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# Cooperation and deception through stigmergic interactions in human groups

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**Stigmergy is a generic coordination mechanism widely used by animal societies, in which traces left by individuals in a medium guide and stimulate their subsequent actions. In humans, new forms of stigmergic processes have emerged through the development of online services that extensively use the digital traces left by their users. Here, we combine interactive experiments with faithful data-based modeling to investigate how groups of individuals exploit a simple rating system and the resulting traces in an information search task in competitive or non-competitive conditions. We find that stigmergic interactions can help groups to collectively find the cells with the highest values in a table of hidden numbers. We show that individuals can be classified into three behavioral profiles that differ in their degree of cooperation. Moreover, the competitive situation prompts individuals to give deceptive ratings and reinforces the weight of private information versus social information in their decisions.**

social influence | stigmergy | digital traces | collective intelligence | cooperation

The exchange of social information is the core mechanism by which groups of individuals are able to coordinate their activities and collectively solve problems (1–5). Social information allows individuals to adapt to their environment faster and/or better than through collecting personal information alone (6–10). The use of social information thus provides evolutionary advantages to animal groups and occurs in many contexts, such as foraging, decision-making, division of labor, nest building, or colony defense (1, 2, 11, 12).

Quite often, social information is indirectly shared between individuals: some of them leave traces of their activities in the environment and others can use this information to guide their own behavior and inform their own decisions (13). This form of indirect communication, also called stigmergy, in which the trace of an action left on a medium stimulates the performance of a subsequent action which produces another trace and so on, is widely used by animal societies and especially social insects to self-organize their collective behaviors (14–16). These stigmergic interactions that allow the emergence of coordinated activities out of local independent actions likely played a major role in the evolution of cooperativity within groups of organisms (17, 18).

In humans, with the digitalization of society and economies, social information has increasingly taken the form of digital traces, which are the data individuals leave either actively or passively when using the Internet (19–21). New forms of stigmergic processes have been identified since these digital traces are largely exploited in social networks and in electronic commerce, in particular through the use of rating and recommendation systems that can help participants to discover

new options and make better choices (22–26). However, individuals do not use social information in the same way. Some individuals exploit it to make their choices, while others may simply ignore it and only use their own private information, or can even go against the message delivered by social information (27). In fact, the same individual can even change the way they provide and uses social information depending on the context (28).

Moreover, the use of digital traces is very sensitive to noise and manipulation (29, 30). Indeed, in competitive situations, malicious spammers can manipulate social information by deliberately giving high (respectively, low) ratings to certain low (respectively, high) quality items. Therefore, knowing the way individuals share and use digital traces in different contexts is a crucial step to understanding how groups of individuals can cooperate through stigmergic interactions and can exhibit collective intelligence. Despite their increasing importance in human groups, very little research on stigmergic processes has been done so far (31, 32).

The aims of this study are twofold. First, we study through a combination of experiments and computational modeling how indirect interactions between individuals in a human group involving the use of traces allow them to cooperate during an information search task. Secondly, we study how a competitive or non-competitive context influences the way

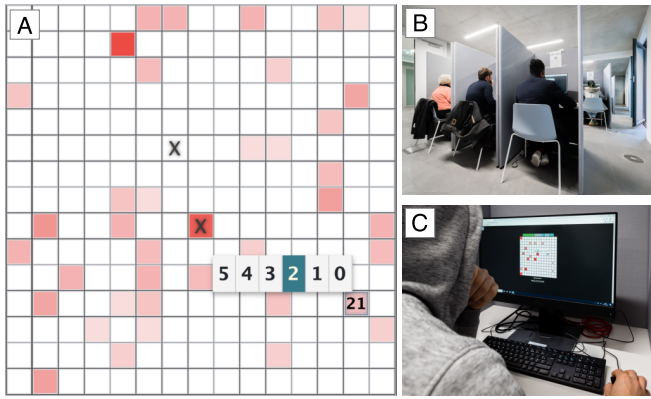
## Significance Statement

Most online services and applications on the Internet rely on digital traces resulting from choices made by their users, in particular, by means of rating-based recommendation systems. Therefore, it is crucial to understand how such traces affect individual and collective decision-making. We have conducted experiments to measure how groups of individuals interact with digital traces and determine how they could use these traces to cooperate and find the cells with the highest values in a table of hidden numbers. Our experiments and data-driven model show that digital traces spontaneously induce cooperation between individuals. However, the way individuals use the traces to deliver information to others and the reliability of that information largely depends on the degree of competition between individuals.

C.S. and G.T. designed research; A.B., T.B., S.C., R.E., C.S., and G.T. performed research; M.D. and T.B. designed the web interface, with inputs from all other authors; T.B., C.S., and G.T. analyzed data; T.B. and C.S. designed the model; T.B. performed numerical simulations; T.B., C.S., and G.T. wrote the article.

The authors declare no conflict of interest.

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**Fig. 1. Experimental setup.** (A) Screenshot of the table at round  $t = 10$ , as seen by a participant. In this round, the participant has already visited and rated two cells marked with black crosses. The participant just visited the third cell of value 21 and must rate that cell on a 5-star scale. The score of the participant will then depend on the considered rule: in the non-competitive Rule 1, the score will increase by 0, and by 21 in the competitive Rule 2. (B) Pictures of the experimental room and (C) of the user interface that participants used during the experiment.

56 in which individuals exchange and use the social information  
 57 embedded in the traces of their past actions to perform the  
 58 information search task.

59 Through the development of an interactive web application  
 60 and the use of data-based modeling, we identify the behavioral  
 61 and cognitive strategies combined with stigmergic interactions  
 62 that govern individual decisions. The simulation results of our  
 63 faithful computational model provide clear evidence that the  
 64 collective behavioral dynamics observed in experiments can be  
 65 predicted with the precise knowledge of the way individuals  
 66 use and combine private and social information.

## 67 Experimental Design

68 The experimental setup was designed to investigate in fully con-  
 69 trollable conditions how groups of individuals leave and exploit  
 70 digital traces using a simple 5-star rating system similar to the  
 71 ones used by many online marketplaces and platforms. There,  
 72 users can evaluate products, services, or sellers, and exploit  
 73 the ratings to help them find the best options corresponding  
 74 to their expectation.

75 Here, we study the individual and collective performance  
 76 of groups of 5 individuals in a task where each participant has  
 77 to find the highest values in a  $15 \times 15$  table of 225 cells, each  
 78 containing a hidden value (see Fig. 1A). In our setup, the cells  
 79 would represent the available options and their value would  
 80 correspond to their intrinsic quality. SI-Appendix, Fig. S1A  
 81 presents an example of a table used in our experiments, where  
 82 the cell values are explicitly shown. Numbers with values  
 83 ranging from 0 to 99 were randomly distributed in the cells of  
 84 the table, and SI-Appendix, Fig. S1B shows the distribution of  
 85 these cell values. To carry out these experiments, we developed  
 86 an interactive web application that allows the 5 group members  
 87 to independently explore the same table (see Fig. 1 B and C).

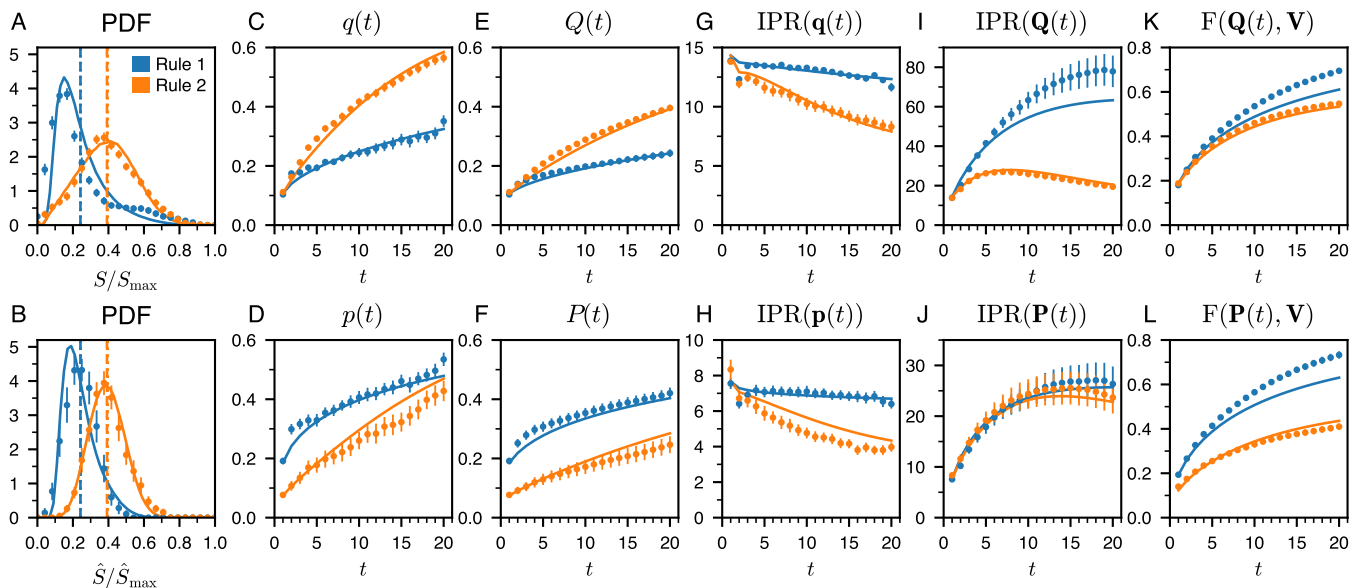
88 Each experiment includes 20 successive rounds. During  
 89 each round, each participant has to successively visit and rate  
 90 3 distinct cells. Once a participant discovers the hidden value  
 91 of a cell, they must rate that cell on a 5-star scale. The  
 92 round ends when everyone in the group has visited and rated  
 93 3 different cells.

At the start of the next round, the color of each cell in  
 the table is updated according to the fraction of stars that  
 have been used to rate the cell since the beginning of the  
 experiment, that is, the number of stars in the cell divided by  
 the total number of stars in all cells. The color scale varies  
 between white (0%) and black (100%) through a gradient of  
 shades of red (see SI-Appendix, Fig. S1C). Thus, the cells that  
 have received the highest fraction of stars since the beginning  
 of the experiment will be clearly visible to all the individuals  
 belonging to the same group. The resulting color map on the  
 table acts like a cumulative long-term collective memory for  
 the group, which is updated at each round. Note that the  
 subjects cannot infer the precise value of the fraction of stars  
 in a cell from its color, but only a rough estimate. However,  
 they can certainly exploit the colors to compare the fraction  
 of stars in the different cells of the table and to identify the  
 cells with a high fraction of stars. Fig. 1A shows an example  
 of a table displaying the participants' ratings as a color map  
 after 10 rounds during one experiment.

We also investigate the impact of a competitive versus a  
 non-competitive condition on the behavior of participants,  
 and the individual and collective performance. In particular,  
 we focus our analysis on the way individuals visit and rate  
 cells and how they use the traces resulting from their ratings  
 and those left by the other group members to guide their  
 choices. In each experiment, we studied the individual and  
 collective behaviors of two groups performing the same task in  
 parallel and independently. In the non-competitive condition,  
 hereafter called Rule 1, the actions (cell visits and ratings)  
 of the participants do not affect the amount of reward they  
 received at the end of an experiment that always remains  
 constant. On the other hand, in the competitive condition,  
 hereafter called Rule 2, the score of a participant increases at  
 each round by *the value of the cells they visit*, but remains  
 unaffected by their rating of these cells. Then, the cumulative  
 score of participants over an entire session (12 experiments)  
 determines their monetary reward, which depends on their  
 ranking among the 10 participants and not just among the 5  
 members of their group (see Materials and Methods for the  
 actual payment method).

This experimental design allowed us to study the impact  
 of an intragroup competition, since each individual in a group  
 competes with the 4 other members of their group. However,  
 there is also an implicit intergroup competition, since each  
 individual also competes with the 5 members of the other  
 group for the best rank. SI-Appendix, Fig. S2 illustrates the  
 actions performed by each participant in one group and the  
 color maps associated with the cells in the table resulting  
 from their ratings. SI-Appendix, Movies S1A (Rule 1) and  
 S2A (Rule 2) show examples of the dynamics of a typical  
 experimental run where the participants achieved a group score  
 near the observed mean group score. In the corresponding  
 SI-Appendix, Movies S3 and S4, we present an experimental  
 run where the participants obtained a group score 50% higher  
 than the observed mean group score. SI-Appendix, Movie S5  
 features the same results as Movies S1–S4 but without the  
 cell values, to better identify the different shades of red and  
 to better reflect what the subjects actually saw during the  
 experiment.

In the next section, we present the results of this exper-  
 iment mimicking several processes at play in actual 5-star



**Fig. 2. Collective performance and dynamics of collective exploration and ratings.** For the non-competitive Rule 1 (blue) and competitive Rule 2 (orange), the symbols correspond to the experimental results, and the solid lines are the predictions of the model. (A) Probability distribution function (PDF) of the scores of individuals  $S$ , and (B) of the groups  $\hat{S}$ , respectively normalized by their theoretical maxima  $S_{\max}$  and  $\hat{S}_{\max} = 5S_{\max}$ . The dotted vertical lines are the mean score in the experiment, and the dashed vertical lines are the mean scores in the model. (C) Average value of the cells visited at round  $t$ ,  $q(t)$  and (E) up to round  $t$ ,  $Q(t)$ . (D) Average value of the cells visited weighted by their ratings at round  $t$ ,  $p(t)$  and (F) up to round  $t$ ,  $P(t)$ . (G) and (I) Inverse participation ratio of the visits,  $\text{IPR}(q(t))$  and  $\text{IPR}(Q(t))$ , measuring the effective number of cells over which the visits are distributed at round  $t$  and up to round  $t$ , respectively. (H) and (J) Inverse participation ratio of the ratings,  $\text{IPR}(p(t))$  and  $\text{IPR}(P(t))$ , measuring the effective number of cells over which the ratings are distributed at round  $t$  and up to round  $t$ , respectively. (K) Fidelity to the cell value distribution of the distribution of visits,  $F(Q(t), \mathbf{V})$ , and, (L) of ratings,  $F(P(t), \mathbf{V})$ .

