

Social learning strategies regulate the wisdom and madness of interactive crowds

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Abstract

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Why groups of individuals sometimes exhibit collective ‘wisdom’ and other times mal-adaptive ‘herding’ is an enduring conundrum. Here we show that this apparent conflict is regulated by the social learning strategies deployed. We examined the patterns of human social learning through an interactive online experiment with 699 participants, varying both task uncertainty and group size, then used hierarchical Bayesian model-fitting to identify the individual learning strategies exhibited by participants. Challenging tasks elicit greater conformity amongst individuals, with rates of copying increasing with group size, leading to high probabilities of herding amongst large groups confronted with uncertainty. Conversely, the reduced social learning of small groups, and the greater probability that social information would be accurate for less-challenging tasks, generated ‘wisdom of the crowd’ effects in other circumstances. Our model-based approach provides evidence that the likelihood of collective intelligence versus herding can be predicted, resolving a longstanding puzzle in the literature.

15 Understanding the mechanisms that account for accurate collective decision-making amongst
16 groups of animals – ‘collective intelligence’ – has been a central focus of animal behaviour re-
17 search¹⁻⁵. There are a large number of biological examples showing that collectives of poorly
18 informed individuals can achieve a high performance in solving cognitive problems under un-
19 certainty⁶⁻¹⁰. Although these findings suggest fundamental cognitive benefits of grouping¹¹,
20 there is also a long-standing recognition, especially for humans, that interacting individuals may
21 sometimes be overwhelmed by the ‘*extraordinary popular delusions and madness of crowds*’¹².
22 Herd behaviour (i.e. an alignment of thoughts or behaviours of individuals in a group) occurs
23 because individuals imitate each other¹³⁻¹⁵, even if each is a rational decision-maker¹⁶. Imita-
24 tion is thought to be a cause of financial bubbles^{12;17}, ‘groupthink’¹⁸ and volatility in cultural
25 markets^{19;20}. More generally, interdependence between individual decisions may undermine the
26 wisdom of crowds effect²¹ (but see²²), whilst potential disadvantages of information transfer are
27 well-recognised in the biological literature^{23;24}. It seems that information transmission among
28 individuals, and making decisions collectively, is a double-edged sword: combining decisions
29 may provide the benefits of collective intelligence, but at the same time, increase the risk of an
30 informational cascade¹⁶. Collectively, an understanding of whether and, if so, how it is possible
31 to prevent or reduce the risk of maladaptive herding, while concurrently keeping or enhancing
32 collective intelligence, is largely lacking.

33 A balance between using individual and social information may play a key role in deter-
34 mining the trade-off between collective wisdom and ‘madness’²⁵. If individuals are too reliant
35 on copying others’ behaviour, any idea, even a maladaptive one, can propagate in the social
36 group through positive feedbacks^{2;26}. For instance, disproportionately strong positive responses

37 to recruitment signals in social insects have been shown to trap the whole colony to exploit a
38 suboptimal, out-dated resource^{24;27}. Likewise, conformity-biased transmission in humans and
39 other animals can potentially lead groups to converge on a maladaptive behaviour^{16;23;28;29}. On
40 the other hand, however, if individuals completely ignore social information so as to be indepen-
41 dent, they will fail to exploit the benefits of aggregating information through social interactions.
42 The extent to which individuals should use social information should fall between these two
43 extremes. Evolutionary models predict that the balance between independence and interdepen-
44 dence in collective decision-making may be changeable, contingent upon the individual-level
45 flexibility and inter-individual variability associated with the social learning strategies deployed
46 in diverse environmental states^{28;30;31}.

47 Experimental studies report that animals (including humans) increase their use of social in-
48 formation as the returns from asocial learning become more unreliable³²⁻³⁷, whilst theory and
49 data suggest that the benefits to individuals of social learning increase with group size^{34;38-42}.
50 Selectivity in the predicted use of social information may impact on collective decision-making
51 because slight differences in the parameter values of social information use are known to be able
52 to alter qualitatively the collective behavioural dynamics^{1;2;5;43;44}. Therefore, researchers should
53 expect populations to exhibit a higher risk of being trapped with maladaptive behaviour with
54 increasing group size and decreasing reliability of asocial learning (and concomitant increased
55 reliance on social learning).

56 From the viewpoint of the classic wisdom of crowds theory, increasing group size may in-
57 crease collective accuracy⁴⁵⁻⁴⁸. The relative advantage of the collective over solitary individuals
58 may also be highlighted by increased task difficulty, because there would be more room for the

59 performance of difficult tasks to be improved compared to easier tasks in which high accuracy
60 can be achieved by asocial learning only. To understand the collective decision performance of
61 social learners fully requires fine-grained quantitative studies of social learning strategies and
62 their relations to collective dynamics, linked to sophisticated computational analysis.

63 The aims of this study were twofold. First, we set to test the hypothesis that the circumstances
64 under which collective decision making will generate ‘wisdom’ can be predicted with knowledge
65 of the precise learning strategies individuals deploy, through a combination of experimentation
66 and theoretical modelling. The choice of an abstract decision-making task allowed us to imple-
67 ment a computational modelling approach, which has been increasingly deployed in quantitative
68 studies of animal social learning strategies^{35;49-51}. In particular, computational modelling al-
69 lowed us to conduct a parametric description of different information-gathering processes and
70 to estimate the parameter values at an individual-level resolution. This approach allows us to
71 characterise the complex relationship between individual-level decision, learning strategies and
72 collective-level behavioural dynamics.

73 Second, we added resolution to our analyses by manipulating both task uncertainty and group
74 size in our web-based experiments with adult human subjects, predicting that these factors would
75 induce heavier use of social information in humans, and thereby alter the balance between col-
76 lective intelligence and the risk of inflexible herding. To do this, we focused on human groups
77 exposed to a simple gambling task called a multi-player ‘multi-armed bandit’, where both asocial
78 and social sources of information were available^{35;51;52}. Through development of an interactive,
79 web-based collective decision-making task, and use of hierarchical Bayesian statistical meth-
80 ods in fitting our computational model to the experimental data, we identify the individual-level

81 learning strategies of participants as well as quantify variation in different learning parameters,
82 allowing us to conduct an informed exploration of the population-level outcomes. The results
83 provide clear evidence that the collective behavioural dynamics can be predicted with knowledge
84 of human social learning strategies.

85 Below, we firstly deploy agent-based simulation to illustrate how the model parameters re-
86 lating to social learning can in principle affect the collective-level behavioural dynamics. The
87 simulation provides us with precise, quantitative predictions concerning the complex relation-
88 ship between individual behaviour and group dynamics. Second, we present the findings of
89 a multi-player web-based experiment with human participants that utilises the gambling task
90 framework. Applying a hierarchical Bayesian statistical method, we estimated the model's pa-
91 rameters for each of 699 different individuals, allowing us to (i) examine whether and, if so, how
92 social information use is affected by different group size and task uncertainty, and (ii) whether
93 and how social-information use affects both collective intelligence and the risk of maladaptive
94 herding.

95 **1 Results**

96 **1.1 The relationship between social learning and the collective behaviour**

97 Figure 1 shows the relationship between the average decision accuracy and individual-level social
98 information use obtained from our individual-based model simulations, highlighting the trade-
99 off between accuracy and flexibility of collective decision-making. When the mean *conformity*
100 *exponent* is small (i.e. $\bar{\theta} = (\sum_i \theta_i)/individuals = 1$), large groups are able to recover the decision

101 accuracy quickly as do small groups after the location of the optimal option has been switched,
102 whereas overall improvement by increasing group size in decision accuracy is subtle when the
103 average *social learning weight* is also small (i.e. $\bar{\sigma} = (\sum_i \sum_t \sigma_{i,t}) / (\text{individuals} \times \text{rounds}) = 0.3$;
104 Figure 1A and 1C). On the other hand, when both the conformity exponent $\bar{\theta}$ and the social
105 learning weight $\bar{\sigma}$ are large, average performance is no longer monotonically improving with in-
106 creasing group size, and it is under these circumstances that the strong herding effect becomes
107 prominent (Figure 1D). Although the high conformity bias with low social learning weight makes
108 large groups more accurate before the environment changes, larger groups are less flexible in per-
109 formance recovery (Figure 1B). The pattern is robust for other parameter regions (Supplementary
110 Figure 2).

