341 monkeys faithfully copied the exact movements – the form of the behaviour - displayed by
342 their conspecifics.

343

344 We found the strongest support for the global model suggesting that vervet monkeys
345 use multiple social learning strategies simultaneously. Comparison of parameter effect sizes

346 across models, model predictions, and WAIC values all suggest that payoff- and rank-biased
347 learning guided diffusion of peanut processing techniques in both groups of wild vervet
348 monkeys. These results do not fully align with those of a previous study on vervet monkeys at
349 our field site [19] that can be explained by methodological differences. In Bono et al. study,
350 payoff was operationalized as a different quantity of food provided by a two-action design –
351 one item versus five. In our study, socially observed payoffs were the mean observed
352 probability of a technique being successful in the previous 20 minutes. While only
353 observations of trained demonstrators were taken into account in Bono et al. study, here
354 observed payoffs are unique to each individual’s full observation experience. Bono et al.
355 found that only males chose the technique used by the male model more when it received five
356 food items compared to a female model receiving only one item [19]. We find that females
357 and juveniles relied more on payoff-biased social learning than males and adults conversely.
358 We believe this discrepancy in results can be explained by methodological differences
359 between both studies. First, in Bono et al. study [19], only two models, a male and a female,
360 that were both adults and of high rank, were available in each group, while in our study,
361 numerous individuals of both sexes and various ages and ranks could opportunistically serve
362 as demonstrators. Second, we tested behavioural responses of individuals towards a novel and
363 unknown food while Bono et al. [19] tested monkeys in a two-action box experiment filled
364 with known food. It is possible that monkeys got accustomed to boxes’ affordance across the
365 numerous experiments of this kind they had previously experienced at the Inkawu Vervet
366 Project. Different strategies could be at play in different environmental contexts, i.e. in a
367 familiar foraging situation *versus* a novel one. Our results suggest thus that females - the
368 philopatric sex – are maybe less conservative in their social learning than previously thought
369 and that their conservatism decreases in a novel context after an environmental change. When
370 it has been suggested that females would stick to their habits compared to males who are

371 expected to show more behavioural flexibility [19], our findings challenge this hypothesis.
372 Indeed, in vervet monkeys, females are the philopatric sex, meaning that they remain all their
373 life in their social group while males disperse to new groups several times within their
374 lifetime. Females possibly possess thus more detailed knowledge than males about the
375 distribution of existing food resources or objects such as boxes they encounter in their
376 territory, which could make them a valuable source of directed social learning in these
377 common situations. However, we suggest that when facing an unknown foraging situation,
378 females can show flexibility, decrease their conservatism and rely more than males on the
379 social information available.

380 Other recent studies used a similar multilevel dynamic learning model in great tits [18]
381 and in capuchins [17]. Great tits have been found to switch to an alternative higher payoff
382 variant when given a choice between a low and a high payoff option [18]. As we found in
383 vervet monkeys, young birds were more likely to use social information than older birds [18].
384 Barrett et al. [17] offered *Sterculia apetala* fruits to a naïve group of wild capuchins and
385 followed the spread of the processing techniques. They found that, of multiple biases, payoff-
386 biased social learning was the one responsible for the spread of the most successful
387 techniques [17], and that age was a strong predictor in the heterogeneity of learning among
388 individuals. We can hypothesize that this maintained preference for CMS technique could be
389 at the origin of cultural transmission of peanut processing techniques if this food was made
390 available on the long term in vervet monkeys' environment and if other groups developed a
391 preference for another technique.

392

393 Here, we also report a rank bias in agreement with the 'use preferentially the
394 behaviour displayed by higher-ranked individuals' strategy found in chimpanzees [27] and
395 vervet monkeys [28]. In this latter study, we used another modelling approach – NBDA - to

396 identify the typical pathways of transmission of boxes opening techniques in an open
397 diffusion experiment. We tested whether the diffusion followed specific social networks
398 representing different pathways of learning such as learning from females, older individuals,
399 related individuals or higher rankers. We discovered evidence of a transmission bias
400 favouring learning from higher-ranked individuals, with no evidence for age, sex or kin bias
401 [28]. Present results are thus in accordance with these previous findings. In this previous
402 study, we could not test for frequency-dependent learning and payoff-biased learning, nor for
403 the interplay between the use of social and individual information, but this is precisely what
404 we assessed here. This means that higher rankers are not only considered as models for the
405 first learning event but that this bias is maintained across time.