155 rating systems: (i) the exploration by the participants of  
 156 available options (cells in our experiment), which is greatly  
 157 influenced by their current ratings; (ii) the rating on a 5-star  
 158 scale of the options selected by the participants, which ulti-  
 159 mately affects the future ratings of these different options. The  
 160 ratings in our experiments, seen by all participants, are digital  
 161 traces eliciting stigmergic processes allowing the participants  
 162 to collectively identify the best options. In addition, our basic  
 163 research study also explores the impact of competition in this  
 164 exploration/rating context, by submitting the participants to  
 165 non-competitive or competitive incentives. Although this com-  
 166 petitive aspect is less relevant in real-life situations exploiting  
 167 5-rating systems, our experimental setup and our modeling  
 168 approach allow us, more generally, to study the interplay be-  
 169 tween exploration strategies, rating strategies, private and  
 170 shared information, and competition.

## 171 Results

172 **Collective Dynamics.** In this section, we analyze the perfor-  
 173 mance of individuals and groups, as well as the dynamics of  
 174 collective exploration and ratings in both rules. To do so, we  
 175 introduce a set of precise observables, which are described in  
 176 detail in Materials and Methods: the score of individuals or  
 177 the mean score of their group; the mean value of the cells  
 178 weighted by the fraction of stars or the fraction of visits at  
 179 round  $t$  ( $p(t)$  and  $q(t)$ ) or up to round  $t$  ( $P(t)$  and  $Q(t)$ ); the  
 180 effective number of cells (inverse participation ratio; IPR) over  
 181 which the stars and visits are distributed at round  $t$  and up  
 182 to round  $t$ ; the fidelity  $F$ , which quantifies whether the distri-  
 183 bution of stars or visits in each cell coincides with the actual  
 184 distribution of the cell values.

185 Fig. 2 A and B show respectively the probability distribu-

186 tion functions (PDF) of the score  $S$  of individuals obtained  
 187 after the 20 rounds and the score  $\hat{S}$  of groups, i.e., the sum  
 188 of the scores of the individuals belonging to the same group.  
 189 In Rule 1, all scores are equal to 0. Thus, in order to com-  
 190 pare the individual and collective performance in the two  
 191 rules, each individual is assigned a virtual score computed  
 192 in the same way as in Rule 2. The mean score is higher  
 193 in Rule 2, showing that this competitive condition provides  
 194 a stronger incentive to visit high-value cells than in Rule 1:  
 195  $\langle S/S_{\max} \rangle = 0.24 \pm 0.01$  in Rule 1 vs.  $\langle \hat{S}/\hat{S}_{\max} \rangle = 0.40 \pm 0.01$   
 196 in Rule 2, where  $S_{\max} = 5420$  is the maximum theoretical  
 197 score.

198 Fig. 2 C–F show that the average value of the visited  
 199 cells increases with the number of rounds as the participants  
 200 discover, visit, and rate cells with higher values. Although  $p(t)$   
 201 and  $P(t)$  are higher in Rule 1 than in Rule 2 (Fig. 2 D and  
 202 F), the average value of visited cells at round  $t$ ,  $q(t)$ , and up  
 203 to round  $t$ ,  $Q(t)$ , are significantly higher in Rule 2 (Fig. 2 C  
 204 and E). As we will see later, this apparent paradox is due to  
 205 the fact that the strategies used by individuals to rate cells  
 206 in Rule 1 and Rule 2 are very different. In particular, in the  
 207 competitive Rule 2, some individuals choose to give an average  
 208 or even a low rating to cells having a high value, presumably  
 209 to avoid reporting these cells to the other members of their  
 210 group.

211 Fig. 2 G and I show that individuals visit significantly  
 212 more different cells in Rule 1 than in Rule 2, with  $\text{IPR}(Q(t))$   
 213 growing up to the final round  $t = 20$  in Rule 1, while it starts  
 214 decaying after round  $t = 7$  in Rule 2. In particular, at the final  
 215 round  $t = 20$  of the experiment,  $\text{IPR}(Q(t = 20))$  is roughly  
 216 four times larger in Rule 1 than in Rule 2. As we will see in  
 217 the next section, the lower exploration observed in Rule 2 is

218 mostly due to the fact that the individuals revisit a lot more  
 219 cells with high values instead of exploring new cells, in order  
 220 to maximize their score. Moreover, in each round, individuals  
 221 allocate more stars in Rule 1 compared to Rule 2 (see Fig. 2H),  
 222 but overall, they allocate stars to the same number of cells  
 223 (see Fig. 2J).

224 Fig. 2 K and L show that in both conditions, the fidelity  
 225 increases with the round  $t$ , suggesting that the correlations  
 226 between the participants' visits/ratings and the cell values  
 227 increase with time. In the final round of the experiment, the  
 228 fidelity of ratings  $F(\mathbf{P}(t = 20), \mathbf{V})$  is significantly higher in  
 229 Rule 1 than in Rule 2. As we mentioned previously, in Rule 1,  
 230 the participants explore the table a lot more and their ratings  
 231 better reflect the value of the cells that they have discovered.

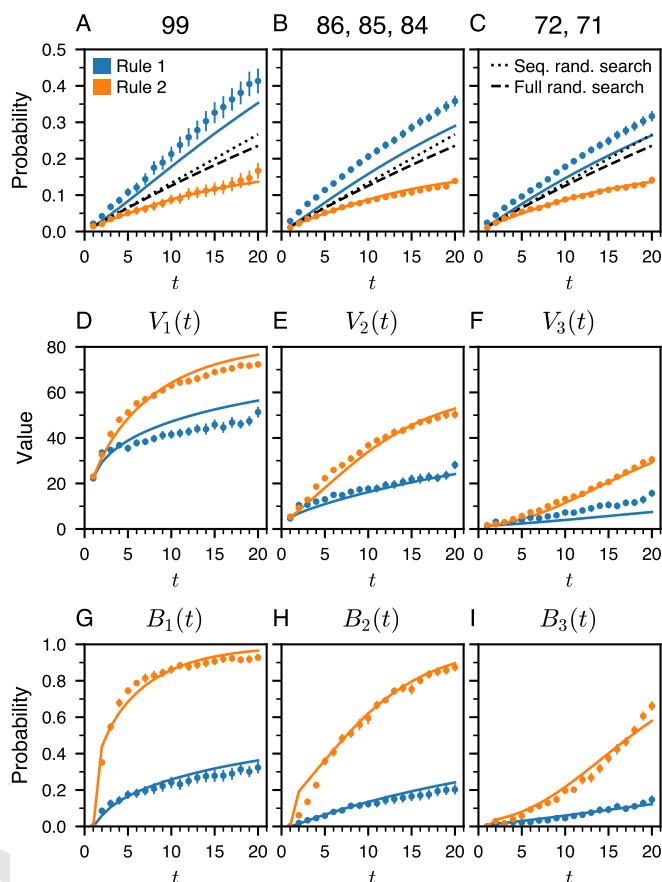
232 **Individual Behaviors.** In this section, we characterize the behav-  
 233 iors of individuals and their strategies to visit and rate cells,  
 234 i.e., the way they use social information in the form of colored  
 235 traces resulting from their collective past actions. Moreover,  
 236 we also quantify the impact of intragroup competition on their  
 237 behaviors.

238 **Choosing the cells to be visited.** The probabilities of finding the  
 239 cells with the highest values are higher in Rule 1 than in Rule 2  
 240 (see Fig. 3 A–C and SI-Appendix, Fig. S3). In Rule 1, individ-  
 241 uals find the best cells more often than would be expected if  
 242 they had searched randomly, illustrating the cooperative effect  
 243 induced by the use of the digital traces by individuals within  
 244 groups. In Rule 2, we observe the opposite phenomenon: individ-  
 245 uals often revisit the cells that they consider high enough to  
 246 improve their score, without taking the risk of exploring new  
 247 low-value cells. However, this kind of hedging also hampers  
 248 their ability to discover even better cells.

249 We define  $V_1(t)$ ,  $V_2(t)$ , and  $V_3(t)$  as the average of the  
 250 first-, second-, and third-best values of the cells visited by  
 251 the participants at round  $t$ . Fig. 3 D–F shows that in both  
 252 conditions, the average values of these 3 cells increase with  
 253 round  $t$ . However, their average values are higher in Rule 2.  
 254 Note that this is not in contradiction with the results shown  
 255 in Fig. 3 A–C. As a matter of fact, in Rule 1, individuals  
 256 have no incentive to revisit cells with high values, so they  
 257 continue exploring the table even if they have already found  
 258 those cells. As already mentioned, in Rule 2, individuals have  
 259 a clear incentive to revisit cells with high values that they can  
 260 remember, and thus to explore the table less, so that they  
 261 ultimately discover the cells with the highest values less often.

262 To confirm this interpretation, we quantify the way individ-  
 263 uals revisit cells by defining, for  $t > 1$ ,  $B_1(t)$ ,  $B_2(t)$ , and  
 264  $B_3(t)$  as the probability of revisiting at round  $t$  the cells with  
 265 the first-, second-, and third-best values of the previous round  
 266 ( $t - 1$ ). Figure 3 G–I show that individuals tend to revisit  
 267 the cells with the best values, and more so as the value of  
 268 the visited cells increases over time. In the final round of  
 269 Rule 2, individuals revisit their first-, second-, and third-best  
 270 cells of the previous round with respective probabilities 93 %,  
 271 87 %, and 66 %. In addition, these observables confirm that  
 272 individuals explore the table more in Rule 1 than in Rule 2:  
 273 at any round  $t \geq 5$ , the values of  $B_1(t)$ ,  $B_2(t)$ , and  $B_3(t)$   
 274 in Rule 1 are typically less than one-third of the value in Rule 2.

275 Altogether, these results illustrate the strong impact of a  
 276 competitive condition on the way individuals explore the table  
 277 and select the cells they visit at each round.



278 **Fig. 3. Quantification of individual behaviors for visiting cells.** For the non-  
 279 competitive Rule 1 (blue) and the competitive Rule 2 (orange), symbols correspond  
 280 to the experimental results, while solid lines are the predictions of the model. (A)  
 281 Probability to find the best cell, of value 99. (B) Probability to find one of the four  
 282 cells whose values are 86 ( $\times 2$ ), 85, or 84. (C) Probability to find one of the four  
 283 cells whose values are 72 ( $\times 2$ ) or 71 ( $\times 2$ ). The black dashed and dotted lines  
 284 correspond to the expected probabilities of two different visiting strategies: *i*) cells  
 285 chosen randomly (full random search, dashed lines), and *ii*) cells chosen randomly  
 among those that have not been already visited (sequential random search, dotted  
 lines). (D–F)  $V_1(t)$ ,  $V_2(t)$ ,  $V_3(t)$  are respectively the value of the first-best cell,  
 second-best cell, and third-best cell visited by the participants, as a function of the  
 round  $t$ . (G–I) Probability  $B_1(t)$ ,  $B_2(t)$ ,  $B_3(t)$  to revisit the first-best cell, the  
 second-best cell, and the third-best cell of the previous round, as a function of the  
 round  $t > 1$ .

278 **Rating the visited cells.** SI-Appendix, Fig. S4 shows the average  
 279 fraction of stars  $\rho(v)$  that has been used to rate cells with  
 280 value  $v$  at the end of the experiment.  $\rho(v)$  increases with  $v$ ,  
 281 showing that, on average, individuals give higher ratings to  
 282 cells having high values and also revisit them more often. The  
 283 experimental data can be fitted to the following functional  
 284 form:

$$285 \rho_{\varepsilon, \alpha}(v) = \varepsilon \frac{1}{N} + (1 - \varepsilon) \frac{v^\alpha}{\sum_w N_w w^\alpha} \quad [1]$$

286 where  $\varepsilon \in [0, 1]$  and  $\alpha$  are two parameters,  $N = 225$  is the  
 287 total number of cells in a table, and  $N_v$  is the number of cells  
 288 with value  $v$ , such that  $\sum_v N_v \rho_{\varepsilon, \alpha}(v) = 1$ . Note that the first  
 289 term  $\varepsilon/N$  quantifies the fraction of stars uniformly deposited  
 290 in the cells, while the second term involving  $\alpha$  accounts for  
 291 the fact that high-value cells should attract more stars.