111 **Figure 2** indicates that when both $\bar{\theta}$ and $\bar{\sigma}$ are large the collective choices converged either on
112 the good option or on one of the poor options almost randomly, regardless of the option's quality,
113 and that once individuals start converging on an option the population gets stuck. As a result,
114 the distribution of the groups' average performance over the replications becomes a bimodal
115 'U-shape'. Interestingly, however, the maladaptive herding effect remains relatively weak in
116 smaller groups (see Figure 1D; the dotted line). This is because the majority of individuals in
117 smaller groups (i.e. two individuals out of three) are more likely to break the cultural inertia by
118 simultaneously exploring another option by chance than are the majority in larger groups (e.g.
119 six out of ten).

120 In summary, the model simulation suggests an interaction between social learning weight
121 $\bar{\sigma}$ and conformity exponent $\bar{\theta}$ on decision accuracy and the risk of inflexible herding. When
122 the conformity exponent is not too large, increasing group size can increase decision accuracy

123 while concurrently retaining decision flexibility across a broad range of the mean social learning
124 weights. When the conformity bias becomes large, however, the risk of inflexible herding arises,
125 and, when both social learning parameters are large, collective intelligence is rare and inflexible
126 herd behaviour dominates.

127 **1.2 Collective performance of human participants**

128 Figure 3A shows behavioural dynamics of human participants in different group sizes and dif-
129 ferent task uncertainty conditions (see Supplementary Figure 3 for each group's behaviour). The
130 average decision performance of collectives (i.e. group size ≥ 2) exceeded that of solitary in-
131 dividuals (i.e. group size = 1) in the Moderate-uncertainty condition (i.e. the 95% Bayesian
132 CI of ξ_t exceeds 0 at regions $t \in [9, 40]$ and $[67, 70]$; Figure 3B). In other uncertainty condi-
133 tions, no global positive effect of grouping was observed, suggesting that collective intelligence
134 was prominent only in the Moderate-uncertainty condition. However, the main effect of group
135 size was positive in the post-change period of the Low-uncertainty condition (mean and the 95%
136 Bayesian CI of $\omega_2 = 0.67 [0.44, 0.91]$; Table 1), suggesting that the average performance of large
137 groups (e.g. $12 \leq \text{group size} \leq 16$) were better, and hence more flexible, than smaller groups
138 and solitaries (Figure 3A). On the other hand, in the Moderate-uncertainty condition, the aver-
139 age performance of the collectives dropped below that of the solitaries after the environmental
140 change (i.e. $\xi_t < 0$ at a region $t \in [42, 45]$; Figure 3B). Also, the main effect of group size
141 was negative in the post-change period (mean and the 95% Bayesian CI of $\omega_2 = -0.26 [-0.44,$
142 $-0.11]$; Table 1), suggesting that larger groups were more likely to get stuck in the out-dated op-
143 tion in the Moderate-uncertainty condition. In the High-uncertainty condition, the main effect of

144 group size was positive in the prior-change period and negative post-change (mean and the 95%
145 Bayesian CIs are $\omega_1 = 0.07$ [0.00, 0.15] and $\omega_2 = -0.10$ [-0.17, -0.02]; Table 1), although the
146 effect size was too small to differentiate performances of different group sizes visually (Figure
147 3A). Using monetary earnings as an outcome variable of decision performance did not change
148 our conclusions qualitatively (supporting Supplementary Figure 4 and Supplementary Table 2).

149 Our phenomenological model regression established that manipulating both task uncertainty
150 and group size indeed affected the collective decision dynamics. Below, we address whether or
151 not the pattern could be explained with knowledge of human social learning strategies estimated
152 through our learning and decision-making computational model.

153 1.3 Estimation of human social information use

154 Using posterior estimation values obtained by the hierarchical Bayesian model fitting method
155 (Table 2), we were able to categorise the participants as deploying one of three different learn-
156 ing strategies based on their fitted conformity exponent values; namely, the ‘positive frequency-
157 dependent copying’ strategy ($\theta_i \gg 0$), the ‘negative-frequency dependent copying’ strategy
158 ($\theta_i \ll 0$) and the ‘random choice’ strategy ($\theta_i \approx 0$). Note that we could not reliably detect
159 the ‘weak positive’ frequency-dependent strategy ($0 < \theta_i \leq 1$) due to the limitation of statisti-
160 cal power (Supplementary Figure 5). Some individuals whose ‘true’ conformity exponent fell
161 between zero and one would have been categorised as exhibiting a random choice strategy (Sup-
162 plementary Figure 7). Individuals identified as exhibiting a positive frequency-dependent copiers
163 were mainly those whose conformity exponent was larger than one ($\theta_i > 1$).

164 Figure 4A show the estimated frequencies of different learning strategies. Generally speak-

165 ing, participants were more likely to utilize a positive frequency-dependent copying strategy
166 than the other two strategies (the 95% Bayesian CI of the intercept of the GLMM predicting the
167 probability to use the positive frequency-dependent copying strategy is above zero, [1.05, 2.50];
168 Supplementary Table 4). We found that positive frequency-dependent copying decreased with
169 increasing task uncertainty (the 95% Bayesian CI of task uncertainty effect is below zero, [-1.88,
170 -0.25]; Supplementary Table 4). We found no clear effects of either the group size, age or gender
171 on adoption of the positive frequency-dependent copying strategy, except for the negative inter-
172 action effect between age and task uncertainty (the 95% Bayesian CI of the age \times uncertainty
173 interaction = [-1.46, -0.15]; Supplementary Table 4).

174 We also investigated the effects of group size and task uncertainty on the fitted individual
175 parameter values. We found that the individual mean social learning weight parameter (i.e. $\bar{\sigma}_i =$
176 $(\sum_t \sigma_{i,t})/(\text{total rounds})$) increased with group size (the 95% Bayesian CI = [0.15, 0.93]; Figure
177 4B; Supplementary Table 5), and decreased with uncertainty (the 95% Bayesian CI = [-0.98,
178 -0.22]), and age of subject (the 95% Bayesian CI = [-0.36, -0.02]). However, the negative effects
179 of task uncertainty and age disappeared when we focused only on $\bar{\sigma}_i$ of the positive frequency-
180 dependent copying individuals, and only the positive effect of the group size was confirmed
181 (Supplementary Table 6; Supplementary Figure 6). It is worth noting that the meaning of the
182 social learning weight is different between these three different strategies: The social learning
183 weight regulates positive reactions to the majorities' behaviour for positive frequency-dependent
184 copiers, whereas it regulates avoidance of the majority for negative-frequency dependent copiers,
185 and determines the probability of random decision-making for the random choice strategists.

186 The individual conformity exponent parameter θ_i increased with task uncertainty (the 95%

187 Bayesian CI = [0.38, 1.41]), but we found no significant effects of group size, age, gender or
188 interactions (Figure 4C; Supplementary Table 7). These results were qualitatively unchanged
189 when we focused only on the positive frequency-dependent copying individuals (Supplementary
190 Table 8; Supplementary Figure 6).

191 We observed extensive individual variation in social information use. The greater the task's
192 uncertainty, the larger were individual variances in both the mean social learning weight and the
193 conformity exponent (the 95% Bayesian CI of the GLMM's variation parameter for $\bar{\sigma}_i$ was [1.11,
194 1.62] (Supplementary Table 5) and for θ_i was [1.07, 1.54] (Supplementary Table 7)). This was
195 confirmed when focusing only on the positive frequency-dependent copying individuals: The
196 Bayesian 95% CIs were [1.14, 1.80] (Supplementary Table 6) and [0.71, 1.10] (Supplementary
197 Table 8), respectively.

198 The manner in which individual variation in social-information use of positive frequency-
199 dependent copying individuals changes over time is visualised in Figure 5. The social learn-
200 ing weights generally decreased with experimental round. However, some individuals in the
201 Moderate- and the High-uncertain conditions accelerated rather than decreased their reliance on
202 social learning over time. Interestingly, those accelerating individuals tended to have a larger
203 conformity exponent (Supplementary Figure 5). In addition, the time-dependent $\theta_{i,t}$ in our al-
204 ternative model generally increased with experimental round in the Moderate- and the High-
205 uncertainty conditions (Supplementary Figure 10), although the fitting of $\theta_{i,t}$ in the alternative
206 model was relatively unreliable (Supplementary Figure 9). These findings suggest that con-
207 formists tended to use asocial learning at the outset (i.e. exploration asocially) but increasingly
208 started to conform as the task proceeded (i.e. exploitation socially).