406 While higher rankers were manipulating more boxes and were more successful, they
407 were not observed more than low rankers in our previous study [28]. Instead, observations of
408 higher-ranked individuals had a greater effect on observers' behaviour than observations of
409 lower-ranked individuals. Here, we found that higher rankers manipulated and successfully
410 processed more peanuts, probably because they can monopolize access to food. We did not
411 find any difference in observation rate between individuals but, we reported that higher
412 rankers, adults and males were observed more than lower rankers, juveniles and females. This
413 difference might be due to experimental novelty arousing a different attentional pattern.
414 Indeed, in a box experiment, vervet monkeys showed a selective attention to female models
415 [26] when all models were of high rank. This is in accordance with literature on chimpanzees
416 and capuchins in which older and more proficient nut crackers are more observed than others
417 [42, 43].

418

419 We tested whether individuals showed a preference for the most frequent or the least
420 frequent behaviour, or whether they showed no frequency bias. We found little evidence for

421 any frequency-dependent learning, our population being slightly positive frequency-
422 dependent. A previous study on vervet monkeys reported that migrant males conformed to
423 their new group norm by abandoning their natal feeding preference, thus following a
424 functional definition of conformity [29]. The authors' claim of conformity [29] has been
425 considered a premature conclusion regarding the mechanism of conformity, as the authors did
426 not have the observational data of who the males attended to before switching and could not
427 prove that the males observed the foraging choice of a majority before switching [44]. Here,
428 we did not test for such a conformity bias based on the number of individuals using the same
429 processing technique, but we rather tested for a conformity bias based on the frequency of
430 technique observed. We thus tested whether individuals were i) more likely to use a technique
431 frequently observed; ii) as likely to use a technique as it is observed or iii) less likely to use it.
432 Such biases have been tested in great tits where the establishment of a foraging tradition has
433 been found to rely on positive frequency-dependence; individuals adopting the most frequent
434 local variant [30]. Barrett et al. [18] found no evidence for a conformity bias, but they found
435 evidence of weak anti-conformity meaning that rare techniques attracted more attention in
436 capuchins.

437 We found no evidence for kin- or sex-biased social learning. Previous studies reported
438 that infant vervet monkeys ate the same food as their mother [29] and that females were
439 preferred as models over males [26]. However, these studies tested for a single bias at a time
440 while we tested here for several biases simultaneously, weighing each strategy against the
441 other and compared to asocial learning which makes the analysis more powerful. Our results
442 are furthermore consistent with a previous study testing for several model biases in a single
443 analysis that did not identify such biases either [28]. We believe that testing for several biases
444 in a single analysis allow to disentangle between potential confounding factors such as age,

445 sex and rank and can highlight instances of equifinality where multiple social learning
446 strategies produce the same signature in a population [45].

447

448 In the present study, the two innovators were an infant and a low-ranking adult male.
449 In another open diffusion experiment [28], the alpha male and female were the two innovators
450 in the same two groups when tested one year before. We believe that this difference can be
451 linked to the aforementioned experiments' methodological considerations. In Canteloup et al.
452 study [28], groups were tested in a two-action box experiment for which individuals may get
453 accustomed to boxes' affordances despite the use of new design. Some studies suggested that
454 juveniles and low rankers are often innovators [46, 47] although this depends on the type of
455 behaviour [48], while other studies suggest neophilia and boldness have been found to better
456 predict innovation [49]. We hypothesize that innovators' identity also depends on task
457 novelty. Monkeys being neophobic, an unknown food can be considered as a source of stress,
458 which suggests that low rankers were the initiators and that juveniles were quicker to first
459 succeed to extract peanuts because of their usual limited access to resources. When the task is
460 not completely new, dominants are more expected to be the innovators.

461 We reported that, in the global model, social information influenced behaviour more
462 heavily in adults than juveniles and in females than males, but these patterns were not
463 consistent across all models. In the global and payoff-bias models, juveniles and females were
464 most affected by payoff-based social information whereas adults and males were most
465 affected by rank-based social information. Despite being in disagreement with what has been
466 previously found in vervet monkeys [19], this suggests that juveniles and females would be
467 more sensitive to behaviours' payoffs while adults and males would be more sensitive to rank
468 cues associated with a demonstrator. Overall, we found that adults weighed past experience
469 more heavily than recent experience compared to juveniles, suggesting that memory strongly

470 influences their behaviour as previously found in birds and capuchins [17, 18]. Vervet
471 monkeys are used to extracting encased seeds from acacia pods like from pods of acacia
472 nilotica (*Vachellia nilotica*). The habit of extracting seeds from these pods, although flatter
473 and texturally different than unshelled peanuts, may influence the technique used by monkeys
474 to open peanuts. However, personal experience prior to the experiment unlikely drives the
475 diffusion of peanut opening techniques, as social learning models reliably predict its
476 diffusion.