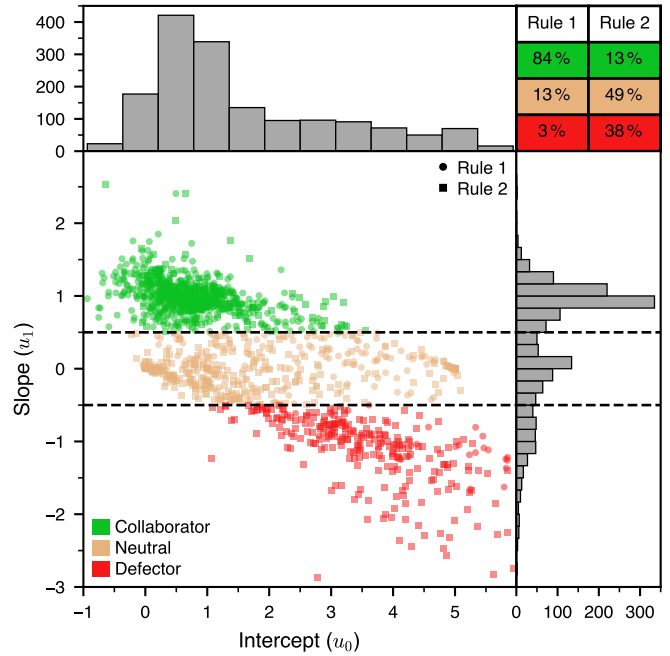
292 SI-Appendix, Fig. S5 shows the average number of stars  
 293 used to rate a cell as a function of its value  $v$ . In Rule 1, the

294 average number of stars increases almost linearly with  $v$ . On  
 295 average, individuals give 1 star to the cells with low values  
 296 and 4.3 stars to the ones with very high values. In Rule 2  
 297 the situation is quite different, individuals give 2.5 stars to  
 298 low-value cells, and then the average rating decreases to reach  
 299 a plateau at about 1.5 stars for values higher than  $v = 25$ .  
 300 Thus, a cell will receive similar ratings regardless of its value  
 301 between 35 and 99. This phenomenon suggests that in Rule 2,  
 302 many participants adopt a non-cooperative/deceptive rating  
 303 strategy, which effectively makes the information conveyed  
 304 by the digital trace less discriminating. Overall, these results  
 305 show that individuals give a much fairer rating to the cells  
 306 they visit in Rule 1, as the examination of the fidelity has  
 307 previously revealed.

308 **Behavioral profiles of individuals.** SI-Appendix, Figs. S6 and S7  
 309 show the average number of stars used to rate a cell as a  
 310 function of its value  $v$ , for each participant, in Rule 1 and  
 311 Rule 2, leading to three emerging rating patterns. Some  
 312 individuals rate cells somewhat proportionally to their value,  
 313 some rate cells independently of their value, and some others  
 314 give ratings somewhat oppositely proportional to the cell  
 315 values.

316 To quantify and classify these three behavioral profiles, we  
 317 fit the average rating of each individual with a linear function  
 318 of the cell value  $v$ ,  $u_0 + u_1 \times 5v/99$ , where  $u_0$  is the intercept  
 319 and  $u_1$  is the slope of the line.  $u_0 = 0$  and  $u_1 = 1$  would  
 320 correspond to a strict linear rating of cells of value 0 to 99,  
 321 with 0 to 5 stars. Fig. 4 shows the distribution of  $u_0$  and  
 322  $u_1$  for all individuals. We identify three classes of behavioral  
 323 profiles associated with two thresholds at  $u_{\text{def-neu}} = -0.5$  and  
 324  $u_{\text{neu-col}} = 0.5$  corresponding to the two minima found in the  
 325 distribution of  $u_1$ . Note that the two thresholds for these  
 326 three classes are close to the thresholds found using Ward's  
 327 clustering method on the slope parameter  $u_1$ :

- 328 • The ratings of individuals with  $u_1 \geq u_{\text{neu-col}}$  increase  
 329 with the cell values, i.e., they rate cells whose values are  
 330 the lowest (resp. whose values are the highest) with a  
 331 small number of stars (resp. a large number of stars;  
 332 see Fig. 5A). Hereafter, we will dub these individuals as  
 333 *collaborators*, since their rating strategy helps the other  
 334 members of their group to identify the best cells (84% in  
 335 Rule 1 and 13% in Rule 2).
- 336 • Individuals with  $u_{\text{def-neu}} \leq u_1 < u_{\text{neu-col}}$  rate cells with  
 337 almost the same number of stars (on average, 3 stars in  
 338 Rule 1, and 1.5 stars in Rule 2) regardless of their values  
 339 (see Fig. 5B). Since the ratings of these individuals do not  
 340 provide any distinctive information to the other group  
 341 members, we will dub them as *neutrals* (13% in Rule 1  
 342 and 49% in Rule 2). Note that these neutral individuals  
 343 do not form a homogeneous group. Indeed, some of  
 344 them with  $u_0$  close to 0 always give 0 or a very few stars  
 345 whatever the cell value, hence essentially not participating  
 346 in the rating and the marking of the cells. Some other  
 347 neutrals with  $u_0$  close to 5 always give a large number of  
 348 stars or even 5 stars, thus marking all the cells they visit,  
 349 while others do not have any consistent logic in the way  
 350 they rate cells. This explains the wide range of intercepts  
 351  $u_0 \in [0, 5]$  observed for neutrals in Fig. 4. Despite not  
 352 giving distinctive ratings, most neutrals effectively help  
 353 the other members of their group to identify the best

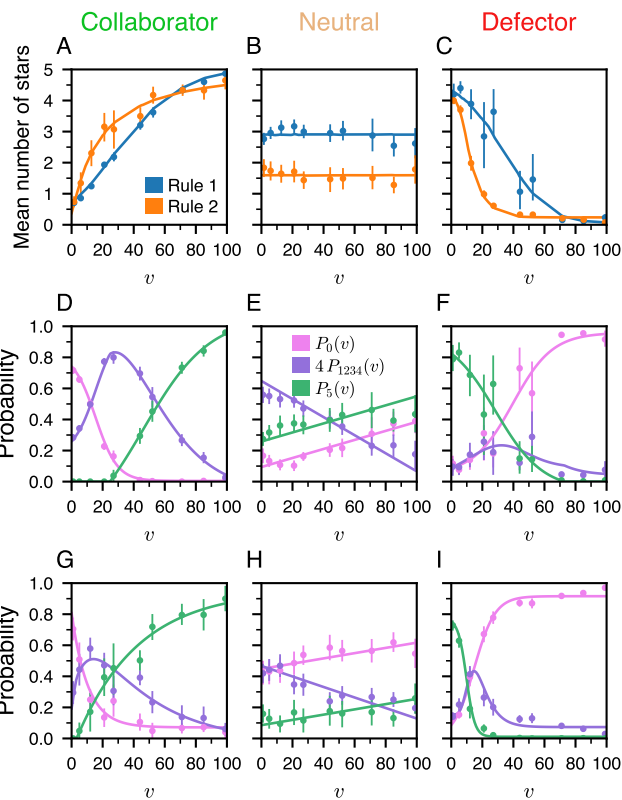


354 **Fig. 4. Behavioral profiles of individuals.** (Bottom-left) Scatter plot of the values  
 355 of the two parameters  $u_0$  and  $u_1$  of the linear function,  $u_0 + u_1 \times 5v/99$ , used  
 356 to fit each participant's ratings as a function of the value of the visited cells. In the  
 357 non-competitive Rule 1, individuals are represented by circles, and in the competitive  
 358 Rule 2, individuals are represented by squares. The color of the symbols corresponds to  
 359 the behavioral profile of the individuals: collaborator (green), neutral (brown), and  
 360 defector (red). The two horizontal lines at  $u_{\text{def-neu}} = -0.5$  and  $u_{\text{neu-col}} = 0.5$  are the  
 361 delimitations between the profiles. (Top-left) Histogram of the values of  $u_0$ . (Bottom-  
 362 right) Histogram of the values of  $u_1$ . (Top-right) The table gives the percentage of  
 363 individuals for each of the behavioral profiles. See also SI-Appendix, Fig. S8A (for  
 364 Rule 1 only) and B (for Rule 2 only).

365 cells, since they often revisit these cells, and hence make  
 366 them darker. We also address this point in the section  
 367 below about optimized agents and in section B.2 of the  
 368 SI-Appendix, Supplementary Text.

- 369 • Individuals with  $u_1 < u_{\text{def-neu}}$  rate the cells in the oppo-  
 370 site way to collaborators, resulting in deceptive ratings.  
 371 Indeed, they attribute a small number of stars (resp. a  
 372 large number of stars) to the cells whose values are the  
 373 highest (resp. whose values are the lowest; see Fig. 5C).  
 374 We will call these individuals *defectors* (3% in Rule 1 and  
 375 38% in Rule 2), since we interpret that the strong traces  
 376 left on cells with very low values are meant to mislead  
 377 other group members and prevent them from finding the  
 378 best cells, especially in Rule 2. In addition, they also  
 379 decide not to share the position of the best cells they have  
 380 discovered, by giving them low ratings, and hence not  
 381 marking them on the table.

382 Fig. 5 A, D, and G show that collaborators mostly rate  
 383 cells whose values are less than 20 with 1 star, while the cells  
 384 whose values are greater than 80 are rated with 5 stars. By  
 385 contrast, Fig. 5 B, E, and H show that for the neutral indi-  
 386 viduals, the probability of rating a cell with a given number  
 387 of stars does not depend on the cell value. Finally, Fig. 5  
 388 C, F, and I show that the defectors' distribution of ratings  
 389 presents an inverse pattern compared to that of the collab-  
 390 orators. Defectors poorly rate cells with high values, hence



**Fig. 5. Rating strategies for the three behavioral profiles.** (A–C) Mean number of stars used to rate cells as a function of the cell’s value  $v$  for (A) collaborators, (B) neutrals, and (C) defectors in the non-competitive Rule 1 (blue) and the competitive Rule 2 (orange). (D–I) Probability of rating a cell with 0 stars ( $P_0(v)$ ; magenta), 1 to 4 stars ( $P_{1234}(v)$ ; violet) and 5 stars ( $P_5(v)$ ; green) as a function of its value  $v$ , for the collaborators, neutrals, and defectors, and for the two rules. The probabilities of rating a cell of value  $v$  with 1 to 4 stars have been averaged in  $P_{1234}(v)$ . The dots are the experimental data, and the solid lines are the predictions of the model.

380 hiding them from the other members of their group. Conversely, they rate cells having low values with a high number of stars, hence misleading others. Ultimately, defectors have access to more information than the other group members. Indeed, the defectors benefit from collaborators who give high ratings to cells having high values. Simultaneously, defectors strategically withhold their knowledge regarding the best cells that they have discovered, by refraining from marking such cells. Thanks to this asymmetric information (33), adopting a defecting behavior can be beneficial in a competitive environment. Indeed, defectors have a higher probability of having the highest score in their group (see SI-Appendix, Fig. S9). However, in the absence of competition, there is no benefit in deception and one should expect fewer defectors. This is what we observe in our experiments, where Fig. 4 (inset table) shows that almost every participant adopts a cooperative behavior in Rule 1, while there is a large fraction of defectors in Rule 2.

397 Note that the subjects would participate in 2 experimental runs playing alone before participating in 10 runs with the 4 other members of their group in Rule 1 or Rule 2 (see SI-Appendix, Supplementary Text). As expected, when playing alone, the participants behave as collaborators (with themselves), also showing that the participants understood well the principle of the experiment. This was confirmed by asking them to fill an anonymous questionnaire at the end of the

session.

**Model.** We now introduce a stochastic agent-based model to quantitatively identify the strategies for visiting and rating cells, and to understand their respective effects on individual and collective performance. In the model, we simulate groups of 5 agents playing a sequence of 20 consecutive rounds (3 visited and rated cells per round), exactly following the actual experimental procedure. The model, described in detail in Materials and Methods, consists of two steps that characterize the agents’ visit and rating strategies.

The first step accounts for the visit strategy, i.e., which 3 cells an agent decides to visit in each round. This strategy allows for a variety of behaviors observed in the experiment:

- revisiting the first-, second-, and/or third-best cells already visited in the previous round, depending on their value (private memory; see Fig. 3 G–I);
- exploring a marked or unmarked cell (collective memory; see SI-Appendix, Fig. S4) according to its cumulative fraction of stars represented by the color of the cell in the actual experiment.

The visit strategy is the same for all agents, regardless of their behavioral profile (cooperator, neutral, or defector), as found experimentally, but is allowed to differ for the two conditions, Rule 1 and Rule 2.

The second step of the model addresses the rating strategy, i.e., the number of stars an agent uses to rate a visited cell as a function of its value. In the model, the rating strategy of agents depends on their behavioral profile (see Fig. 5 (D–I)), and is different for the two rules.

**Model predictions.** We consider groups of 5 agents, hereafter called MIMIC (see SI-Appendix, Movies S1B and S2B), reproducing the behaviors of human collaborators, neutrals, and defectors. Their behavioral profiles are drawn according to the corresponding fraction observed in the experiment (inset table of Fig. 4). The parameters for the rating strategies of collaborators, neutrals, and defectors have been estimated by fitting the probability to rate a cell with 0 or 5 stars (see Eqs. 5 and 6 in Materials and Methods) to the experimental data (see lines in Fig. 5 (D–I), and SI-Appendix, Table S1). As for the parameters for the visit strategy, they have been estimated by minimizing the error between the experimental and the model results for a set of observables, using a Monte Carlo method (see SI-Appendix, Table S2). For all graphs, we ran 1,000,000 simulations, so that the error bars in our simulation results are negligible on the scale of the presented graphs.

Fig. 2 shows that simulations of the model with MIMIC agents quantitatively reproduce the performance of individuals and groups and the observables used to characterize the dynamics of collective exploration and ratings in both rules, as measured in the experiment. The model also quantitatively reproduces the dynamics of the average value of the first-best, second-best, and third-best cells visited by individuals during the different rounds (Fig. 3 D–F), along with the probability to revisit each of these 3 best cells at the next turn (Fig. 3 G–I). In addition, the model reproduces fairly the fraction of collaborators, neutrals, or defectors according to their rank at the end of the experiment and the negative impact of the

number of defectors on collective performance (SI-Appendix, Fig. S9). The model also predicts with great accuracy the nontrivial results of Fig. 3 (A–C), and SI-Appendix, Fig. S3 that were commented above.