209 Extensive variation in the temporal dynamics of the social learning weight $\sigma_{i,t}$ was also found
210 for the negative-frequency dependent copying individuals but not found for random choice indi-
211 viduals (Supplementary Figure 5). Individuals deploying a random choice strategy exhibited a
212 $\sigma_{i,t}$ that approached to zero, indicating that their decision-making increasingly relied exclusively
213 on the softmax choice rule, rather than unguided random choices, as the task proceeded.

214 No significant fixed effects were found in other asocial learning parameters such as the learn-
215 ing rate α_i and the mean inverse temperature $\bar{\beta}_i = (\sum_t \beta_{i,t})/(\text{total rounds})$ (Supplementary Table
216 9, Supplementary Table 10 and Supplementary Figure 6).

217 In summary, our experiments on adult humans revealed asymmetric influences of increasing
218 task uncertainty and increasing group size on the social learning parameters. The conformity
219 exponent increased with task uncertainty on average but the proportion of positive frequency-
220 dependent copying individuals showed a corresponding decrease, due to the extensive individual
221 variation emerging in the High-uncertain condition. Conversely, group size had a positive effect
222 on the mean social learning weight, but did not affect conformity.

223 **1.4 Social learning strategies explain the collective dynamics**

224 The post-hoc simulation provides statistical predictions on how likely it is, given the fitted learn-
225 ing model parameters, that groups of individuals make accurate decisions and that they exhibit
226 inflexible herding. Figure 3C shows the change over time in performance with different group
227 sizes and different uncertainty conditions, generated by the post-hoc simulation (see also Sup-
228 plementary Figure 3). The trajectories of the simulated dynamics recovered nicely the pattern
229 observed in the experiment (Figure 3A and 3C), suggesting that the strategic changes in the

230 individual-level social information use (Figure 4) could explain the collective-level behavioural
231 pattern.

232 Figure 3D shows that larger groups are more likely to make accurate decisions than are
233 both small groups and solitaries in the period prior to change across all uncertainty conditions,
234 suggesting collective intelligence was operating. In the post-change period, however, perfor-
235 mance differed between the conditions. In the Low-uncertainty condition, where we found that
236 the participants were most likely to have a relatively weak positive frequency-dependence (i.e.
237 $\bar{\theta} = 1.65$), large groups performed better than did small groups over 59.5% of total 10,000
238 repetitions. However, in the Moderate-uncertainty condition, where we found that participants
239 were most likely to have strong positive frequency dependence ($\bar{\theta} = 3.00$, c.f. 1.65 in the Low-
240 uncertainty condition), the large groups were more likely to get stuck on the suboptimal option,
241 and hence the small groups performed better than did the large groups over 69.5% of repetitions
242 (Figure 3D). The decision accuracy did not substantially differ with group size in the post-change
243 period in the High-uncertainty condition although the large groups performed slightly better than
244 did the small groups (50.8% of the repetitions).

245 Interestingly, although their relatively low conformity biases, there were some groups in the
246 Low-uncertainty condition that seemed to exhibit herding (the ‘humped’ area at the lefthand side
247 to the peak of the performance distribution in the post-change period; Figure 3D). This might be
248 due to the lower softmax exploration rates among social learners in the Low-uncertainty condition
249 (i.e. both $\mu_{\beta_0^*}$ and μ_ϵ were large; Table 2): the whole population gets stuck because all individuals
250 are very exploitative on their past experience.

251 **2 Discussion**

252 We investigated whether and how human social learning strategies regulate the trade-off between
253 collective intelligence and inflexible herding behaviour using a collective learning-and-decision-
254 making task combined with simulation and model fitting. We examined whether manipulat-
255 ing the reliability of asocial learning and group size would affect the use of social information,
256 and thereby alter the collective human decision dynamics, as suggested by our computational
257 model simulation. Although a theoretical study has suggested that reliance on social learning
258 and conformity bias would play a role in collective dynamics^{2:5:53}, thus far no empirical studies
259 have quantitatively investigated the population-level consequences of these two different social
260 learning processes. Our high-resolution, model-based behavioural analysis using a hierarchi-
261 cal Bayesian statistics enabled us to identify individual-level patterns and variation of different
262 learning parameters and to explore their population-level outcomes. The results provide **quanti-**
263 **tative** support for our hypothesis that the collective decision performance can be predicted with
264 quantitative knowledge of social learning strategies.

265 Overall, our individual-based computational model recovered the behavioural pattern sug-
266 gested by the phenomenological regression (Figure 3). Using the post-hoc simulation with
267 individually-fit model parameters, we confirmed that in the Low-uncertainty condition, where
268 individuals had weaker positive frequency bias (i.e. $\bar{\theta} \approx 1.65$), larger groups **were able to be**
269 **more accurate than smaller groups while retaining flexibility in their decision-making⁹**, although
270 their low asocial exploration rates seemed to undermine the potential flexibility. However, in the
271 Moderate- and the High-uncertain conditions where individuals had the higher conformity ex-

272 ponent parameters (i.e. $\bar{\theta} \approx 3.0$ and 2.7 , respectively), larger groups performed better prior to
273 environmental change but were vulnerable to getting stuck with an out-dated maladaptive option
274 post change. Therefore, the changes in the level of conformity in human individuals^{34;41} indeed
275 incurred a trade-off between the collective intelligence effect and the risk of inflexible herding.

276 Although the social learning weight increased with increasing group size, the overall mean
277 value was $\bar{\sigma}_i \approx 0.3$ (Figure 4B; Supplementary Figure 5; Supplementary Figure 6) and it de-
278 creased on average as the task proceeded (Figure 5). This implies a weaker social than asocial
279 influence on decision-making as reported in several other experimental studies^{35;54-56} although
280 evolutionary models tend to predict heavier reliance on social learning than experimental studies
281 report^{57;58}. Thanks to this relatively weak reliance of social learning, the kind of extreme herding
282 that would have blindly led a group to any option regardless of its quality, such as the ‘symmetry
283 breaking’ known in trail-laying ant collective foraging systems^{2;5;26}, did not occur (Figure 2).

284 Individual differences in rates of exploration might also help to mitigate potential herding.
285 Although a majority of participants adopted a positive frequency-dependent copying strategy,
286 some individuals exhibited negative frequency dependence or random decision-making (Figure
287 4A). The random choice strategy was associated with more exploration than the other strate-
288 gies, because it led to an almost random choice at a rate σ_i , irrespective of the options’ quality.
289 Negative-frequency dependent copying individuals could also be highly exploratory. These indi-
290 viduals tended to avoid choosing an option upon which other people had converged and would ex-
291 plore the other two ‘unpopular’ options. Interestingly, in the High-uncertain condition the mean
292 social learning weights of the negative-frequency dependent copying individuals ($\bar{\sigma}_i \approx 0.5$) were
293 larger than that of the other two strategies ($\bar{\sigma}_i \approx 0.1$, Supplementary Figure 5), indicating that

294 these individuals engaged in such majority-avoiding exploration relatively frequently. Such a
295 high variety in social information use⁵⁹⁻⁶² and exploratory tendencies would prevent individuals
296 from converging on a single option, leading to a mitigation of herding but concurrently dimin-
297 ishing the decision accuracy in high-uncertainty circumstances (Figure 3).

298 A methodological advantage of using computational models to study social learning strate-
299 gies is its explicitness of assumptions about the temporal dynamics of behaviour, which enabled
300 us to distinguish different learning strategies⁶³⁻⁶⁵. For example, very exploitative asocial re-
301 inforcement learners (i.e. for whom exploitation parameter $\beta_{i,t}$ is large and the social learning
302 weight $\sigma_{i,t}$ is nearly zero, as seen in the Low-uncertainty condition) and conformity-biased social
303 learners (where the conformity exponent θ_i is large and $\sigma_{i,t}$ is positive, as seen in the Moderate-
304 uncertain condition) would eventually converge on the same option, resulting in the same final
305 behavioural steady state. However, how they explored the environment, as well as how they re-
306 acted to the other individuals in the same group, are significantly different and they could produce
307 qualitatively different collective temporal dynamics.

308 However, our computational model could not fully capture other, potentially more sophisti-
309 cated forms of social learning strategies that participants might deploy, which might be a reason
310 for the seemingly low rate of social learning observed in the experiment compared to theory^{57,58}.
311 Indeed, the post-hoc simulation sometimes failed to recover the observed behavioural trajecto-
312 ries. **In particular, experimental groups with $n = 12$, $n = 16$, and one group in $n = 9$, in the**
313 **Low-uncertainty condition performed very well, exceeding the 95% CIs of the post-hoc simu-**
314 **lation after the environmental change (Supplementary Figure 3). This indicates that collective**
315 **behaviour in these groups was more flexible than our model predicted. Further empirical studies**

316 that consider a wider range of possible social learning strategies, e.g. ‘copy-rapidly-increasing-
317 option’ strategy⁶⁶ or Bayesian updating^{57;67}, are needed to explore computational underpinnings
318 of social learning and collective behaviour.