477

478 We show that payoff-biased social learning likely underlies the origin of the spread of
479 novel food processing techniques in vervet monkeys, and that this content bias likely acts
480 concurrently with rank-biased learning. EWA models consider exactly what behaviours and
481 which demonstrators an individual uniquely observes both prior to their observing a
482 successful solution and after they learn how to solve the task. This detailed time-varying
483 modelling approach makes the analysis particularly powerful in uncovering the interplay
484 between personal and social information use, which makes social learning adaptive and
485 efficient [35]. Because it is very rare that the initial innovation event and its spread are
486 recorded through observational studies, we believe that controlled experiments coupled with
487 dynamic, theory-informed modelling are a useful approach to track the diffusion of new
488 behaviours and to disentangle between different social learning strategies.

489

490

491 Materials and Methods

492

493 Study site and subject details

494 The study was conducted at the Inkawu Vervet Project (IVP) in a 12,000-hectare
495 private game reserve: Mawana (28°00.327S, 031°12.348E) in KwaZulu Natal province, South
496 Africa. The vegetation of the study site consisted in a savannah characterized by a mosaic of
497 grasslands and clusters of trees of the typical savannah thornveld, bushveld and thicket
498 patches. We studied two groups of wild vervet monkeys (*Chlorocebus pygerythrus*): ‘Noha’
499 (NH) and ‘Kubu’ (KB). NH was composed of 34 individuals (6 adult males; 9 adult females;
500 6 juvenile males; 7 juvenile females; 5 infant males; 1 infant female) and KB was composed
501 of 19 individuals (1 adult male; 6 adult females; 3 juvenile males; 4 juvenile females; 3 infant
502 males; 2 infant females; Table S1). Males were considered as adults once they dispersed, and
503 females were considered as adults after they gave their first birth. Individuals that did not
504 fulfil these criteria were considered as juveniles [28] and infants were aged less than one year
505 old. IN EWA models, infants and juveniles were lumped in a single category “juveniles”.
506 Each group had been habituated to the presence of human observers: since 2010 for NH and
507 since 2013 for KB. All individuals were identifiable thanks to portrait photographs and
508 specific individual body and face features (scars, colours, shape etc.).

509 This research adhered to the “Guidelines for the use of animals in research” of
510 Association for Study of Animal Behaviour and was approved by the relevant local authority,
511 Ezemvelo KZN Wildlife, South Africa.

512

513 Hierarchy establishment

514 Agonistic interactions (aggressor behaviour: stare, chase, attack, hit, bite, take place;
515 victim behaviour: retreat, flee, leave, avoid, jump aside) were collected from May 2018 to
516 October 2018, aside from experiment days, on all the adults and juveniles of both groups via
517 *ad libitum* sampling [50] and food competition tests (i.e. corn provided to the whole group
518 from a plastic box). Data were collected by CC, MBC and different observers from the IVP

519 team. Before beginning data collection, observers had to pass an inter-observer reliability test
520 with 80% reliability for each data category between two observers. Data were collected on
521 tablets (Vodacom Smart Tab 2) equipped with Pendragon version 8.

522 Individual hierarchical ranks were determined by the outcome of dyadic agonistic
523 interactions recorded *ad libitum* and through food competition tests using Socprog software
524 version 2.7 (50). Hierarchies in both groups were significantly linear (NH: $h' = 0.27$; $P <$
525 0.0001 ; KB: $h' = 0.42$; $P < 0.0001$) and ranks were assessed by I&SI method (52).

526

527 Open diffusion experiment

528 The experimental apparatus consisted of provisioning the group with two transparent
529 rectangular plastic boxes (34x14x12 cm) containing ~ 2 kg unshelled peanuts in sufficient
530 quantities to prevent a single individual from monopolizing the boxes. The monkeys were
531 never provided with peanuts before the experiment and peanuts were not available in their
532 environment. Thus, unshelled peanuts were a novel, nutritious food that required processing
533 to be extracted from their shells before consumption.