These results suggest that the behavioral mechanisms implemented in the model constitute an excellent representation of the processes by which individuals leave and use the traces to guide their choice, and how these processes are modulated in the presence of competition between individuals.

Finally, in the SI-Appendix, Supplementary Text, we also explore the model predictions for larger group sizes, larger tables, longer durations, and different types of visit and rating strategies.

#### Optimization of agents' performance according to specific objectives.

We have also exploited our model to find agents that are optimized in different situations. To do this, we have used a Monte Carlo method to obtain all the parameters of the model that characterize the corresponding visit and rating strategies.

We first consider a situation in which we wish to maximize the score  $S$  (as defined in Rule 2) of 5 identical agents (Opt-1 agents) in the same group and exploiting the same strategy (see SI-Appendix, Figs. S15 and S19A and SI-Appendix, Tables S1G and S2). The inspection of the Opt-1 agents' resulting parameters and SI-Appendix, Fig. S15 show that they essentially only rate cells that have very high values, which they revisit at almost every round so that there is almost no exploration. These Opt-1 agents are strong collaborators, and their average score ( $S/S_{\max} = 67\%$ ) is markedly higher than the score of the human subjects in Rule 2 ( $S/S_{\max} = 40\%$ ). Note that, since the 5 Opt-1 agents are identical, they also maximize the total score of the group. This suggests that a situation where groups would compete (instead of individuals; intergroup instead of intragroup competition) should lead to the emergence of a collaborative behavior within the groups, a situation that we plan to explore experimentally in a future work.

We then consider a situation in which we maximize the score of one agent competing with 4 MIMIC agents (see SI-Appendix, Figs. S16 and S19B and SI-Appendix, Tables S1H and S2). This scenario represents a more realistic situation where an individual seeks to maximize their score while competing against four other typical individuals. In this condition, the behavior of this optimized agent (Opt-2) is markedly different from that of Opt-1 agents, since the presence of MIMIC agents behaving as neutrals and defectors forces the Opt-2 agent to adapt its visit and rating strategy to cope with indiscriminate or even false social information. Interestingly, the optimization process leads to a neutral agent assigning 0 star to every visited cell, and hence not participating at all in the rating process. Note that, as already mentioned in the description of neutral agents above (and in section B.2 of the SI-Appendix, Supplementary Text), a neutral agent assigning a non-zero number of stars to visited cells would effectively help the other members of its group to identify the best cells, since it would often revisit these cells. The average score of the Opt-2 agents is  $S/S_{\max} = 43\%$ , which is only slightly better than the average score of human subjects or MIMIC agents.

However, in our experiment, to obtain the maximum monetary reward, individuals were not strictly required to maximize their score but rather had to optimize their ranking among the 10 individuals in the two groups of 5 participants. In this

condition, the optimized Opt-3 agent competing against 4 (in its group) plus 5 (in the other group) MIMIC agents behaves as a defector (see SI-Appendix, Figs. S17 and S19C and SI-Appendix, Tables S1I and S2). On average, the Opt-3 agent obtains a rank of 4.57 (compared to a mean rank of 5.5) when ranked among the 10 agents of the two groups, and a rank of 2.50 within its own group (mean rank equal to 3). It is remarkable that the model predicts that deception is an emerging behavior in the conditions of our experiment.

Finally, it is interesting to consider the visit and rating strategies maximizing the fidelity of the distribution of ratings to the distribution of cell values in the final round,  $F(\mathbf{P}(t = 20), \mathbf{V})$  (see SI-Appendix, Fig. S18 and SI-Appendix, Tables S1 and S2). If the number of rounds were infinite, the optimal strategy for these agents (Opt-4) would be to explore the table randomly and to rate cells proportionally to their value on a full scale of 0 to 5 stars (corresponding to  $u_0 = 0$  and  $u_1 = 1$  in Fig. 4). By using this strategy, the agents achieve a fidelity of 0.76 at round 20 (compared to 0.4 in Fig. 2L), and the fidelity would ultimately converge to 1 in the limit of an infinite number of rounds. Clearly, these Opt-4 agents achieve a very mediocre mean score of  $S/S_{\max} = 11\%$  compared to that of the previous optimized agents, and even compared to MIMIC agents reproducing the experimental results, and to the human participants. It is worth noting that there could exist a better strategy to maximize the fidelity at round  $t = 20$ , specifically tailored for the finite 20-round setting used in the actual experiment.

## Discussion

The ability to exploit the traces left in the environment by the action of organisms is one of the simplest and oldest mechanisms used to coordinate collective behaviors in biological systems (34–36). In humans, over the past thirty years, the massive development of the Internet, together with applications that extensively use digital traces left voluntarily or not by their users, have reinforced the need to understand how these traces influence individual and collective behaviors (25, 37–39).

In this work, we have measured and modeled the way groups of individuals leave and use digital traces in an information search task implementing a 5-star rating system similar to the ones used by many online marketplaces and platforms such as Amazon, TripAdvisor, or eBay, in which users can evaluate products, services, or sellers. Although we certainly do not claim that our experimental setup captures all the processes at play in these real-life situations, it shares with them an exploration of the available options (cells in our experiment; products for an online store) greatly influenced by their current ratings, and a rating of the selected options by the participants, allowing the ratings to evolve dynamically. However, real rating systems usually provide the users with not only the mean rating of an available option, but also the number of ratings for this option, which allows them to modulate their confidence in the different ratings.

Our experiment considered two different rules, with Rule 2 implementing a monetary incentive for participants to perform well, resulting in an explicit competition, absent in Rule 1.

Our experimental results show that groups of individuals can use colored traces resulting from their ratings to coordinate their search and collectively find the cells with the highest



584 values in a table of hidden numbers. These traces constitute  
585 a form of long-term collective memory of the past actions  
586 performed by the group (21, 40). Combined with the individual  
587 short-term memory of the value of the cells already visited,  
588 these traces determine the choice of the cells ultimately visited  
589 by the participants.

590 However, our results have also revealed profound disparities  
591 in the way individuals use social information resulting from  
592 these colored traces to guide them in their tasks, and also  
593 in the way they choose to deliver information to other group  
594 members through their ratings. We have identified three be-  
595 havioral profiles (collaborators, defectors, and neutrals) that  
596 essentially account for the way in which individuals rate cells.  
597 Collaborators cooperate by leaving a trace whose intensity  
598 positively correlates with the hidden value of the cells, while  
599 the defectors adopt an opposite behavior. Neutral individuals  
600 constitute a sizable fraction of the group members (13% in  
601 Rule 1 and 49% in Rule 2) and their ratings are essentially  
602 uncorrelated with the actual value of the cells. Yet, the marks  
603 that they leave, even if they do not directly inform about  
604 the value of the cells, nevertheless induce a cooperative be-  
605 havior, since neutrals often revisit the high-value cells in a  
606 way statistically indistinguishable from the collaborators and  
607 defectors.

608 The information contained in the traces can thus be manip-  
609 ulated by individuals depending on the context, competitive  
610 or not, in which the task is performed. Therefore, one may  
611 expect that when a situation becomes competitive, individuals  
612 should pay less attention to the socially generated traces since  
613 the reliability of the information contained in the trace de-  
614 creases. Previous works in social decision-making have indeed  
615 shown that there exists a causal link between mistrust and  
616 a decrease in information sharing, and that the fear of being  
617 exploited can be a reason for group members to withhold  
618 accurate information (41, 42). This clearly occurs in Rule 2,  
619 where 87% of individuals provide indiscriminate (neutrals)  
620 or false (defectors) information, whereas 84% of individuals  
621 (collaborators) provide reliable information in Rule 1.

622 Despite participants achieving higher scores in the competi-  
623 tive Rule 2 than in Rule 1, by exploring less and revisiting the  
624 best cells more, the fidelity of the cumulative trace resulting  
625 from their ratings is more faithful to the actual distribution of  
626 cell values in Rule 1 than in Rule 2. In other words, there is  
627 a better relation (more faithful) between the final rating of a  
628 cell and its true value in Rule 1 than in Rule 2, although this  
629 relation that we measured remains nonlinear.

630 We used these experimental observations to build and cali-  
631 brate a model that quantitatively reproduces the dynamics  
632 of collective exploration and ratings, as well as the individual  
633 and collective performances observed in both experimental  
634 conditions. In particular, this agreement between the model  
635 and the experiment is quantified by exploiting a series of subtle  
636 observables: PDF of the score, fidelity, inverse participation  
637 ratio, probability of revisiting cells depending on their values...  
638 Note that an important added value of our model is to offer  
639 (via the analysis of its parameters) a direct and quantitative  
640 interpretation of the visit and rating strategies for the three ob-  
641 served behavioral profiles of human participants, and also for  
642 different types of optimized agents. The analysis of individual  
643 behaviors combined with the simulations of the computational  
644 model shows that competition reinforces the weight of private

information (i.e., the individual's memory of the cells already  
visited) compared to social information (i.e., the collective  
memory of the group shown on the shared colored table) in  
the choice of cells that are visited.

645 The analysis of the model shows that a cooperative effect  
646 induced by the trace emerges as soon as there exists a minimal  
647 level of marking on cells, and that the fidelity of the ratings  
648 increases with cooperation. The model also shows that the  
649 trace induces weak cooperation even in groups of defectors,  
650 provided they rate cells with a large enough number of stars,  
651 simply because they revisit the cells whose values are the  
652 highest. In this case, individual memory plays a major role  
653 in the collective performance of these defectors. Furthermore,  
654 the model predicts that the cooperative effect induced by the  
655 traces and the average performance of individuals increases  
656 with group size. This property results from the stigmergic in-  
657 teractions between individuals that make it possible to amplify  
658 at the group level the information about the location of cells  
659 whose values are the highest. Similar properties are observed  
660 in many species of ants that use pheromone trail laying to  
661 coordinate collective foraging activities and to find the best  
662 food sources in their environment (43, 44). The model also  
663 allowed us to explore the dynamics of the system in different  
664 conditions (number of agents and their behavioral strategy,  
665 size of the table, number of rounds...), and to investigate the  
666 optimal agents' strategy depending on diverse specified objec-  
667 tives. Our analysis shows that the maximal score is obtained  
668 for collaborative agents (Opt-1), suggesting that inner-group  
669 collaboration should emerge from intergroup competition. In-  
670 terestingly, the model also predicts that a defector behavior  
671 emerges for an agent (Opt-3) aiming at optimizing its rank  
672 among the 10 participants of 2 groups, in the same conditions  
673 as in our experiment.

674 As our model was deliberately designed to prioritize relative  
675 simplicity, it consequently presents a notable limitation by not  
676 incorporating a possible explicit time-dependence in the pa-  
677 rameters that quantify the visit and rating strategies. Indeed,  
678 the perceived importance of a cell with a given color may vary  
679 between the beginning and the end of an experimental run. In  
680 fact, in the model, the time-dependence of a subject's actions  
681 only results from the explicit time-dependence of the cell colors  
682 and of their 3 best discovered cells. Again, we did not consider,  
683 say, time-dependent visit parameters ( $\epsilon$  and  $\alpha$  parameters),  
684 for the sake of simplicity of the model, but also due to the  
685 fact that identifying the possible time-dependence of these  
686 parameters with reasonable statistical accuracy would require  
687 a much larger dataset. Yet, despite the model's imperfection  
688 in reproducing certain observables, the worst agreement be-  
689 tween experimental and model results typically remains within  
690 2 experimental standard errors (for instance, see Fig. 2I for  
691 Rule 1). Considering the number and diversity of observables  
692 that we have considered (see figures in the main text and  
693 the SI-Appendix), this level of agreement can be regarded as  
694 very satisfactory, suggesting that the model grasps the main  
695 ingredients of the actual visit and rating dynamics.

696 Finally, we would like to strongly emphasize that our exper-  
697 imental setup coupled to our predictive model is extremely rich  
698 and versatile. Indeed, it can be straightforwardly adapted to  
699 the investigation of many other interesting aspects of stigmer-  
700 gic processes, as well as the respective impacts of intragroup  
701 and intergroup competition on the emergence of cooperation  
702  
703  
704  
705

706 in human groups. In fact, our web application also permits  
 707 the inclusion of bots (for instance, MIMIC or OPT agents)  
 708 competing with human subjects in the same group of con-  
 709 trollable size, which offers the possibility to investigate the  
 710 behavior of a subject depending on the composition of their  
 711 group. Moreover, we have also designed an identical version  
 712 of our interactive web application which can be deployed on  
 713 the Internet, and which could be used to conduct large-scale  
 714 experiments. We plan to explore these different avenues in  
 715 future works.

716 Ultimately, understanding and modeling the processes that  
 717 govern the influence of social information embedded in digital  
 718 traces on individual and collective behavior is a crucial step to  
 719 developing personalized decision-making algorithms as well as  
 720 artificial collective intelligence systems based on stigmergy (26,  
 721 45, 46).

## 722 Materials and Methods

723 **Ethics statement.** The aims and procedures of the experiments were  
 724 approved by the Ethics Committee of the Toulouse School of Eco-  
 725 nomics (TSE). All participants provided written consent for their  
 726 participation.