319 The Internet-based experimentation allowed us to conduct a real-time interactive behavioural
320 task with larger subject pools than a conventional laboratory-based experiment. This enabled us
321 not only to quantify the individual-level learning-and-decision processes⁶⁸ but also to map these
322 individual-level processes on to the larger-scale collective behaviour^{5;15;20}. Although there are
323 always questions about the validity of participants’ behaviour when recruited via web-based tools,
324 we believe that the computational modelling approach coupled with higher statistical power due
325 to the large sample size, compensates for any drawbacks. The fact that our learning model could
326 approximate the participants’ decision trajectories effectively suggest that most of the participants
327 engaged seriously with solving the task. An increasing body of evidence supports the argument
328 that web-based behavioural experiments are as reliable as results from the laboratory^{69;70}.

329 The diverse effects of social influence on the collective wisdom of a group has been draw-
330 ing substantial attention^{19;21;22;71;72}. The bulk of this literature, including many jury models and
331 election models^{45;73}, has focused primarily on the static estimation problem, where the ‘truth’ is
332 fixed from the outset. However, in reality, there are many situations under which the state of the
333 true value is changing over time so that monitoring and tracking the pattern of change is a crucial
334 determinant of decision performance⁷⁴. In such temporally dynamic environments, decision-
335 making and learning are coordinated to affect future behavioural outcomes recursively⁷⁵. Our
336 experimental task provides a simple vehicle for exploring collective intelligence in a dynamic
337 situation, which encompasses this learning-and-decision-making feedback loop. Potentially, in-

338 tegrating the wisdom of crowds with social learning and collective dynamics research will facil-
339 itate the more tractable use of collective intelligence in a temporary changing world.

340 In summary, a combination of experimentation and theoretical modelling sheds light on when
341 groups of individuals will exhibit the wisdom of the crowds and when inflexible herding. Our
342 analysis implies that herding is most likely amongst individuals in large groups exposed to chal-
343 lenging tasks. That is because challenging tasks lead to greater uncertainty and thereby elicit
344 greater conformist learning amongst individuals, whilst rates of copying increase with group
345 size. Difficult tasks, by definition, render identification of the optimal behaviour harder, allow-
346 ing groups sometimes to converge on maladaptive outcomes. Conversely, the reduced conformity
347 levels of individuals in small groups, and the greater probability that social information would
348 be accurate for less-challenging tasks, generated ‘wisdom of the crowd’ effects in most other cir-
349 cumstances. Our findings provide clear evidence that the conflict between collective intelligence
350 and maladaptive herding can be predicted with knowledge of human social learning strategies.

351 **3 Material and methods**

352 **3.1 Participants**

353 The experimental procedure was approved by the Ethics Committee at the University of St An-
354 drews (BL10808). A total of 755 subjects (354 females, 377 males, 2 others and 22 unspecified;
355 mean age ($1\ SD.$) = 34.33 (10.9)) participated through Amazon’s Mechanical Turk. All partic-
356 ipants consented to participation through an online consent form at the beginning of the task.

357 We excluded subjects who disconnected to the online task before completing at least the first 30

358 rounds from our computational-model fitting analysis due to unreliability of the model-parameter
359 estimation, resulted in 699 subjects (573 subjects entered the group (i.e. $N \geq 2$) and 126 entered
360 the solitary (i.e. $N = 1$) condition). The task was only available for individuals who had greater
361 than or equal to 90% HIT approval rate and who accessed from the United States. Although
362 no sample-size calculation was performed in advance, our parameter recovery test confirmed
363 that the sample size was sufficient for estimation of individual parameters using a hierarchical
364 Bayesian method.

365 **3.2 Design of the experimental manipulations**

366 The three uncertainty conditions were: Low-uncertainty condition (differences between mean
367 payoffs were 1.264), Moderate-uncertainty condition (differences between mean payoffs were
368 0.742) and High-uncertainty condition (differences between mean payoffs were 0.3). The mean
369 payoff associated with the ‘excellent’ slot in all three conditions was fixed to 3.1 cents (Supple-
370 mentary Figure 1). Each task uncertainty condition was randomly assigned for each different HIT
371 session, and participants were allowed to participate in one HIT only. Sample size after the data
372 exclusion for each uncertainty condition was: $N = 113$ (Low-uncertainty condition), $N = 132$
373 (Moderate-Uncertain condition), and $N = 454$ (High-uncertain condition). We assigned more
374 sessions to the High-uncertainty condition compared to the other two because we expected that
375 larger group sizes would be needed to generate the collective wisdom in noisier environments.

376 To manipulate the size of each group, we varied the capacity of the waiting room from 10 to
377 30. Because the task was being advertised on the Worker website at AMT for approximately 2
378 hours, some participants occasionally arrived after the earlier groups had already started. In that

379 case the participant entered the newly opened waiting room which was open for the next 5 min-
380 utes. The number of participants arriving declined with time because newly posted alternative
381 HITs were advertised on the top of the task list, which decreased our task's visibility. This meant
382 that a later-starting session tended to begin before reaching maximum room capacity, resulting
383 in the smaller group size. Therefore, the actual size differed between groups (Supplementary
384 Figure 3, Supplementary Table 1). Data collection and analysis were not performed blind to the
385 conditions of the experiments.

386 **3.3 The multi-player three-armed bandit task**

387 To study the relationship between social information use and collective behavioural dynamics,
388 we focused on a well-established learning-and-decision problem called a 'multi-armed bandit'
389 task, represented here as repeated choices between three slot machines (Supplementary Figure 1,
390 Video 1, for detail see Supplementary Method). Participants played the task for 70 rounds. The
391 slots paid off money noisily (in the US cents), varying around two different means during the
392 first 40 rounds such that there was one 'good' slot and two other options giving poorer average
393 returns. From the round 41st, however, one of the 'poor' slots abruptly increased its mean payoff
394 to become 'excellent' (i.e. superior to 'good'). The purpose of this environmental change was
395 to observe the effects of maladaptive herding by potentially trapping groups in the out-of-date
396 suboptimal (good) slot, as individuals did not know whether or how an environmental change
397 would occur. Through making choices and earning a reward from each choice, individuals could
398 gradually learn which slot generated the highest rewards.

399 In addition to this asocial learning, we provided social information for each member of the

400 group specifying the frequency with which group members chose each slot. All group mem-
 401 bers played the same task with the same conditions simultaneously, and all individuals had been
 402 instructed that this was the case, and hence understood that the social information would be in-
 403 formative.

404 Task uncertainty was experimentally manipulated by changing the difference between the
 405 mean payoffs for the slot machines. In the task with the least uncertainty, the distribution of
 406 payoffs barely overlapped, whilst in the task with the greatest uncertainty the distribution of
 407 payoffs overlapped considerably (Supplementary Figure 1).

408 3.4 The computational learning-and-decision-making model

409 We modelled individual behavioural processes by assuming that individual i makes a choice for
 410 option m at round t , in accordance with the choice-probability $P_{i,t}(m)$ that is a weighted average
 411 of social and asocial influences:

$$P_{i,t}(m) = \sigma_{i,t} \times \text{Social influence}_{i,m,t} + (1 - \sigma_{i,t}) \times \text{Asocial influence}_{i,m,t}, \quad (1)$$

412 where $\sigma_{i,t}$ is the *social learning weight* ($0 \leq \sigma_{i,t} \leq 1$).