534 Experiments took place at sunrise at monkeys' sleeping sites during the dry, food-
535 scarce winter to maximize their motivation for novel food. The two boxes of peanuts were
536 offered to the monkeys, spaced apart by about 1 to 10 meters. CC led the experiment with the
537 help of two to four field assistants. All monkeys were free to come to the boxes within the
538 constraints of the social group dynamics. Experiments were video recorded using JVC
539 cameras (EverioR Quad Proof GZ-R430BE) to which the experimenter said aloud the
540 identities of the actor and of the attending neighbours for each manipulation event. A
541 manipulation event was defined either as an attempt to extract a peanut from its shell (i.e. the
542 individual acted on the peanut failing to fully open it and to get access to the food) or as a
543 success (i.e. the individual succeeded to fully open a shell and to extract the peanut from the

544 shell). A conspecific was considered as attending when it had its head or body oriented in an
545 unobstructed line towards the demonstrator manipulating the peanut and was located within 0-
546 30m from the actor. Several individuals could thus be registered as attending to one or several
547 demonstrators simultaneously.

548 The open diffusion experiments ran from May 2018 to August 2018 to maximise
549 individuals' likelihood of participating in the experiment. A total of 11 sessions of open
550 diffusion experiments were run in NH and 10 in KB. The average duration of an experimental
551 session was 46m:46s for NH and 42m:47s for KB.

552

553 Video analysis

554 Video recordings were viewed and analysed by MBC with Media Player Classic
555 Home Cinema software version 1.7.11. Twenty percent of the video were analysed by CC and
556 inter-observer reliability was substantial ($\kappa = 0.78$). During video analysis in slow motion or
557 frame by frame, the following variables were coded in an excel sheet: date, exact time of
558 each manipulative event, actor identity, the technique used (crack with hand: 'CH'; crack with
559 mouth from the top of the peanut: 'CMT'; crack with mouth from the side of the peanut:
560 'CMS'; see Movies S1-S3) and the identity of attending individuals.

561

562 Quantification and statistical analysis

563 Following Barrett et al. [17], we used a suite of hierarchical experience-weighted
564 attraction (EWA) models to analyse data collected in the open-diffusion experiment. EWA
565 models are time-series models that evaluate the joint influence of personal experience and
566 social information on the probability of an individual displaying a behaviour [38] and are
567 increasingly utilized in cross-taxa studies of cultural transmission [16-18, 27, 53].

568 This analytical approach has several strengths: It permits evaluation of multiple
569 hypothesized learning strategies against each other and individual learning alone, utilizes a
570 dynamic social learning network unique to each individual, and links individual variation in
571 behaviour and cognition to population level-cultural dynamics. Working with time-series of
572 behaviour unique to each individual is important as population-level signatures can often be
573 misleading [54] or exhibit equifinality, particularly if individuals vary in experience,
574 observation opportunities or the social learning strategies they employ [45]. The mathematical
575 specification of our analytical approach also minimizes ambiguity of what types of social
576 learning we are evaluating. This is important as verbal definitions are imprecise, and
577 terminologies are differently interpreted in studies of social learning. Most importantly, this
578 approach links theory to data. Instead of using a theoretically uninformed analytical approach
579 to find results consistent with theory, we bypass quantitative proxies and translate theoretical
580 models to statistical models. We fit a series of EWA models evaluating the following learning
581 strategies:

- 582 1. Individual learning alone
- 583 2. Frequency-dependent learning (preference for behaviours that is based on their
584 frequency in the population)
- 585 3. Female-biased learning (preference for the technique displayed by females in group
586 i.e. matrilineal sex in vervets)
- 587 4. Matrilineal kin-biased learning (preference for the technique displayed by closely
588 related individuals)
- 589 5. Compare means payoff-biased learning (preference for the most successful or efficient
590 behaviour)
- 591 6. Rank-biased learning (preference for the technique displayed by high-ranking
592 individual)

593 7. Sex-biased learning (preference for the behaviours of individuals that are of the same
594 sex)

595 8. Global model that includes 1-7.

596 All social learning models (models 2-8) also include an individual learning component.

597 For each behavioural choice, social information used by an actor was the average
598 value of each cue observed in a time window of 20 minutes prior to the observation (Table 1).

599 As individuals access social information at different timescales, and this window choice was
600 somewhat arbitrary, we also evaluated social info at 30, 10, and 5-minute timescales. These
601 analyses yielded similar results and were robust to time windows.

602 We ran the EWA models using regularizing priors, which are sceptical of extreme
603 effects and reduce the risk of overfitting, and a Cholesky decomposition for estimating
604 varying effects. Models were fit using RStan version 2.19.3 [55]. Models were compared
605 using widely applicable information criteria (WAIC), which can inform which model best
606 predicts the observed data while penalizing models that underfit or overfit. Models with lower
607 WAIC scores best predict the observed data.