727 **Experimental procedure.** We conducted two series of experiments,  
 728 the first one in December 2021 to study the competitive condi-  
 729 tion (Rule 2) and the second one in December 2022 to study the  
 730 non-competitive condition (Rule 1). A total of 175 participants  
 731 were recruited, of which 75 (40 females, 35 males) participated in  
 732 experiments with Rule 1 and 100 (47 females, 53 males) participated  
 733 in experiments with Rule 2. Each participant could participate in a  
 734 maximum of two different sessions. The participants were mostly  
 735 students at the University of Toulouse, with an average age of 22.

736 All experiments were carried out at the TSE Experimental Lab-  
 737 oratory. After entering the experimental room and before starting  
 738 the experiment, the participants signed the consent form, were ex-  
 739 plained the rules, the payment conditions, the anonymity warranty,  
 740 and were asked to shut down their mobile phones. The participants  
 741 would then be seated in randomly assigned cubicles (anonymously  
 742 linked to an ID in our database) that prevented interactions between  
 743 them (see Fig. 1B).

744 Experiments were conducted using a custom-made interactive  
 745 web application developed in part in collaboration with the company  
 746 Andil ([www.andil.fr](http://www.andil.fr)). Participants were presented with the same  
 747  $15 \times 15$  table of 225 cells on their respective computer screen,  
 748 with each cell associated with a hidden value in the range 0 – 99.  
 749 Examples of such tables were provided during the instruction phase.  
 750 The tables used in the experiments were generated by randomly  
 751 shuffling the same set of values (see SI-Appendix, Fig. S1B). Thus,  
 752 all tables contained the same set of values, only randomly arranged  
 753 in the table (see SI-Appendix, Fig. S1A).

754 We conducted a total of 10 sessions with Rule 1 and 15 sessions  
 755 with Rule 2. At the beginning of each session, each participant  
 756 performed two consecutive experiments alone (see SI-Appendix,  
 757 Supplementary Text for the analysis of these experiments). The  
 758 main goal was to ensure that each participant understood the use  
 759 of the web interface and to measure their spontaneous behavior  
 760 when the only information available was the digital trace resulting  
 761 from its own activity. Then, the participants were randomly divided  
 762 into two groups of five and performed 10 successive experiments.  
 763 During each experiment, the two groups explored different tables  
 764 that changed during the different experiments.

765 Each experiment consisted of 20 consecutive rounds, in which  
 766 each participant had to visit and rate 3 different cells within a  
 767 recommended time of 20 seconds per round, beyond which a warning  
 768 would flash on the screen of late participants. A round would end  
 769 when all participants in the group had visited and rated 3 cells, and  
 770 the color of the cells in the table would be updated according to a  
 771 palette of shades of red that translate the fraction of stars allocated  
 772 to each cell since the start of the experiment (see SI-Appendix,  
 773 Fig. S1C). Participants would then move on to the next round.

774 In the non-competitive condition (Rule 1), each participant had  
 775 to find the cells with the highest values in the table, but their actions  
 776 (visiting and rating cells) were not translated into a score. In the  
 777 competitive condition (Rule 2), the score of each participant would  
 778 increase at each round by the value of the 3 cells they had visited,  
 779 but it remained independent of the ratings given to these visited  
 780 cells. Hence, in Rule 2, the participants' main task was to discover  
 781 the cells with the highest values, while maximizing their score, and  
 782 ultimately, their payment at the end of the session. Note that we  
 783 ultimately introduced a notion of score in Rule 1, to compare the  
 784 results in the two rules (see Fig. 2 A and B), although, again, the  
 785 participants in Rule 1 experiments were never told about any notion  
 786 of score.

787 Accordingly, all participants were paid the same 10 € at the end  
 788 of a Rule 1 session. In Rule 2, the 10 participants, from the 2 groups  
 789 of 5, were ultimately ranked and paid according to their cumulated  
 790 score at the end of the session. The participant ranked first was  
 791 paid 25 €, the second was paid 20 €, the third was paid 15 €, and  
 792 the participants ranked from the 4th to the 10th place were paid  
 793 10 € each.

794 **Observables used to quantify the collective behavior.** We define  $p_c(t)$   
 795 as the fraction of stars received by a cell  $c$  at round  $t$ . The set of  
 796  $p_c(t)$  for all cells  $c$  forms a vector  $\mathbf{p}(t)$  of size 225 (vectors are shown  
 797 in boldface). Another vector of interest is the vector  $\mathbf{P}(t)$  of the  
 798 cumulated fraction of stars  $P_c(t)$  that have been attributed to each  
 799 cell from the beginning up to round  $t$  included. Similarly,  $\mathbf{q}(t)$  and  
 800  $\mathbf{Q}(t)$  are vectors whose coordinates  $q_c(t)$  and  $Q_c(t)$  represent the  
 801 fraction of visits received by each cell at round  $t$  and up to round  $t$ ,  
 802 respectively.

803 From the definition of  $p_c(t)$  and  $P_c(t)$ , we can define the aver-  
 804 age value of cells visited by the participants weighted by their  
 805 ratings (fraction of stars) at round  $t$ ,  $p(t) = \sum_c p_c(t) V_c / v_{\max_1}$ ,  
 806 where  $v_{\max_1} = 99$  is the highest value of a cell. In general, we  
 807 have  $p(t) \leq 1$ , and  $p(t) = 1$  would correspond to all members  
 808 of a group only giving a non-zero number of stars to the cell of  
 809 value 99 at round  $t$ . Similarly, we define the cumulated quantity,  
 810  $P(t) = \sum_c P_c(t) V_c / v_{\max_1}$ , the average value of cells visited by  
 811 the participants weighted by their ratings (fraction of stars) up  
 812 to round  $t$ . Hence,  $p(t)$  and  $P(t)$  quantify the instantaneous and  
 813 cumulated distribution of stars in relation to the value of the visited  
 814 cells. In particular, a high value of  $P(t)$  (in particular at the final  
 815 round  $t = 20$ ) indicates that the participants have concentrated the  
 816 allocation of stars on high-value cells. Conversely, a low value of  
 817  $P(t)$  suggests a degree of deception, with participants allocating  
 818 a high fraction of stars to low-value cells, as observed for Rule 2  
 819 where many participants are defectors.

820 In both rules, participants were explicitly asked to discover cells  
 821 having high values. However, in Rule 2, their score would increase  
 822 by the value of the cells they visit, thus providing an incentive  
 823 that affects the way they visit and/or revisit cells during successive  
 824 rounds. To quantify this (re)visiting behavior, we consider the  
 825 normalized average value of the cells visited at round  $t$ ,  $q(t) =$   
 826  $\sum_c q_c(t) V_c \times 3 / (v_{\max_1} + v_{\max_2} + v_{\max_3})$ , where  $\mathbf{V}$  is the vector  
 827 of the cell values  $V_c$ , and  $v_{\max_1}$ ,  $v_{\max_2}$ ,  $v_{\max_3}$  are respectively the  
 828 first-best, second-best, and third-best values of the cells in the table.  
 829 This observable is normalized so that  $q(t) = 1$  corresponds to the  
 830 best theoretical performance, i.e., when every individual would visit  
 831 the three best cells of the table at round  $t$ . Similarly, we introduce  
 832  $Q(t)$  that cumulates all visits up to round  $t$  and which is defined by  
 833 the same expression replacing  $q_c(t)$  by  $Q_c(t)$ . Note that, in Rule 2,  
 834 since the score of the participants is increased by the value of their  
 835 visited cells,  $q(t)$  and  $Q(t)$  directly quantify the instantaneous and  
 836 cumulated performance of the group. In Rule 1, the participants  
 837 had no notion of score, but  $q(t)$  and  $Q(t)$  allow us to characterize  
 838 the dynamics of their visits, and to compare it with that for Rule 2.

839 To quantify the exploration behavior of the table by the partic-  
 840 ipants, we introduce the inverse participation ratio (IPR) of the  
 841 probability vectors  $\mathbf{q}(t)$ ,  $\mathbf{Q}(t)$ ,  $\mathbf{p}(t)$ , and  $\mathbf{P}(t)$ . For a given  
 842 probability distribution  $\mathbf{X} = \{X_c\}$ , the IPR of  $\mathbf{X}$  is defined as  
 843  $\text{IPR}(\mathbf{X}) = 1 / \sum_c X_c^2$ . For the 4 vectors considered here, the IPR  
 844 measures the effective number of cells on which the visits or the  
 845 ratings are concentrated, at round  $t$  or up to round  $t$ . Indeed, if a  
 846 probability vector  $\mathbf{X}$  is equally distributed over  $n$  cells among  $N$ ,

we have  $X_c = 1/n$  on these cells, and  $\text{IPR}(\mathbf{X}) = 1/[n \times (1/n)^2] = n$ , showing that the IPR measures the effective number of cells over which a probability distribution is spread.

We are also interested in the relationship between the hidden values of the cells in the table and the fraction of visits or ratings that these cells have received up to round  $t$ . This relation is quantified by the fidelity  $F$ , which is defined as  $F(\mathbf{X}, \mathbf{V}) = \sum_c \sqrt{X_c V_c} / \sum_{c'} \sqrt{V_{c'}}$ , where  $\mathbf{X}$  is  $\mathbf{Q}(t)$  or  $\mathbf{P}(t)$ . The fidelity  $F$  takes values in the interval  $[0, 1]$  and is equal to 1 if and only if the probability vector  $\mathbf{X}$  is proportional to the vector of cell values  $\mathbf{V}$ , which then corresponds to a perfect fidelity. Indeed, the fidelity can be seen as the scalar product between the vector of coordinates  $\sqrt{X_c}$  (of unit Euclidean norm, since  $\sum_{c'} \sqrt{X_{c'}}^2 = \sum_{c'} X_{c'} = 1$ ) and the normalized vector proportional to  $\sqrt{V_{c'}}$ . Hence, the fidelity measures how well-aligned these two vectors are and is in fact related to the Hellinger distance between the two distributions. In the context of a real-life 5-star rating system, a high fidelity of the cumulated ratings  $\mathbf{P}(t)$  would indicate that the ratings provide a fair representation of the actual value of the different options. Of course, in this context, these intrinsic values of the available options are generally unknown. But our experimental setup provides a simpler context where this relation between the ratings (or the visits) of the different options (the cells, in our experiment) and their intrinsic value (the cell values) can be investigated.

**Model.** The agent-based stochastic model includes two components: (i) the agents' strategy for visiting cells; (ii) their strategy for rating the visited cells.

**Visit strategy.** In the first round ( $t = 1$ ), the agents have no information, therefore the selection of the 3 cells is fully random. For the other rounds ( $t > 1$ ), the agents adopt the following strategy. For each cell  $i = 1, 2, 3$  to visit, they either choose the  $i$ -th best cell visited in the previous round, of value  $V_i(t-1)$ , with probability  $P_i^R(V_i(t-1))$ , or explore other cells with probability  $1 - P_i^R(V_i(t-1))$ , with:

$$P_i^R(V_i(t-1)) = \begin{cases} 0 & \text{if } V_i(t-1) < a_i \\ \frac{V_i(t-1) - a_i}{99} b_i & \text{if } a_i \leq V_i(t-1) < a_i + \frac{99}{b_i} \\ 1 & \text{otherwise} \end{cases} \quad [2]$$

where  $a_i$  and  $b_i > 0$  are parameters. An agent never replays a cell of value  $V_i(t-1) < a_i$  and always replays a cell of value  $V_i(t-1) > a_i + 99/b_i$  (when this threshold is less than 99, the maximum value of a cell). Between these two thresholds, the probability to revisit the  $i$ -th best cell linearly interpolates between 0 and 1. The functional form in Eq. 2 is rich enough to be able to capture diverse behaviors, while only using 2 free parameters for each of the 3-best cells, and is in fact consistent with indirect measurements of these probabilities.

When an agent does not visit one of the 3 cells visited in the previous round, it explores other cells in the table. This is done by associating to each cell  $c$  a probability  $P^E(c, t)$  to be selected at round  $t$ :

$$P^E(c, t) = \varepsilon \frac{1}{N} + (1 - \varepsilon) \frac{P_c^\alpha(t-1)}{\sum_{c'} P_{c'}^\alpha(t-1)} \quad [3]$$

where  $P_c(t-1)$  is the fraction of stars deposited in cell  $c$  up to time  $t-1$ , and  $\varepsilon \in [0, 1]$  and  $\alpha > 0$  are parameters. If the selected cell is one of the 3 cells visited in the previous round, another one is selected according to Eq. 3. In Eq. 3, the parameter  $\varepsilon$  controls the amount of exploration of unmarked cells compared to the marked ones: the higher the value of  $\varepsilon$ , the more random the selection, i.e., independent of the cell color. The exponent  $\alpha$  controls the selection of a cell among the marked ones. A high value for  $\alpha$  would result in a preferential selection of the highly marked cells, while a small value for  $\alpha$  would lead to a more homogeneous selection of a cell among the marked ones. The simple functional form in Eq. 3 is inspired by the experimental results of SI-Appendix, Fig. S4, which are well-fitted by the similar functional form in Eq. 1.

The values of the 8 parameters appearing in Eqs. 2 and 3 and characterizing the visit strategy of MIMIC agents in Rule 1 and Rule 2 are reported in SI-Appendix, Table S2.