413 For the social influence, we assumed a frequency-dependent copying strategy by which an
 414 individual copies others' behaviour in accordance with the distribution of social frequency infor-
 415 mation [49–51:55](#):

$$\text{Social influence}_{i,m,t} = \frac{\left(F_{t-1}(m) + 0.1\right)^{\theta_i}}{\sum_{k \in \text{options}} \left(F_{t-1}(k) + 0.1\right)^{\theta_i}}, \quad (2)$$

416 where $F_{t-1}(m)$ is a number of choices made by other individuals (excluding her/his own choice)
 417 for the option m in the preceding round $t - 1$ ($t \geq 2$). θ_i is individual i 's *conformity exponent*,
 418 $-\infty \leq \theta_i \leq +\infty$. When this exponent is larger than zero, higher social influence is given
 419 to an option which was chosen by more individuals (i.e. positive frequency bias). When this
 420 exponent is larger than zero ($\theta_i > 0$), higher social influence is afforded to an option chosen
 421 by more individuals (i.e. positive frequency bias), with conformity bias arising when $\theta_i > 1$,
 422 such that disproportionately more social influence is given to the most common option²⁸. When
 423 $\theta_i < 0$, on the other hand, higher social influence is afforded to the option that fewest individuals
 424 chose in the preceding round $t - 1$ (i.e. negative frequency bias). To implement the negative
 425 frequency dependence, we added a small number 0.1 to F so that an option chosen by no one
 426 (i.e. $F_{t-1} = 0$) could provide the highest social influence when $\theta_i < 0$. Note, there is no social
 427 influence when $\theta_i = 0$ because in this case the 'social influence' favours an uniformly random
 428 choice, i.e., $S_{i,t}(m) = f_m^0 / (f_1^0 + f_2^0 + f_3^0) = 1/3$, independent of the social frequency distribution.
 429 Note also that, in the first round $t = 1$, we assumed that the choice is only determined by the
 430 asocial softmax function because there is no social information available.

431 For the asocial influence, we used a standard reinforcement learning with 'softmax' choice
 432 rule⁷⁵, widely applied in human social learning studies e.g.^{35:51;55}. An individual i updates the
 433 estimated average reward associated with an option m at round t , namely Q-value ($Q_{i,t}(m)$), ac-
 434 cording to the Rescorla-Wagner rule as follows:

$$Q_{i,t+1}(m) = Q_{i,t}(m) + \alpha_i \mathbb{1}(m, m_{i,t}) (r_{i,t}(m) - Q_{i,t}(m)), \quad (3)$$

435 where α_i ($0 \leq \alpha_i \leq 1$) is a *learning rate* parameter of individual i determining the weight given to

436 new experience and $r_{i,t}(m)$ is the amount of monetary reward obtained from choosing the option
 437 m in round t . $\mathbb{1}(m, m_{i,t})$ is the binary action-indicator function of individual i , given by

$$\mathbb{1}(m, m_{i,t}) = \begin{cases} 1, & \text{if } m_{i,t} = m \text{ or } t = 1, \\ 0, & \text{otherwise.} \end{cases} \quad (4)$$

438 Therefore, $Q_{i,t}(m)$ is updated only when the option m was chosen; when the option m was not
 439 chosen, $Q_{i,t}(m)$ is not updated (i.e. $Q_{i,t+1}(m) = Q_{i,t}(m)$). Note that, only in the first round $t = 1$,
 440 all Q-values are updated by using the chosen option's reward $r_{i,1}(m)$, so that the individual can
 441 set a naive 'intuition' about the magnitude of reward values she/he would expect to earn from a
 442 choice in the task; namely, $Q_{i,t=2}(1) = Q_{i,t=2}(2) = Q_{i,t=2}(3) = \alpha_i r_{i,t=1}(m)$. In practical terms,
 443 this prevents the model from being overly sensitive to the first experience. Before the first choice,
 444 individuals had no prior preference for either option (i.e. $Q_{i,1}(1) = Q_{i,1}(2) = Q_{i,1}(3) = 0$).

445 The Q-value is then translated into the asocial influence through the softmax (or logit choice)
 446 function:

$$A_{i,t}(m) = \frac{\exp(\beta_{i,t} Q_{i,t}(m))}{\sum_{k \in \text{options}} \exp(\beta_{i,t} Q_{i,t}(k))}, \quad (5)$$

447 where $\beta_{i,t}$, called *inverse temperature*, manipulates individual i 's sensitivity to the Q-values (in
 448 other words, controlling the proneness to explore). As $\beta_{i,t}$ goes to zero, asocial influence ap-
 449 proximates to a random choice (i.e. highly explorative). Conversely, if $\beta_{i,t} \rightarrow +\infty$, the aso-
 450 cial influence leads to a deterministic choice in favour of the option with the highest Q-value
 451 (i.e. highly exploitative). For intermediate values of $\beta_{i,t}$, individual i exhibits a balance be-
 452 tween exploration and exploitation^{35:68}. We allowed for the possibility that the balance between

453 exploration-exploitation could change as the task proceeds. To depict such time dependence in
 454 exploration, we used the equation: $\beta_{i,t} = \beta_{i,0}^* + \epsilon_i t/70$. If the slope ϵ_i is positive (negative), aso-
 455 cial influence $A_{i,t}$ becomes more and more exploitative (explorative) as round t increases. For a
 456 model fitting purpose, the time-dependent term $\epsilon_i t$ is scaled by the total round number 70.

457 We allowed that the social learning weight $\sigma_{i,t}$ could also change over time as assumed in
 458 the inverse temperature $\beta_{i,t}$. To let $\sigma_{i,t}$ satisfy the constraint $0 \leq \sigma_{i,t} \leq 1$, we used the following
 459 sigmoidal function:

$$\sigma_{i,t} = \frac{1}{1 + \exp(-(\sigma_{i,0}^* + \delta_i t/70))}. \quad (6)$$

460 If the slope δ_i is positive (negative), the social influence increases (decreases) over time. We
 461 set the social learning weight equal to zero when group size is one (i.e. when an individual
 462 participated in the task alone and/or when $\sum_{k \in \text{options}} F_{t-1}(k) = 0$).

463 We modelled both the inverse temperature $\beta_{i,t}$ and the social learning weight $\sigma_{i,t}$ as a time
 464 function since otherwise it would be challenging to distinguish different patterns of learning in
 465 this social learning task⁶³. The parameter recovery test confirmed that we were able to differenti-
 466 ate such processes under these assumptions (Supplementary Figure 7, Supplementary Figure 8).
 467 While we also considered the possibility of the conformity exponent being time-dependent (i.e.
 468 $\theta_{i,t} = \theta_{i,0}^* + \gamma_i t/70$), the parameter recovery test suggested that the individual slope parameter
 469 γ_i was not reliably recovered (Supplementary Figure 9), and hence we concentrated our anal-
 470 ysis on the time-independent θ_i model. We confirmed that instead using the alternative model
 471 where both social learning parameters were time-dependent (i.e. $\sigma_{i,t}$ and $\theta_{i,t}$) did not qualitatively
 472 change our results (Supplementary Figure 10).

473 One concern might be the asymmetry between the asocial softmax influence which takes
474 many prior experiences into account (depending upon a learning rate) and the social influence
475 referring only the most recent frequency information F_{t-1} . The choice frequency appeared at
476 round t is the most reliable social information, compared to the past frequencies, because it could
477 be the most ‘updated’ information as long as the other individuals have made informed decisions
478 in their best knowledge. In contrast, option’s reward just obtained at $t - 1$, which was inde-
479 pendently and randomly drawn from a probability distribution, is less reliable than accumulated
480 Q-values taking past rewards into account. Although many other formulations for asocial and
481 social learning processes were possible, we believe that our current choice – time-depth asocial
482 reinforcement learning with the most-updated-frequency-dependent copying was a reasonable
483 first step.

484 In summary, the model has six free parameters that were estimated for each individual human
485 participant; namely, α_i , $\beta_{i,0}^*$, ϵ_i , $\sigma_{i,0}^*$, δ_i , and θ_i . To fit the model, we used a hierarchical Bayesian
486 method (HBM), estimating the global means (μ_α , $\mu_{\beta_0^*}$, μ_ϵ , $\mu_{\sigma_0^*}$, μ_δ , and μ_θ) and the global vari-
487 ations (ν_α , $\nu_{\beta_0^*}$, ν_ϵ , $\nu_{\sigma_0^*}$, ν_δ , and ν_θ) for each of the three experimental conditions (i.e. the Low-,
488 Moderate- and High-uncertain condition), which govern overall distributions of individual pa-
489 rameter values. It has become recognised that the HBM can provide more robust and reliable
490 parameter estimation than conventional maximum likelihood point estimation in complex cog-
491 nitive models⁷⁶, a conclusion with which our parameter recovery test agreed (Supplementary
492 Figure 7, Supplementary Figure 8).