608

609 EWA Model Specification

610 EWA models have two parts: a set of expressions that specify how individuals
611 accumulate experience and a second set of expressions that specify the probability of each
612 option being chosen. Accumulated experience is represented by *attraction scores*, $A_{ij,t}$,
613 unique to each behaviour i , individual j , and time t . We update $A_{ij,t}$ with an observed payoff

614 $\pi_{ij,t}$:

$$A_{ij,t+1} = (1 - \phi_j)A_{ij,t} + \phi_j\pi_{ij,t}$$

615 The parameter ϕ_j controls the importance of recent payoffs in influencing attraction scores.
616 When ϕ_j is high, more weight is given to recent experience over past experiences – memory
617 has less of an influence on behavioural choice. This parameter is unique to an individual j ,
618 and we also estimate how it varies by age-class and sex.
619 Attraction scores are converted into probabilities of behavioural choice with a standard
620 multinomial logistic choice rule:

$$Pr(i|A_{ij,t}, \lambda_j) = \frac{\exp(\lambda_j A_{ij,t})}{\sum_k \exp(\lambda_j A_{kj,t})} = I_{ij}$$

621 λ_j controls sensitivity to differences in attraction scores on behavioural choice and is unique
622 to an individual j . A very large λ_j , means the option with the largest attraction score is nearly
623 always selected. Choice is random with respect to attraction score when $\lambda_j = 0$. Individuals
624 were assigned a payoff of zero, $\pi_{ij,t} = 0$, if they failed to open a peanut. If they were
625 successful $\pi_{ij,t} = 1$.

626 Social learning may directly influence choice distinctly from individual learning. $S_{ij} =$
627 $S(i|\theta_j)$ is the probability an individual j chooses behaviour i on the basis of a set of social
628 cues and parameters θ_j . These social cues are traits associated with demonstrators (i.e. age,
629 rank), or a behaviour (i.e. mean payoff), and each cue represents a hypothesized social
630 learning strategy. Behavioural choice is a convex combination specified by:

$$Pr(i|A_{ij,t}, \theta_j) = (1 - \gamma_j)I_{ij,t} + \gamma_j S_{ij,t}$$

631 where γ_j is the weight assigned to social cues, and is bounded by 0 and 1.

632 Social cues are incorporated into $S_{ij,t}$ by use of a multinomial probability expression with a
633 log-linear component $B_{ij,t}$ that is an additive combination of cue frequencies. The probability
634 of displaying each behaviour i , solely as a function of social cues, is:

$$S_{ij,t} = \frac{N_{ij,t}^{f_c} \exp B_{ij,t}}{\sum_m N_{mj,t}^{f_c} \exp B_{mj,t}}$$

635 $N_{ij,t}$ are the observed frequencies of each technique i at time t by individual j . The
636 exponentiated parameter f_c controls the amount and type of frequency dependence. When
637 $f_c = 1$, social learning is unbiased by frequency and techniques influence choice in proportion
638 to their occurrence (sometimes referred to as unbiased transmission). When $f > 1$, social
639 learning is positive frequency-dependent or conformist. When $f < 1$, social learning is
640 negative frequency-dependent, and a bias is shown towards rare behaviours.

641 Other social cues associate with individuals (i.e. rank, age, or relatedness) or behaviours (i.e.
642 payoffs), are incorporated via:

$$B_{ijt} = \sum_k \beta_k$$

643 B_{ijt} is the sum of the products of the influence parameters β_k and the cue values $\kappa_{k,ijt}$. Cues
644 evaluated in these models are explained in detail in Table 1. The above specification is for the
645 global model. Single social learning strategies are subset of this global model in which there
646 is a single cue value or only frequency information is used.

647

648 Other statistics

649 We used generalized linear models (GLMs) with quasi-Poisson error and log link function to
650 test for the effect of group, normalized rank, sex and age on i) the latency of first success of

651 shelling a peanut; ii) the number of peanut shelling successes; iii) the number of peanuts
652 manipulation (attempts + successes); iv) the number of successes observed; v) the number of
653 manipulations observed; vi) the number of times being observed when succeeding and vii) the
654 number of times being observed when manipulating. We added the log of the time each
655 individual had to process peanuts once they first succeeded as an offset (a standard statistical
656 technique for converting a Poisson GLM for analysis of counts into a model for analysing
657 counts per unit of time). All tests were performed with R Studio version 1.2.1335 using R
658 version 3.6.1 [56].