**Rating strategy.** Looking at the probability of rating a cell with  $s$  stars for each profile (SI-Appendix, Fig. S10), one notes that, except for the collaborators in Rule 1, individuals mostly rate a cell with 0 or 5 stars, and that the other ratings with 1, 2, 3, or 4 stars are less common and have a comparable probability. Therefore, in the model, the probabilities of rating a cell with 1 to 4 stars are set equal and are obtained by imposing the probabilistic normalization condition  $\sum_{s=0}^5 P_s(v) = 1$ , for each value of  $v$ . In other words, for  $s = 1, 2, 3, 4$ , we obtain

$$P_s(v) = P_{1234}(v) = \frac{1}{4}(1 - P_0(v) - P_5(v)). \quad [4]$$

For  $s = 0$  and  $s = 5$ , the probability  $P_s(v)$  to rate a cell of value  $v$  with  $s$  stars is given by

$$P_s(v) = \begin{cases} c_s + d_s \tanh\left(\frac{v - e_s}{99} f_s\right) & \text{for collaborators/defectors} \\ c'_s + d'_s \frac{v}{99}, & \text{for neutrals} \end{cases} \quad [5]$$

where  $c_s, d_s, e_s, f_s, c'_s$ , and  $d'_s$  are parameters which must satisfy the property that, for all values of  $v$ ,  $P_0(v) + P_5(v) \leq 1$ .

However, the  $P_{1234}(v)$  approximation is not valid for the collaborators in Rule 1, who use the whole rating scale to rate cells proportionally to their values. Therefore, for these collaborators, we write for  $s = 1, 2, 3, 4, 5$ ,

$$P_s(v) = d''_s \exp\left(-\left(\frac{v - e''_s}{99} f''_s\right)^2\right), \quad [6]$$

where  $d''_s, e''_s$ , and  $f''_s$  are parameters which must satisfy the property that, for all values of  $v$ ,  $\sum_{s=1}^5 P_s(v) \leq 1$ . Finally, we set  $P_0(v) = 1 - \sum_{s=1}^5 P_s(v)$ .

The functional form of Eqs. 5 and 6 are well adapted to fit the corresponding probabilities observed in the experiment (see Fig. 5 (D-I) and SI-Appendix, Fig. S10A), while allowing to capture very diverse behaviors. SI-Appendix, Table S1 presents the values of the parameters appearing in the fitting functional forms of Eqs. 5 and 6.

**Determination of model parameters.** For the MIMIC agents, the 8 parameters of the visit strategy have been determined by minimizing the error between a set of  $n$  round-dependent observables,  $O_1(t), \dots, O_n(t)$ , measured in the experiment (by averaging them over every experiment for each of the two considered rules) and the corresponding set of observables,  $\hat{O}_1(t), \dots, \hat{O}_n(t)$ , obtained from extensive simulations of the model (averaging over 1,000,000 numerical experiments for each rule). The error is hence defined by

$$\Delta = \sum_{i=1}^n \frac{\sum_{t=1}^{20} (\hat{O}_i(t) - O_i(t))^2}{\sum_{t=1}^{20} O_i^2(t)} \quad [7]$$

The set of round-dependent observables considered for the computation of this error  $\Delta$  consists in the following quantities:  $q(t), Q(t), p(t), P(t), \text{IPR}(\mathbf{q}(t)), \text{IPR}(\mathbf{Q}(t)), \text{IPR}(\mathbf{p}(t)), \text{IPR}(\mathbf{P}(t)), F(\mathbf{Q}(t), \mathbf{V}), F(\mathbf{P}(t), \mathbf{V}), V_1(t), V_2(t), V_3(t), B_1(t), B_2(t),$  and  $B_3(t)$ . We checked that other sets – in particular, smaller sets – of observables would lead to very comparable results (in particular, in Figs. 2 and 3), fitting some observables slightly better and some others slightly worse, and leading to similar results for the functions characterizing the visit strategy in Eqs. 2 and 3.

To minimize the error in Eq. 7, we have used a Monte Carlo method at zero temperature. At each Monte Carlo step, a small random change is introduced in one of the randomly selected parameters. If the error  $\Delta$  decreases, the new value of the parameter is accepted; otherwise, the old value of the parameter is conserved. The minimization procedure ends when the error stops decreasing. To account for possible multiple local minima of the error, we started the Monte Carlo simulations from several initial values of the parameters. We kept the final parameters, leading to the smallest error. Note that the final parameters obtained in different low-error Monte Carlo runs were found to result in similar functions characterizing the visit strategy in Eqs. 2 and 3.

Finally, to obtain the parameters of the visit and rating strategies of the optimized agents (Opt-1, Opt-2, Opt-3, Opt-4), we have

973 exploited a similar zero-temperature Monte Carlo method as de-  
974 scribed above. However, instead of minimizing an error, we have  
975 maximized the score (Opt-1 and Opt-2) or the ranking (Opt-3) of  
976 the agent, or the fidelity  $F(\mathbf{P}(t = 20), \mathbf{V})$  in the final round (Opt-4).

977 **Computation of the error bars.** Error bars for the experimentally  
978 measured observables correspond to a level of confidence of 68 % and  
979 were determined by exploiting the bootstrap method. Bootstrap is a  
980 particular type of Monte Carlo method that evaluates the properties  
981 of statistical parameters from an unknown probability distribution  
982 by repeated random drawings with replacement from a sample (47).  
983 The bootstrap method starts by creating  $M$  artificial sets of  $N$   
984 experiments by drawing with replacement  $N$  experiments among  
985 the  $N$  original ones. This means that some actual experiments can  
986 be drawn more than once in an artificial set, while other experiments  
987 may not occur in this set. One can then compute a given observable  
988 on every artificial set and obtain its distribution, ultimately leading  
989 to confidence intervals. In our case, the independent experiments  
990 are the 10 trials played by a group of 5 individuals. Therefore, we  
991 have  $N = 20$  experiments for Rule 1, and  $N = 15$  experiments for  
992 Rule 2, and we used  $M = 10,000$  artificial sets to generate bootstrap  
993 distributions.

994 For the numerical simulations of the model, the results corre-  
995 spond to an average over 1,000,000 runs, so that the error bars are  
996 negligible on the scale of the presented graphs.

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## **Supplementary Information for**

### **Cooperation and deception through stigmergic interactions in human groups**

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#### **This PDF file includes:**

Supplementary text  
Figs. S1 to S20  
Tables S1 to S3  
Legends for Movies S1 to S5  
Legend for Dataset S1

#### **Other supplementary materials for this manuscript include the following:**

Movies S1 to S5  
Dataset S1

## Supporting Information Text

**A. Behavioral Profiles of Individuals Playing Alone versus in a Group.** Before carrying out the experiments in groups, we studied the behavior of the participants playing alone, each individual exploring a different table during two successive rounds and seeing only their own traces (see SI-Appendix, Fig. S11). SI-Appendix, Fig. S12A shows that individuals rate the cells similarly to collaborators in groups, except that they rate a low-value cell with 1 star, presumably to remember the cells that they had already opened. Supplementary Fig. 11 B and C show that in Rule 1, the majority of individuals adopt a collaborative behavior when alone and keep this behavior when they are in a group. On the other hand, in Rule 2, many individuals who adopted a collaborative behavior when playing alone switch to a neutral or defector behavior type when they are in a group.

### B. Additional Model Predictions.

**B.1. Impact of the number of rounds and group size on individual performance and collective dynamics.** SI-Appendix, Fig. S13 shows that after 100 rounds instead of 20 rounds, the normalized score of individuals and groups has increased by 60% in Rule 2. Beyond round 50, the values of the observables used to quantify the dynamics of collective exploration and ratings begin to saturate. From one round to another, the MIMIC agents revisit almost exclusively the same cells whose values are very high. At the end of the 100 rounds, in Rule 2 the value of their best cell is  $V_1(t = 100) \simeq 84$ , and the agents revisit their best cell with a probability  $B_1(t = 100) \simeq 1$ .

SI-Appendix, Fig. S14 shows the impact of group size on the scores of individuals and groups and the dynamics of collective exploration and ratings. We compare the simulation results obtained with groups of 5 MIMIC agents exploring a table of 225 ( $15 \times 15$ ) cells and groups of 20 MIMIC agents exploring a table four times larger, 900 cells ( $30 \times 30$ ). These larger tables were obtained from the combination of four identical tables of 225 cells so that the proportion of each cell value does not change. For instance, in a table of 900 cells, there are four cells with a value of 99, but their proportion ( $1/225$ ) is the same as in the smaller tables. The dynamics of the inverse participation ratio (IPR) of  $\mathbf{p}(t)$ ,  $\mathbf{P}(t)$ ,  $\mathbf{Q}(t)$ , and  $\mathbf{Q}(t)$  reveal that large groups do not visit four times more cells than small groups, but instead, they concentrate their visits on a few cells with high values. Individuals also have a higher probability of finding the cells with the best values. However, despite these differences, the score remains unchanged. Finally, in Rule 1, the probability that individuals find the best cells at the end of an experiment is much larger in groups of 20 MIMIC agents. Altogether, these results suggest that cooperation induced by stigmergic interactions and the way individuals use the traces resulting from past actions increase with group size.

**B.2. Impact of the rating strategy on agents' performance and the fidelity of ratings.** To better understand the impact of the rating strategy on individual performance, we studied the collective behaviors of groups of 5 agents having a *linear* rating strategy. These agents rate a cell in proportion to its value,  $v$ , with  $u_0 + u_1 \times 5v/99$  stars, where  $u_0$  and  $u_1$  are respectively the intercept and the slope of the line (see Fig. 4 of the main text). When  $u_1 > 0$ , the number of stars used to rate a cell increases with its value  $v$  (like for a cooperator), while when  $u_1 < 0$ , the number of stars used to rate a cell decreases with its value  $v$  (like for a defector). As  $u_0$  increases, agents use a larger number of stars to rate a cell of a given value. Moreover, the combinations of parameters  $u_0 \leq 0$  and  $u_1 \leq 0$  correspond to a situation in which the agents rate all cells with 0 star, as some actual neutrals do in the experiment. Finally, the visit strategies of these agents are the same as those used by the MIMIC agents in each of the two conditions, Rule 1 and Rule 2.

SI-Appendix, Fig. S20 presents the result of the respective impact of  $u_0$  and  $u_1$  on (i) the average performance of individuals, (ii) the average value of cells visited by the participants weighted by their ratings, and (iii) the fidelity of ratings with respect to cell values, for each condition Rule 1 and Rule 2.

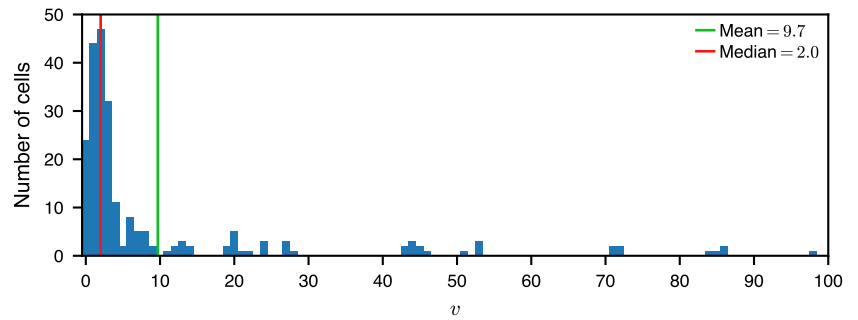
We first observe that when  $u_0 = 0$ , as soon as the agents start rating the cells with a non-zero number of stars, the resulting trace allows them to cooperate and significantly increase their performance, even for very low positive values of  $u_1$ . The results of the simulations also show that the agents get the best scores for negative values of  $u_0$ , which correspond to situations in which there exists a minimum threshold in the value of a cell that triggers the agents to rate that cell (e.g., when  $u_0 = -0.5$  and  $u_1 = 0.5$  the threshold is at  $v = 20$ ). Moreover, the higher the value of  $u_0$ , the worse the performance of the agents. This results from the fact that in that condition, the agents use a very high number of stars with little discrimination in the ratings for different values of  $v$ . The resulting trace left on cells then provides much less information to the agents, leading to a lower level of cooperation and lower performance. Note however that for high values of  $u_0$  (i.e., when  $u_0 > 3$ ) and for weakly negative values of  $u_1$  (i.e., when  $-1 < u_1 < 0$ ), there still exists weak cooperation between the agents. At first glance, this is rather counterintuitive, since for these parameters, agents are classified as neutrals or mild defectors. However, this phenomenon can be explained by the fact that, while the traces left by the agents in the initial rounds may not allow for the identification of cells with higher values, over time, cells with higher values will be revisited more often, resulting in a greater accumulation of marks compared to cells with lower values. Nevertheless, for values of  $u_1$  that are even more negative, indicating strong defection, the tendency of agents to revisit high-value cells is insufficient to counterbalance the negative impact of assigning high ratings to cells with low values, which ultimately leads to decreased performance.

Finally, the presence of competition between agents (Rule 2) amplifies both the positive and negative effects of the trace compared to the non-competitive situation (Rule 1). Indeed, groups of agents with cooperative behavior ( $u_1 > 0$ ) increase their performance in Rule 2 with respect to the reference situation ( $u_0 = u_1 = 0$ ); conversely, groups of agents with defective behavior ( $u_1 < 0$ ) strongly decrease their performance with respect to the reference situation.