493 **3.5 Agent-based model simulation**

494 We ran a series of individual-based model simulations assuming that a group of individuals play
495 our three-armed bandit task for 90 rounds (under the Moderate-uncertainty condition) and that in-
496 dividuals behave in accordance with the computational learning-and-decision model. We varied
497 the group size ($n \in \{3, 10, 30\}$), the mean social learning weight ($\bar{\sigma} \in \{0.01, 0.1, 0.2, 0.3, \dots, 0.9\}$)
498 and the mean conformity exponent ($\bar{\theta} \in \{0.5, 1, 3, 6\}$), running 10,000 replications for each of
499 the possible parameter \times group size combinations. As for the other parameter values (e.g. the
500 asocial reinforcement learning parameters; $\alpha, \beta_0^*, \epsilon$), here we used the experimentally fitted global
501 means (Table 2 and Supplementary Table 3). Relaxation of this assumption (i.e. using a different
502 set of asocial learning parameters) does not qualitatively change our story (Supplementary Fig-
503 ure 2). Note that each individual's parameter values were randomly drawn from the distributions
504 centred by the global mean parameter values fixed to each simulation run. Therefore, the actual
505 composition of individual parameter values were different between individuals even within the
506 same social group.

507 **3.6 Generalised linear mixed models**

508 To directly analyse the effects of group size and task uncertainty on the time evolution of decision
509 performance, we conducted a statistical analysis using a phenomenological model, namely, a
510 hidden Markov process logistic regression without assuming any specific learning-and-decision-
511 making processes. The dependent variable was whether the participant chose the best option (1)
512 or not (0). The model includes fixed effects of grouping ξ , standardised group size ω , and an
513 intercept with a random effect of individuals $\mu + \rho_i$. We assumed that the intercept and the effect

514 of grouping change from round to round, as a random walk process. For the effect of group size
515 we considered the effect of the 1st environment $1 \leq t \leq 40$ and that of the 2nd environment,
516 namely, ω_1 and ω_2 , separately.

517 To examine whether increasing group size and increasing task uncertainty affected individ-
518 ual use of the positive frequency-dependent copying strategy, we used a hierarchical Bayesian
519 logistic regression model with a random effect of groups. The dependent variable was whether
520 the participant used the positive frequency-dependent copying (1) or not (0). The model includes
521 fixed effects of group size (standardised), task uncertainty (0: Low, 0.5: Moderate, 1: High), age
522 (standardised), gender (0: male, 1: female, NA: others or unspecified), and possible two-way
523 interactions between these fixed effects.

524 We also investigated the effects of both group size and the task's uncertainty on the fitted
525 values of the learning parameters. We used a hierarchical Bayesian gaussian regression model
526 predicting the individual fitted parameter values. The model includes effects of group size (stan-
527 dardised), task uncertainty (0: Low, 0.5: Moderate, 1: High), age (standardised), gender (0:
528 male, 1: female, NA: others or unspecified), and two-way interactions between these fixed ef-
529 fects. We assumed that the variance of the individual parameter values might be contingent upon
530 task uncertainty because we had found in the computational model-fitting result that the fitted
531 global variance parameters (i.e. $v_{\sigma_0^*}$, v_δ and v_θ) were larger in more uncertain conditions (Sup-
532 plementary Table 2).

533 **3.7 Statistical analysis**

534 We used a hierarchical Bayesian method (HBM) to estimate the free parameters of our sta-
535 tistical models, including both the phenomenological regression model and the computational
536 learning-and-decision-making model. The HBM allows us to estimate individual differences,
537 while ensures these individual variations are bounded by the group-level global parameters. The
538 HBM was performed under Stan 2.16.2 (<http://mc-stan.org>) in R 3.4.1 ([https://www.
539 r-project.org](https://www.r-project.org)) software. The models contained at least 4 parallel chains and we confirmed
540 convergence of the MCMC using both the Gelman-Rubin statistics and the effective sample sizes.
541 Full details of the model fitting procedure and prior assumptions are shown in the appendix.

542 **3.7.1 Parameter recovery test**

543 To check the validity of our model-fitting method, we conducted a ‘parameter recovery test’
544 so as to examine how well our model fitting procedure had been able to reveal true individual
545 parameter values. To do this, we generated synthetic data by running a simulation with the
546 empirically fitted global parameter values, and then re-fitted the model with this synthetic data
547 using the same procedure. The parameter recovery test showed that the all true global parameter
548 values were fallen into the 95% Bayesian credible interval (Supplementary Figure 7), and at least
549 93% of the true individual parameter values were correctly recovered (i.e. 96% of α_i , 93% of $\beta_{i,0}^*$,
550 95% of ϵ_i , 97% of $\sigma_{i,0}^*$, 96% of δ_i and 97% of θ_i values were fallen into the 95% Bayesian CI.
551 Supplementary Figure 7).

552 **3.7.2 Categorisation of individual learning strategies**

553 Based on the 50% CI of the individual *conformity exponent* parameter values θ_i , we divided
554 the participants into the following three different social learning strategies. If her/his 50% CI
555 of θ_i fell above zero ($\theta_{lower} > 0$), below zero ($\theta_{upper} < 0$) or including zero ($\theta_{lower} \leq 0 \leq$
556 θ_{upper}), she/he was categorised as a ‘positive frequency-dependent copier’, a ‘negative frequency-
557 dependent copier’, or a ‘random choice individual’, respectively. We used the 50% Bayesian CI
558 to conduct this categorisation instead of using the more conservative 95% CI because the latter
559 would cause much higher rates of ‘false negatives’, by which an individual who applied either a
560 positive frequency-dependent copying or a negative-frequency dependent copying strategy was
561 falsely labelled as an asocial random choice individual (Supplementary Figure 7). Four hundred
562 agents out of 572 ($\approx 70\%$) were falsely categorised as a random choice learner in the recovery
563 test when we used the 95% criterion (Supplementary Figure 7). On the other hand, the 50%
564 CI criterion seemed to be much better in terms of the false negative rate which was only 18.5%
565 (i.e. 106 agents), although it might be slightly worse in terms of ‘false positives’: Thirty-seven
566 agents (6.5%) were falsely labelled as either a positive frequency-dependent copier or a negative-
567 frequency dependent copier by the 50% CI, whereas the false positive rate of the 95% CI was
568 only 0.2% (Supplementary Figure 7). To balance the risk of false positives and false negatives,
569 we decided to use the 50% CI which seemed to have more strategy detecting power.

570 **3.7.3 The post-hoc model simulation**

571 So as to evaluate how accurately our model can generate observed decision pattern in our task
572 setting, we ran a series of individual-based model simulation using the fitted individual param-

573 eter values (i.e. means of the individual posterior distributions) for each group size for each
574 uncertainty condition. At the first step of the simulation, we assigned a set of fitted parameters
575 of a randomly-chosen experimental subject from the same group size and the same uncertain
576 condition to an simulated agent, until the number of agents reaches the simulated group size. We
577 allowed duplicate choice of experimental subject in this parameter assignment. At the second
578 step, we let this synthetic group of agents play the bandit task for 90 rounds. We repeated these
579 steps 10,000 times for each group size, task uncertainty.

580 **3.8 Data availability**

581 Both experimental and simulation data are available on an online repository (<https://github.com/WataruToyokawa/ToyokawaWhalenLaland2018>).

583 **3.9 Code availability**

584 The browser based online task was built by Node.js (<https://nodejs.org/en/>) and socket.io
585 (<https://socket.io>), and the code are available on a GitHub repository (<https://github.com/WataruToyokawa/MultiPlayerThreeArmedBanditGame>). Analyses were conducted in
586 R (<https://www.r-project.org>) and simulations of individual based models were conducted
587 in Mathematica (<https://www.wolfram.com>), both are available on an online repository (<https://github.com/WataruToyokawa/ToyokawaWhalenLaland2018>).

590 **4 Competing interest**

591 The authors declare no competing interests.

592 **5 Authors' contributions**

593 WT, AW and KNL planned the study and built the computational model. WT ran simulations.
594 WT and AW made the experimental material, ran the web-base experiment, and collected the
595 experimental data. WT, AW and KNL analysed the data and wrote the manuscript.

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603 **7 Figure captions and tables**

Figure 1: Findings of the individual-based model showing the effects of social information use on the average decision accuracy over replications. The x-axis gives the round and y-axis gives the proportion of individuals expected to choose the optimal slot (i.e. decision accuracy) averaged over all replications. The vertical dashed line indicates the timing of environmental (i.e. payoff) change (at $t = 41$). Different group sizes are shown by different styles (black (dotted): $n = 3$, orange (dashed): $n = 10$, red (solid): $n = 30$). We set the average slopes for the *social learning weight* to be equal to zero for the sake of simplicity; namely, $\mu_\delta = 0$. Other free parameter values (i.e. μ_α , $\mu_{\beta_0^*}$, μ_ϵ , ν_α , $\nu_{\beta_0^*}$, ν_ϵ , ν_σ , ν_δ and ν_θ) are best approximates to the experimental fitted values (see Table 2 and Supplementary Table 1).