659

660

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677

678 Data availability: Reproducible model code and data can be found here:

679 https://zenodo.org/record/4297318#.X8T5jC_pPUo

680

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682

683

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685

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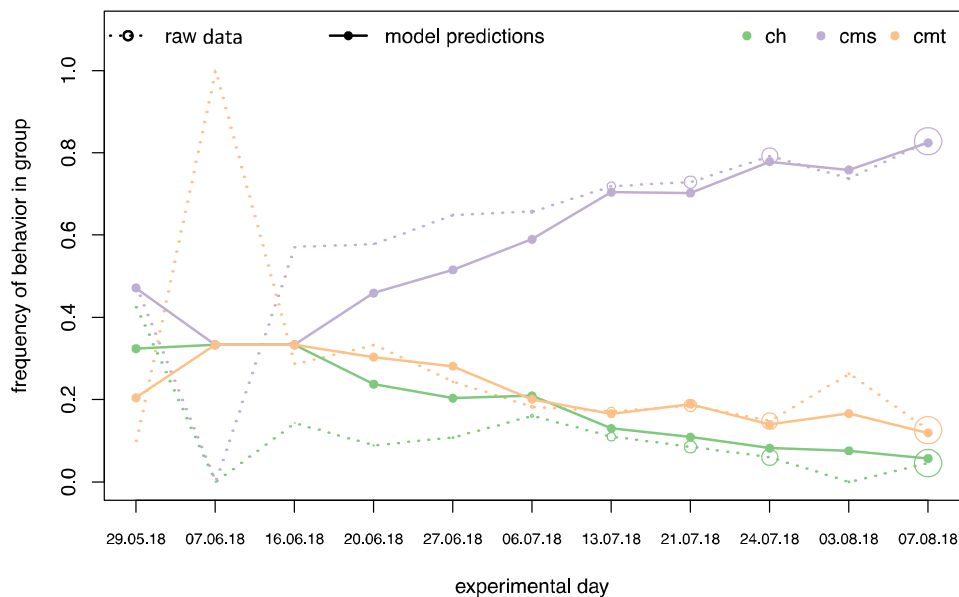
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827 Figures and Tables

828 Figure 1



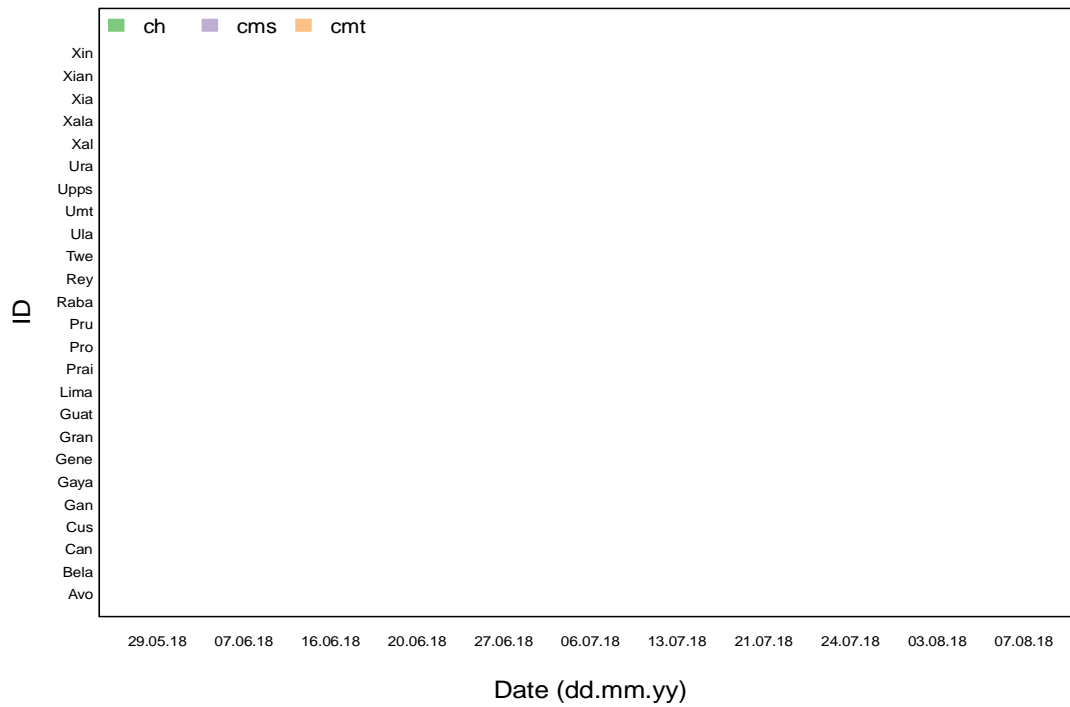
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830

831 Figure 1. Daily mean group probability of observed processing techniques over experimental
832 days for NH. Filled lines and points are posterior mean predictions of the global model
833 averaged across all individuals in NH in an experimental day. Dashed lines and empty points
834 are estimates from raw data averaged across all individuals in NH in an experimental day.
835 Diameter of empty points of raw data scales with daily sample size.