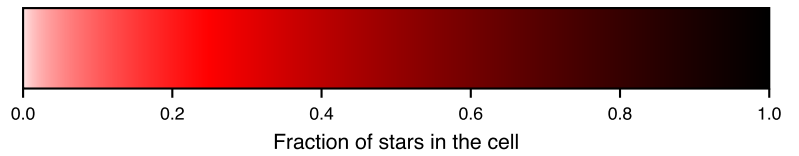
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44	99	0	28	3	0	4	2	1	9	1	0	8	11	1
2	4	44	2	1	1	3	4	2	7	4	2	3	44	3
8	2	3	4	2	2	1	1	2	0	1	3	2	45	0
3	6	2	1	6	2	0	71	3	8	2	3	4	20	20
0	1	46	85	0	2	43	3	1	1	1	1	6	5	2
2	2	13	1	0	0	24	86	0	3	2	2	1	3	20
1	1	20	4	1	2	13	21	22	0	2	2	0	1	6
3	4	13	1	3	2	1	1	24	6	53	3	3	2	19
5	3	84	3	2	0	0	3	2	27	3	1	3	14	2
86	3	2	6	1	45	20	7	24	2	4	27	3	2	3
1	1	7	0	43	7	1	0	4	2	1	1	53	3	0
72	2	2	2	6	8	19	3	1	1	72	1	1	1	14
3	2	4	2	7	0	0	12	0	71	1	3	53	1	9
2	2	1	8	2	1	0	12	1	2	3	2	1	1	1
3	1	2	27	51	2	2	3	2	0	2	0	2	3	6

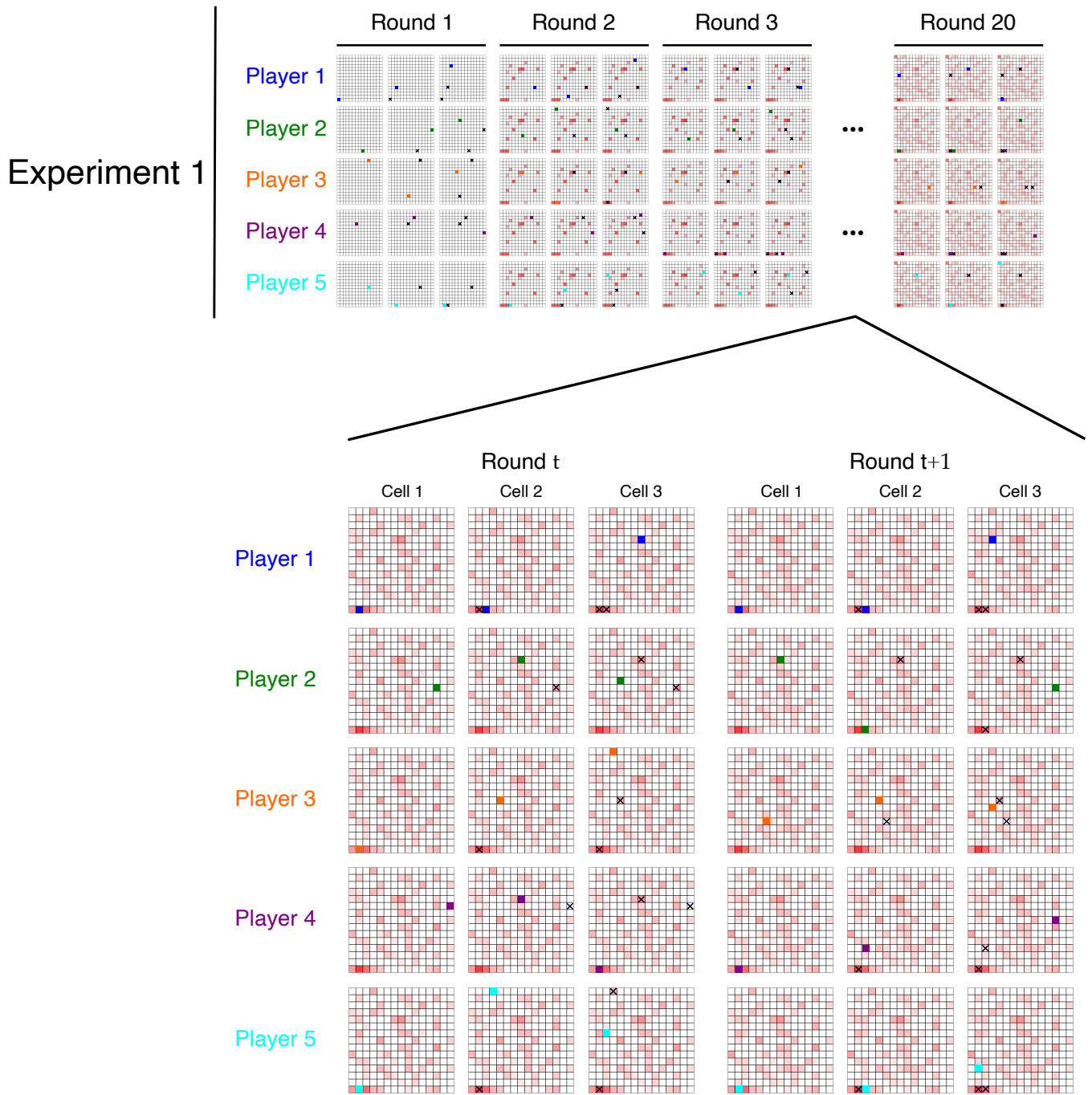
B



C

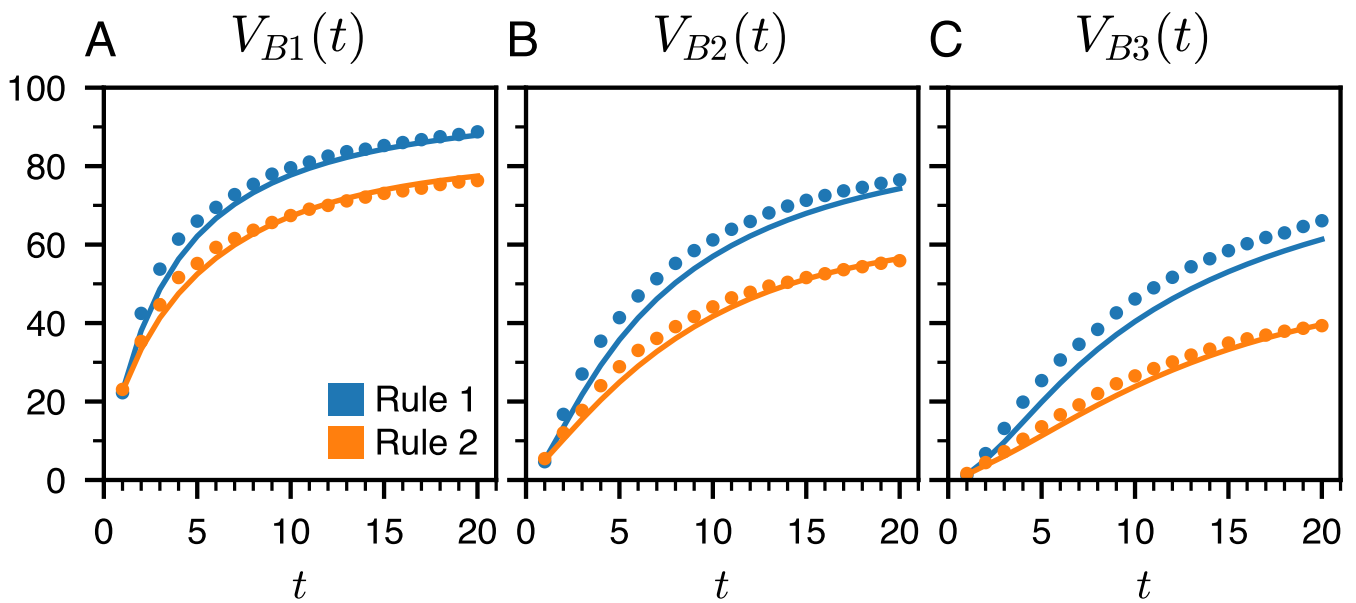


**Fig. S1.** (A) Example of a  $15 \times 15$  table used in the experiments and in the simulations of the model (see also SI-Appendix, Movies 1 and S2). (B) Distribution of the 225 values  $v$  used in the tables. (C) Color scale of the visited cells as a function of the fraction of stars used to rate cells since the beginning of an experiment. White color corresponds to cells that have never been visited or to visited cells that have always been rated with 0 stars.

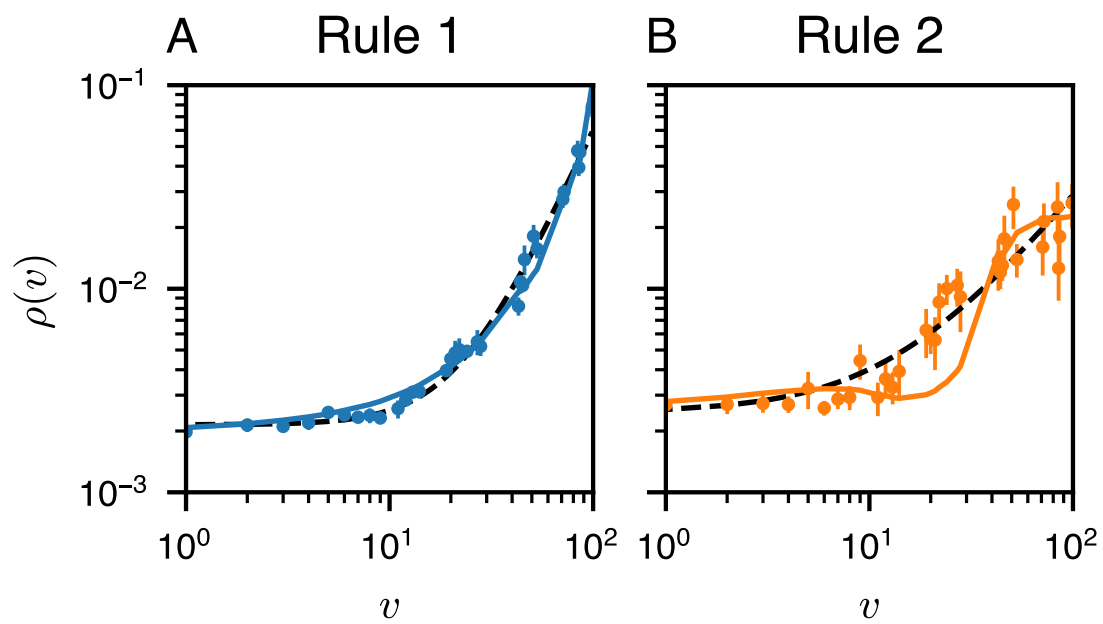


**Fig. S2.** Summary of the experimental protocol. During each round, each participant has to visit and rate successively 3 distinct cells. At the end of each round, the color of each cell in the table is updated according to the percentage of stars that has been used to rate the cell by the five individuals since the first round. The resulting color map on the table acts as a cumulative long-term collective memory for the group.