Figure 2: Results from the individual-based model simulations showing the distribution of each group's mean accuracy before environmental change ($t \leq 40$). The x-axis gives the mean decision accuracy over the first 40 rounds (i.e. the environment 1) for each replication. Different group sizes are shown by different styles (black (dotted): $n = 3$, orange (dashed): $n = 10$, red (solid): $n = 30$). The other free parameter values are the same as in Figure 1.

Table 1: The mean and the 95% Bayesian credible intervals of the posterior for the group size effect at the phenomenological logistic model

| | Low Uncertainty | | Moderate Uncertainty | | High Uncertainty | |
|------------|-----------------|---------------|----------------------|----------------|------------------|----------------|
| ω_1 | 0.08 | [-0.15, 0.33] | 0.10 | [-0.06, 0.26] | 0.07 | [0.00, 0.15] |
| ω_2 | 0.67 | [0.44, 0.91] | -0.26 | [-0.44, -0.11] | -0.10 | [-0.17, -0.02] |

Note: All \hat{R} values are 1.0 and the effective sample sizes are larger than 837.

Figure 3: Time evolutions and distributions of decision performance for each condition. **A:** The average decision accuracies of the experimental participants (red: large groups, orange: small groups, dark grey: lone individuals). All individual performances were averaged within the same size category (solid lines). The light-shaded areas, dark-shaded areas, and dashed curves show the 95%, 50%, and median Bayesian credible intervals of the phenomenological, time-series logistic regression. **Sample sizes for large, small, and lone groups are: $N = 43$, $N = 44$ and $N = 38$ for the Low-uncertainty condition; $N = 52$, $N = 56$ and $N = 37$ for the Moderate-uncertainty condition; and $N = 259$, $N = 168$ and $N = 58$ for the High-uncertainty condition, respectively.** **B:** Change in the main effect of the dummy variable of grouping on the decision accuracy at the phenomenological regression model. The shaded areas are the Bayesian CIs and solid curves are the median. **C, D:** Change and distribution in average decision accuracy of the individual-based post-hoc simulations of the learning process model using the experimentally fit parameter values. **C:** All replications were averaged within the same size category (solid lines). The shaded areas give the 50% quantiles. The experimental horizon (i.e. $t = 70$) is indicated by the vertical line. **D:** Performance was averaged within prior- and post-change periods for each replication for each group sizes category.

Figure 4: Model fitting for the three different task's uncertain conditions (the Low-, Moderate- and High-uncertainty) and the different group size. Three different learning strategies are shown in different styles (red-triangle: positive frequency-dependent learning, blue-circle: negative frequency-dependent learning; grey-circle: nearly random choice strategy). (A) Frequencies of three different learning strategies. Note that a sum of the frequencies of these three strategies in the same group size does not necessarily equal to 1, because there are a small number of individuals eliminated from this analysis due to insufficient data. (B) Estimated social learning weight, and (C) estimated conformity exponent, for each individual shown for each learning strategy. The 50% Bayesian CIs of the fitted GLMMs are shown by dashed lines and shaded areas. The horizontal lines in (C) show a region $-1 < \theta_i < 1$. **Sample sizes for Negative Frequency Dependent, Positive Frequency Dependent, and Random Choice strategies are: $N = 2$, $N = 61$ and $N = 14$ for the Low-uncertainty condition; $N = 3$, $N = 80$ and $N = 15$ for the Moderate-uncertainty condition; and $N = 32$, $N = 260$ and $N = 106$ for the High-uncertainty condition, respectively.**

Figure 5: Change in fitted values (i.e. median of the Bayesian posterior distribution) of the social learning weight $\sigma_{i,t}$ with time for each **Positive Frequency Dependent individual, for each level of task uncertainty.**

Thick dashed lines are the median values of $\sigma_{i,t}$ across the subjects for each uncertainty condition. Individual conformity exponent values θ_i are shown in different colours (higher θ_i is darker). **Sample size for each task uncertainty condition is: $N = 61$ (Low-uncertainty), $N = 80$ (Moderate-uncertainty) and $N = 260$ (High-uncertainty).**

Table 2: The mean and the 95% Bayesian credible intervals of the posterior global means for the parameter values.

The number of participants (N) for each experimental condition are also shown.

| Uncertainty: | Groups | | | Solitary individuals | | |
|------------------------------------|-------------------------|-------------------------|-------------------------|-----------------------|------------------------|-----------------------|
| | Low | Moderate | High | Low | Moderate | High |
| μ_{α^*} (learning rate) | 0.99 [0.34, 1.73] | 0.90 [0.43, 1.44] | 0.61 [0.21, 1.03] | 0.85 [-0.07, 1.95] | -0.17 [-1.27, 0.89] | 0.46 [-0.39, 1.36] |
| $\mu_{\beta_0^*}$ (inv. temp.) | 1.84 [1.15, 2.70] | 1.68 [1.25, 2.18] | 1.38 [1.16, 1.62] | 1.10 [0.69, 1.54] | 1.44 [0.80, 2.07] | 0.85 [0.46, 1.22] |
| μ_{ϵ} (inv. temp.) | 3.70 [1.98, 5.71] | 3.01 [1.88, 4.27] | 2.97 [2.37, 3.60] | 2.39 [1.46, 3.53] | 2.81 [1.64, 4.07] | 2.27 [1.40, 3.31] |
| $\mu_{\sigma_0^*}$ (soc. wight) | -1.55 [-2.71, -0.71] | -2.37 [-4.12, -1.01] | -2.16 [-2.81, -1.63] | – – | – – | – – |
| μ_{δ} (soc. wight) | -1.39 [-2.66, -0.03] | -1.55 [-4.29, 0.91] | -1.87 [-3.04, -0.81] | – – | – – | – – |
| μ_{θ} (conformity coeff.) | 1.65 [0.83, 2.82] | 3.00 [1.57, 4.85] | 2.67 [1.80, 3.73] | – – | – – | – – |
| N | 77 | 98 | 398 | 36 | 34 | 56 |

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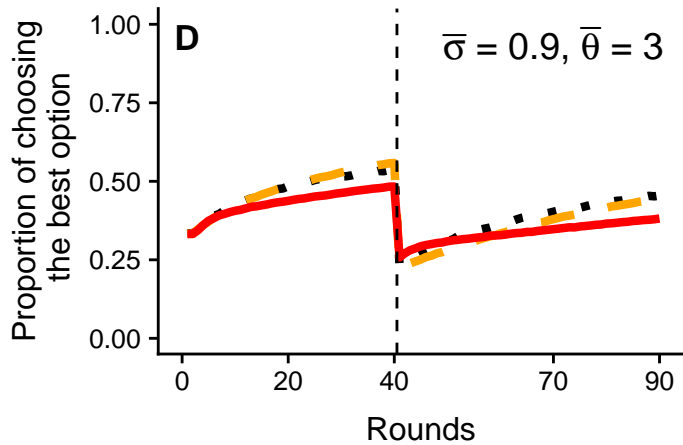
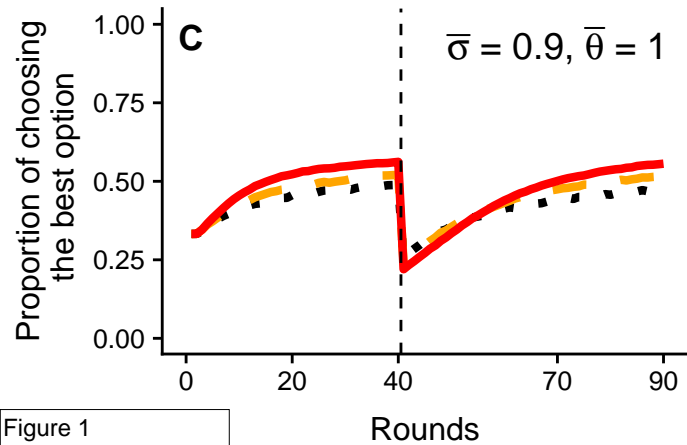
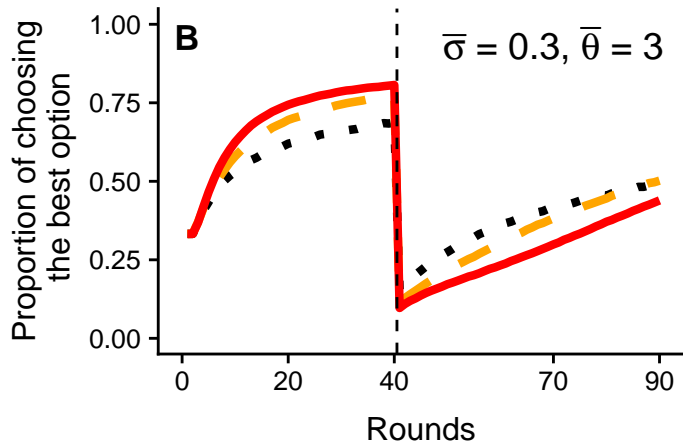
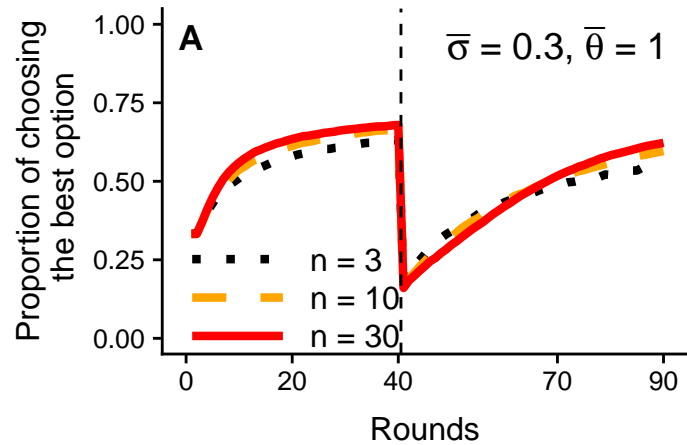