836

837 Figure 2



838

839

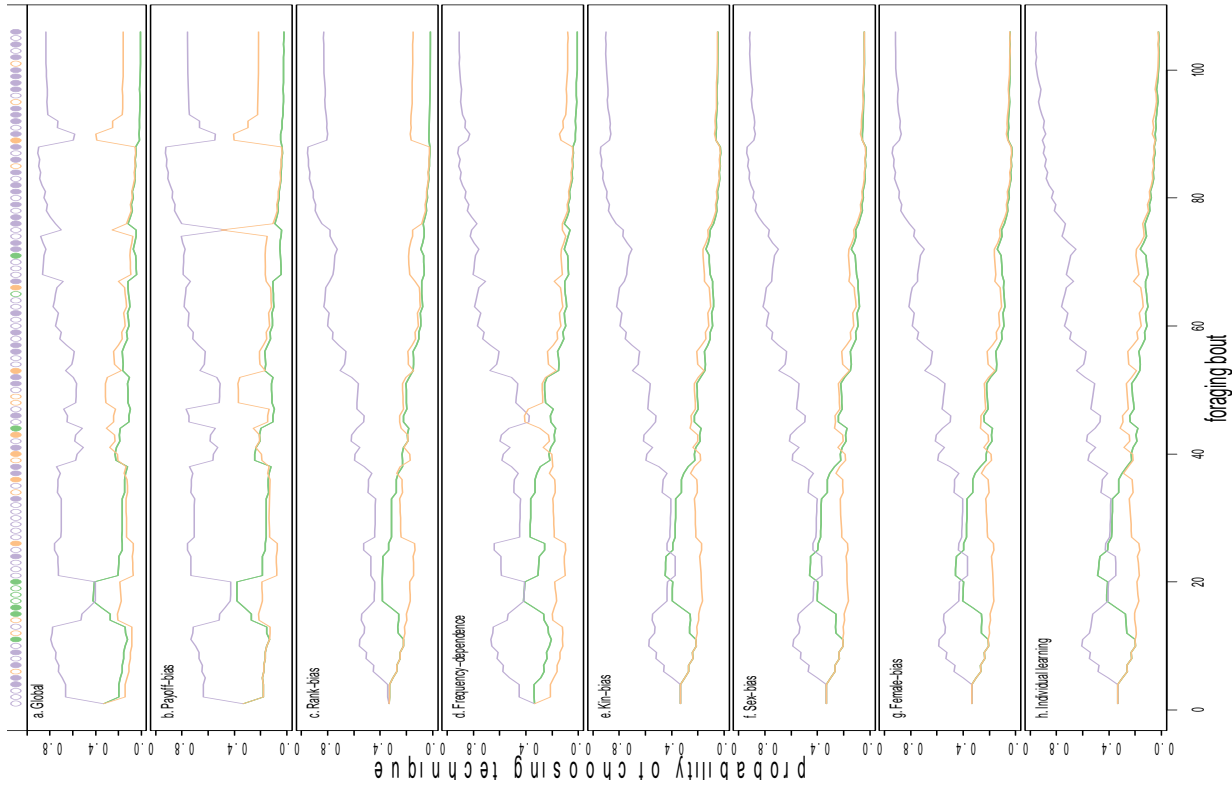
840 Figure 2. Visualization of posterior estimates from the global model of daily mean probability

841 of processing techniques across all foraging individuals in NH. Point diameter scales with

842 probability, with many individuals approaching fixity of CMS on the final day.

843

844 Figure 3



845

846

847 Figure 3. Model predictions of the probability of using a technique across foraging bouts from
848 the seven models for the behavioural time series of individual 'Gran' in NH group. Colours
849 correspond to the three processing techniques (purple: 'CMS'; orange: 'CMT'; green: 'CH').
850 Lines show posterior mean predictions of the probability of choosing a behaviour at each time
851 step. Lines are like three-sided dice whose odds change as a function of observed social and

852 experienced personal information over each foraging bout. The “roll” of each die estimates
853 the processing technique observed by ‘Gran’ at each foraging bout, plotted along the top row.
854 Filled circles are successes, empty circles are failures The shaded interval is a 89% High
855 Posterior Density Intervals (HPDI). 89% HPDI correspond to the range containing 89% of
856 probable values.
857

858 Table 1

Model	Social and Individual Cues
1) Individual learning	$\pi_{ij,t} = 1$ if successful, 0 if not
2) Frequency-dependence	$N_{ij,t}$ = count of times j observed demonstrators perform behavior i
3) Female-bias	$\kappa_{k,ijt} = 1$ if adult female, 0 otherwise
4) Matrilineal kin-bias	$\kappa_{k,ijt}$ = coefficient of relatedness, r , between observer j and demonstrator
5) Payoff-biased learning	$\kappa_{k,ijt}$ = mean observed payoff, $\overline{\pi_{ij,t}}$, of behavior i observed by j
6) Rank-bias	$\kappa_{k,ijt}$ = rank of demonstrator determined by I&SI method
7) Sex-bias	$\kappa_{k,ijt} = 1$ if same sex as observe, 0 if different
8) Global model	all cues in 1-7

859

860 Table 1. Individual information and social cues used in the EWA models. Models 2-8 also

861 incorporate individual experience from model 1. Information observed at timestep t for

862 models 2-8 was the mean of each cue, κ evaluated in the 20 minutes prior to timestep t .

863

864 Table 2

Model	WAIC	SE	dWAIC	weight
Global Model	4707.71	91.09	0.00	1.00
Payoff-bias	4756.90	91.12	49.18	0.00
Rank-bias	4780.21	90.55	72.50	0.00
Frequency-dependence	4796.59	90.92	88.88	0.00
Matrilineal Kin Bias	4856.82	92.46	149.11	0.00
Same-sex-bias	4874.49	92.68	166.78	0.00
Female-bias	4875.25	92.73	167.54	0.00
Individual learning	4920.83	92.00	213.12	0.00

865

866 Table 2. Widely applicable information criteria estimates for all evaluated models with a 20
867 minute window of social information. Standard errors, difference in WAIC and model weight
868 are included.

869

870 Table 3
871

Parameter	Global	Payoff-bias	Rank-bias	Freq-dep.	Kin-bias	Female-bias	Sex-bias	Ind. learn.
λ_f	8.38	20.89	19.17	8.79	15.76	13.73	13.55	7.31
λ_m	6.27	16.93	14.86	6.24	14.69	13.66	13.41	6.36
λ_j	10.04	20.37	19.94	10.73	16.72	15.42	15.13	9.31
λ_a	5.22	17.22	14.22	5.09	13.81	12.14	12.02	4.99
ϕ_f	0.06	0.04	0.04	0.06	0.04	0.05	0.05	0.06
ϕ_m	0.05	0.04	0.04	0.05	0.04	0.04	0.04	0.05
ϕ_j	0.04	0.03	0.03	0.04	0.03	0.03	0.03	0.05
ϕ_a	0.08	0.05	0.05	0.07	0.05	0.06	0.06	0.07
γ_f	0.23	0.30	0.20	0.21	0.14	0.13	0.13	
γ_m	0.20	0.28	0.26	0.21	0.16	0.13	0.13	
γ_j	0.20	0.31	0.18	0.16	0.12	0.09	0.09	
γ_a	0.23	0.28	0.28	0.26	0.19	0.18	0.18	
f_f^c	1.26			1.66				
f_m^c	1.04			1.29				
f_j^c	1.08			1.60				
f_a^c	1.20			1.33				
βfem_f	-0.03					-0.01		
βfem_m	0.09					-0.16		
βfem_j	-0.05					-0.20		
βfem_a	0.11					0.03		
βkin_f	0.53				1.07			
βkin_m	0.75				1.00			
βkin_j	0.63				0.98			

βkin_a	0.65		1.09
βpay_f	1.07	1.46	
βpay_m	0.62	0.87	
βpay_j	1.24	1.46	
βpay_a	0.45	0.87	
$\beta rank_f$	1.18	2.37	
$\beta rank_m$	0.89	2.25	
$\beta rank_j$	0.80	2.22	
$\beta rank_a$	1.26	2.40	
βsex_f	-0.40		0.17
βsex_m	-0.80		0.00
βsex_j	-0.86		-0.07
βsex_a	-0.34		0.24

872

873

874 Table 3. Posterior mean estimates of learning parameters for all evaluated EWA models.

875 Subscripts correspond to male (m), female (f), adult (a), and juvenile (j). Dot plots of these

876 parameters, including 89% HPDI for the global model, including individual and group-level

877 parameters, are in Figures S2-S5.

878