Figure 1

Group size: \dots $n = 3$; \square $n = 10$; \square $n = 30$

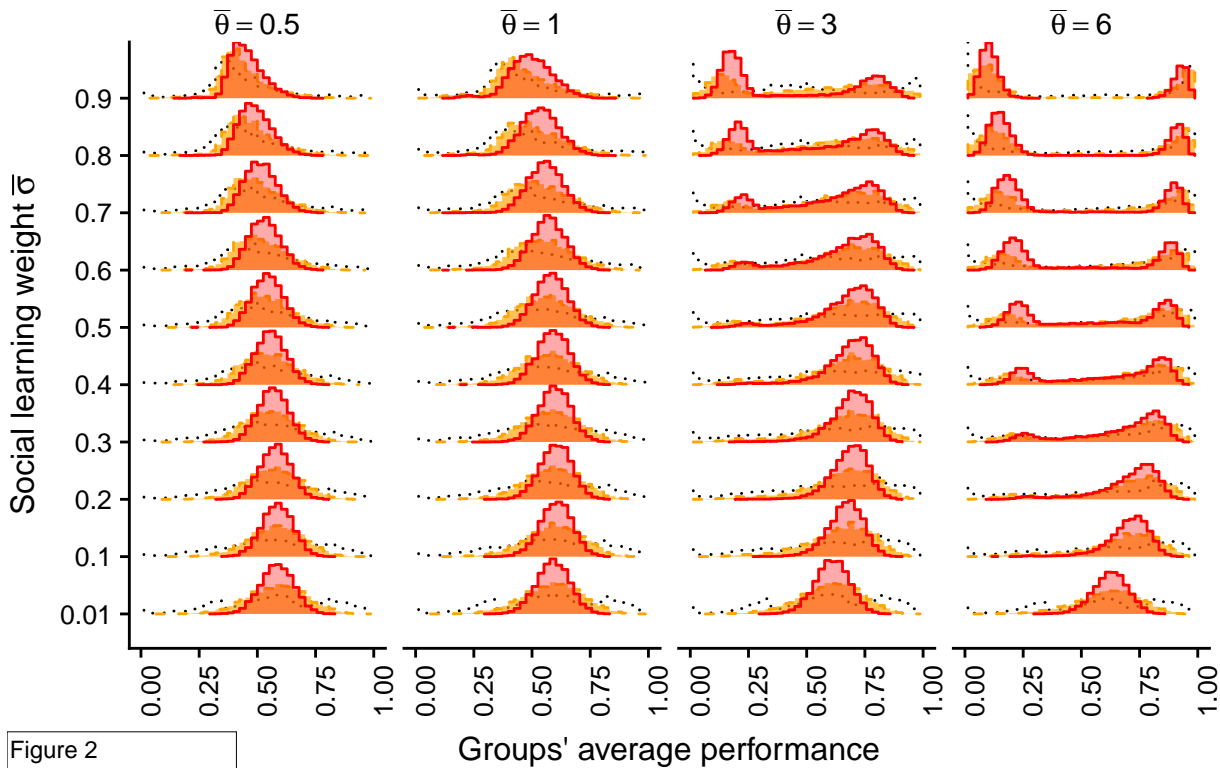


Figure 2

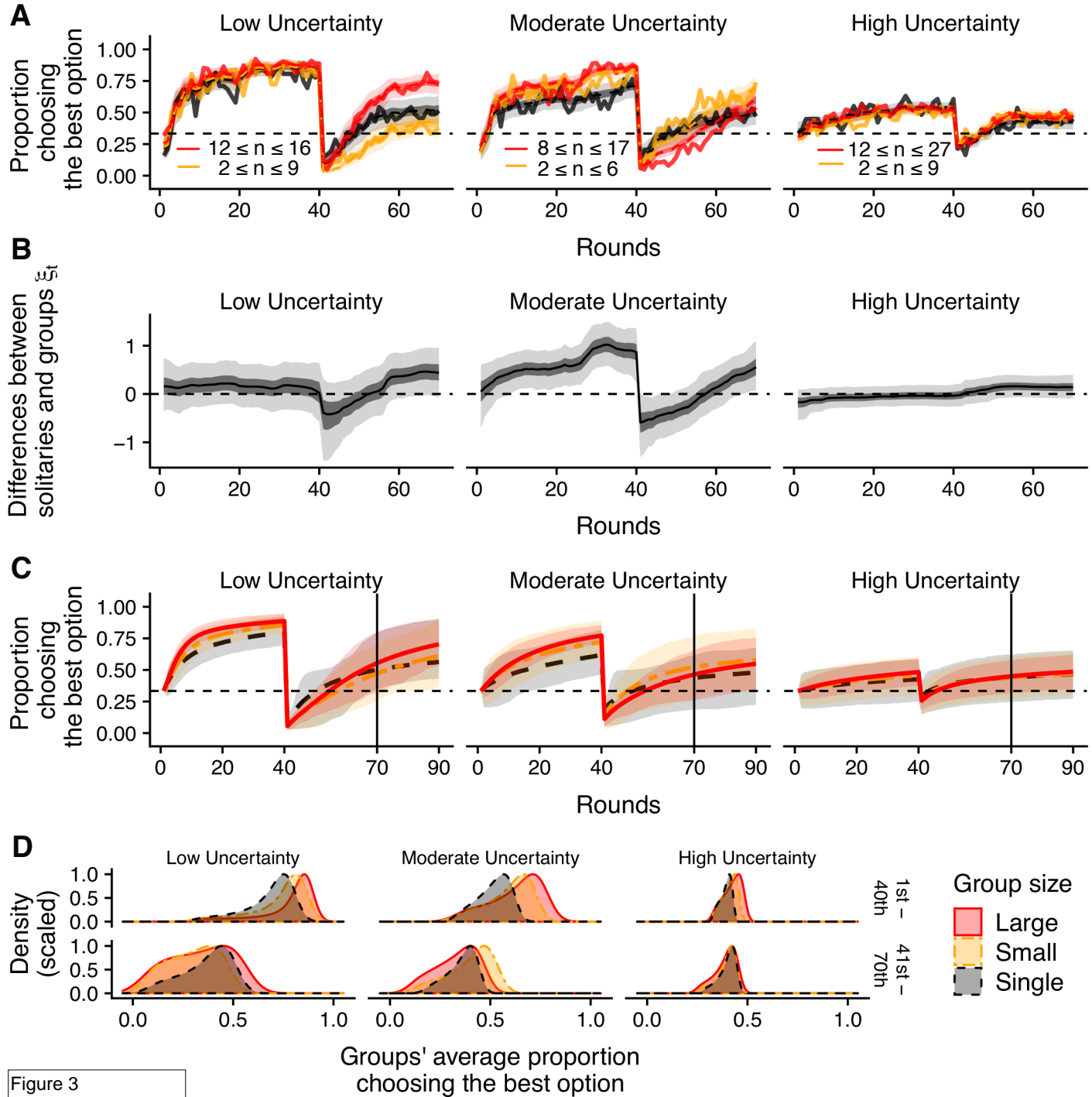


Figure 3