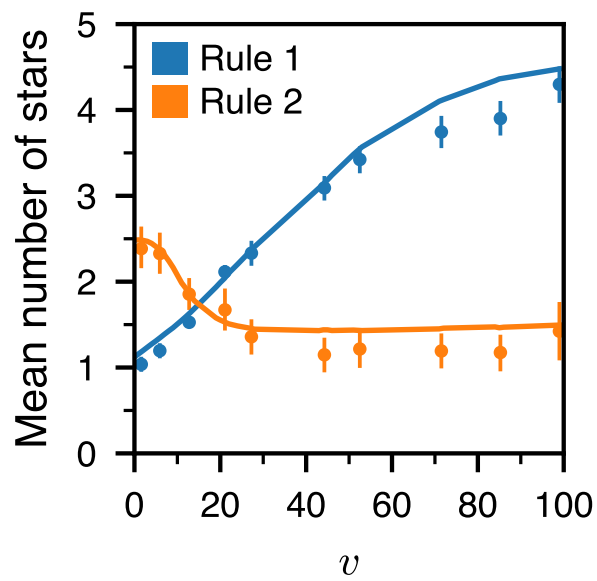




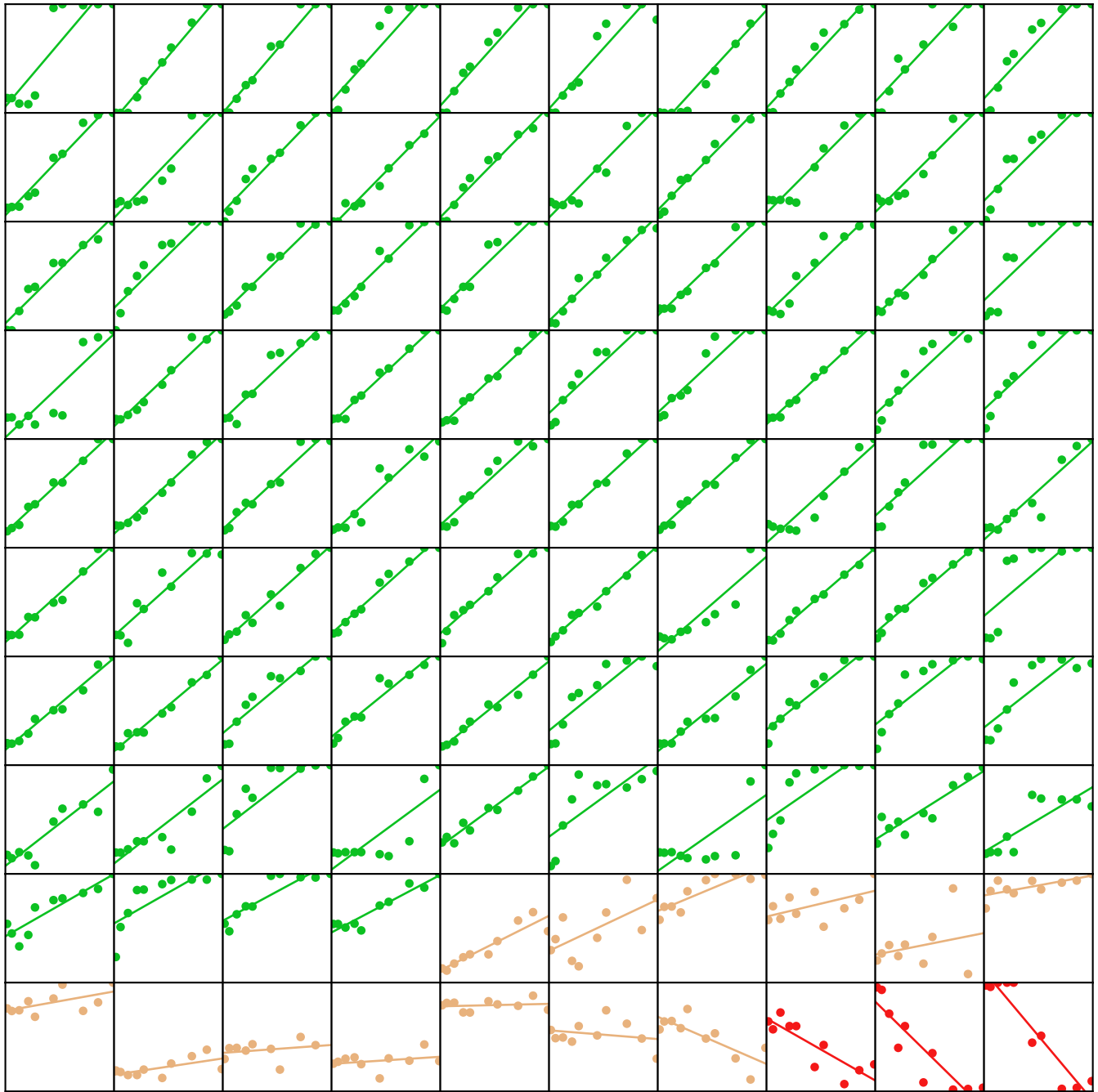
**Fig. S3.** (A) First, (B) second, and (C) third-highest values discovered up to round  $t$ , as a function of the round  $t$ , in the non-competitive Rule 1 (blue) and the competitive Rule 2 (orange). The dots are the experimental data, and the solid lines are the predictions of the model. The highest values discovered are slightly higher in Rule 1 than in Rule 2, showing that the tendency of individuals to revisit cells (and thus to explore less) is higher in Rule 2 than in Rule 1.



**Fig. S4.** Average fraction of stars  $\rho(v)$  used to rate cells of value  $v$  at the final round  $t = 20$  in Rule 1 (A) and Rule 2 (B). The dots are the experimental data, and the solid lines are the predictions of the model. The black dashed lines correspond to Eq. 1 used to fit the data, with  $\varepsilon = 0.48$  and  $\alpha = 2.18$  in Rule 1, and  $\varepsilon = 0.55$  and  $\alpha = 1.22$  in Rule 2.

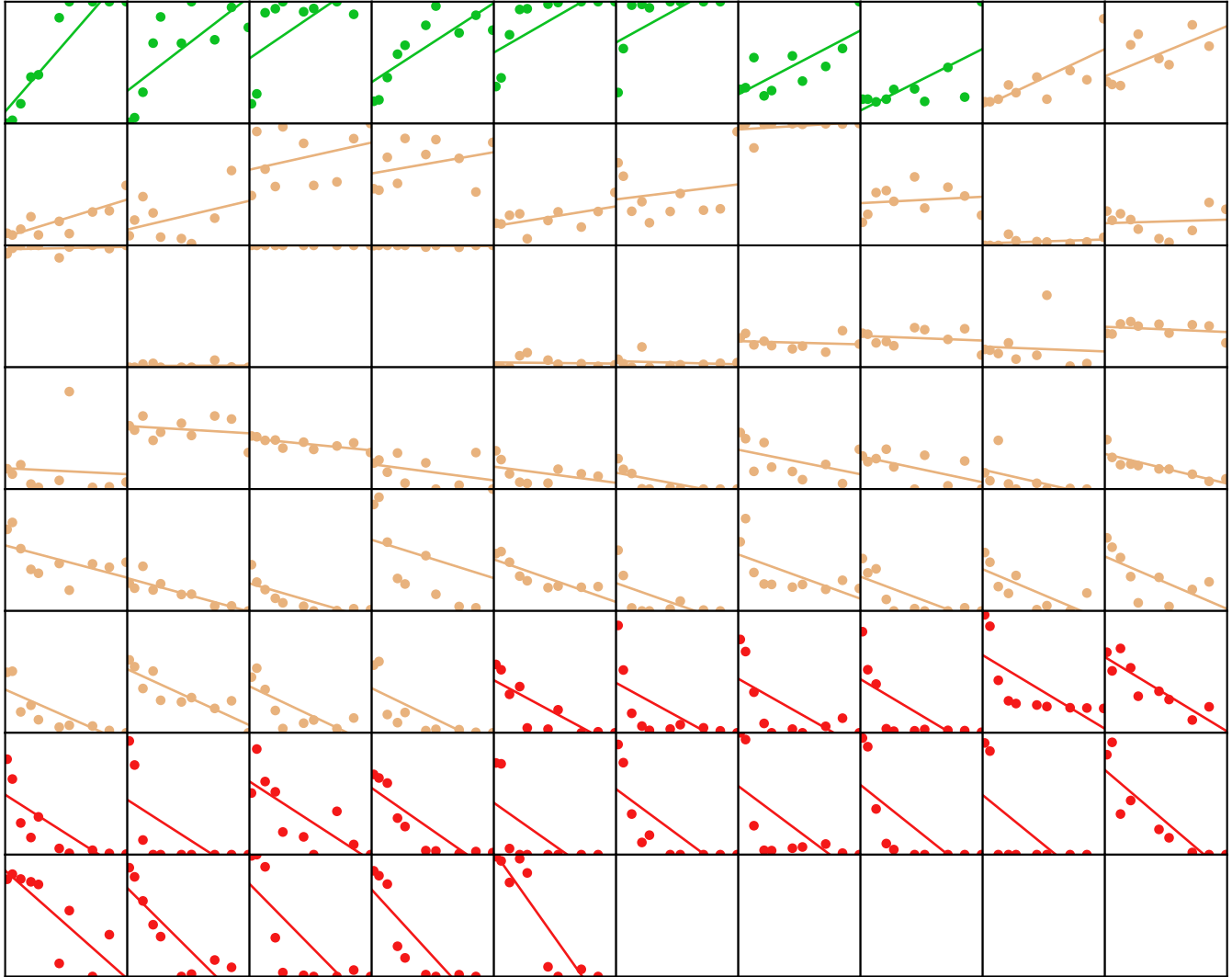


**Fig. S5.** Average number of stars used to rate cells as a function of the cell's value  $v$  in the non-competitive Rule 1 (blue) and the competitive Rule 2 (orange). The dots are the experimental data, and the solid lines are the predictions of the model. In Rule 1, the mean number of stars consistently increases with the value of the cell, showing that collaborators are prevailing in this case. On the other hand, in Rule 2, the early decay and ultimate saturation of the mean number of stars constitute a clear manifestation of the presence of a high fraction of defectors and neutrals among the participants.



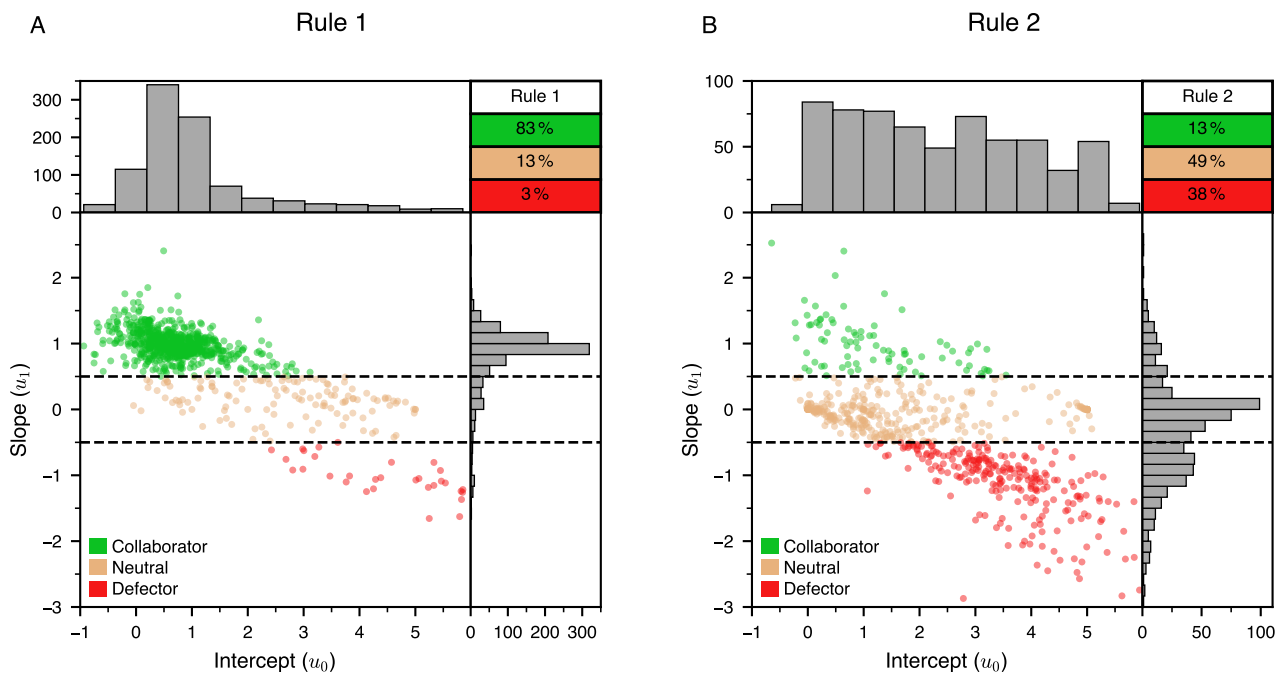
**Fig. S6.** Average number of stars used to rate cells as a function of the cell's value in the non-competitive Rule 1. Each of the rectangles corresponds to the behavior of a single individual aggregated on the 10 experimental runs. The x-axis is the cell's value and goes from 0 to 100 and the y-axis is one-fifth of the number of stars used by the individual to rate a cell of a given value and goes from 0 to 1. The dots are the experimental data, and the line is a linear fit of these data with the function  $u_0 + 5 u_1 v/99$ , where  $u_0$  is the intercept and  $u_1$  is the slope. Individuals are sorted from left to right and from top to bottom according to the value of the slope  $u_1$ . The color corresponds to the behavioral profile aggregated on the 10 experimental runs: green for collaborators, brown for neutrals, and red for defectors.

Note: Although the individuals' behavior has been defined on each experimental run in Fig. 4 of the main text, we chose to represent the aggregate behavior of each individual averaged over the 10 runs they played in a session, in order to limit the number of displayed graphs (100 instead of 1000 if all runs were shown). Therefore, the proportions of each behavioral profile slightly differ from those shown in Fig. 4 (see SI-Appendix, Table S3).

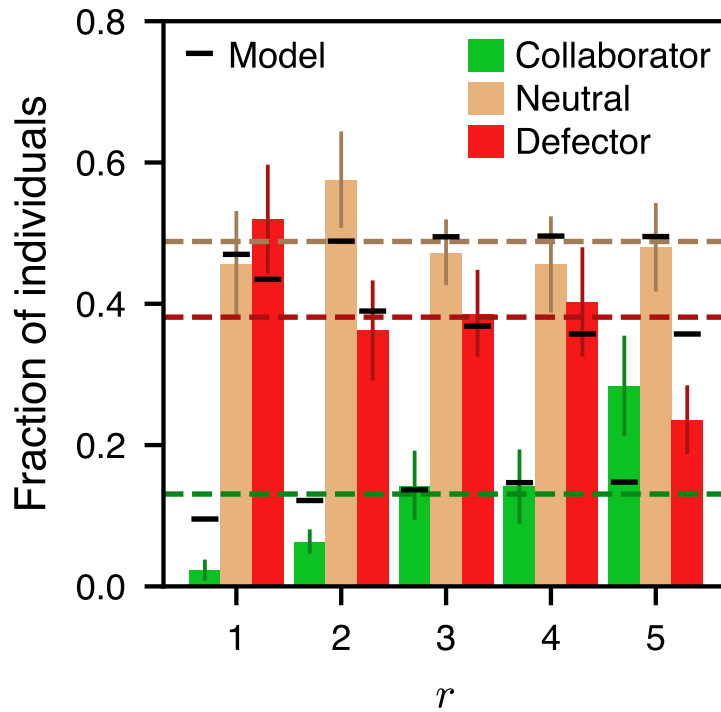


**Fig. S7.** Average number of stars used to rate cells as a function of the cell's value in the competitive Rule 2. Each of the rectangles corresponds to the behavior of a single individual aggregated on the 10 experimental runs. The x-axis is the cell's value and goes from 0 to 100 and the y-axis is one-fifth of the number of stars used by the individual to rate a cell of a given value and goes from 0 to 1. The dots are the experimental data, and the line is a linear fit of these data with the function  $u_0 + 5 u_1 v / 99$ , where  $u_0$  is the intercept and  $u_1$  is the slope. Individuals are sorted from left to right and from top to bottom according to the value of the slope  $u_1$ . The color corresponds to the behavioral profile aggregated on the 10 experimental runs: green for collaborators, brown for neutrals, and red for defectors.

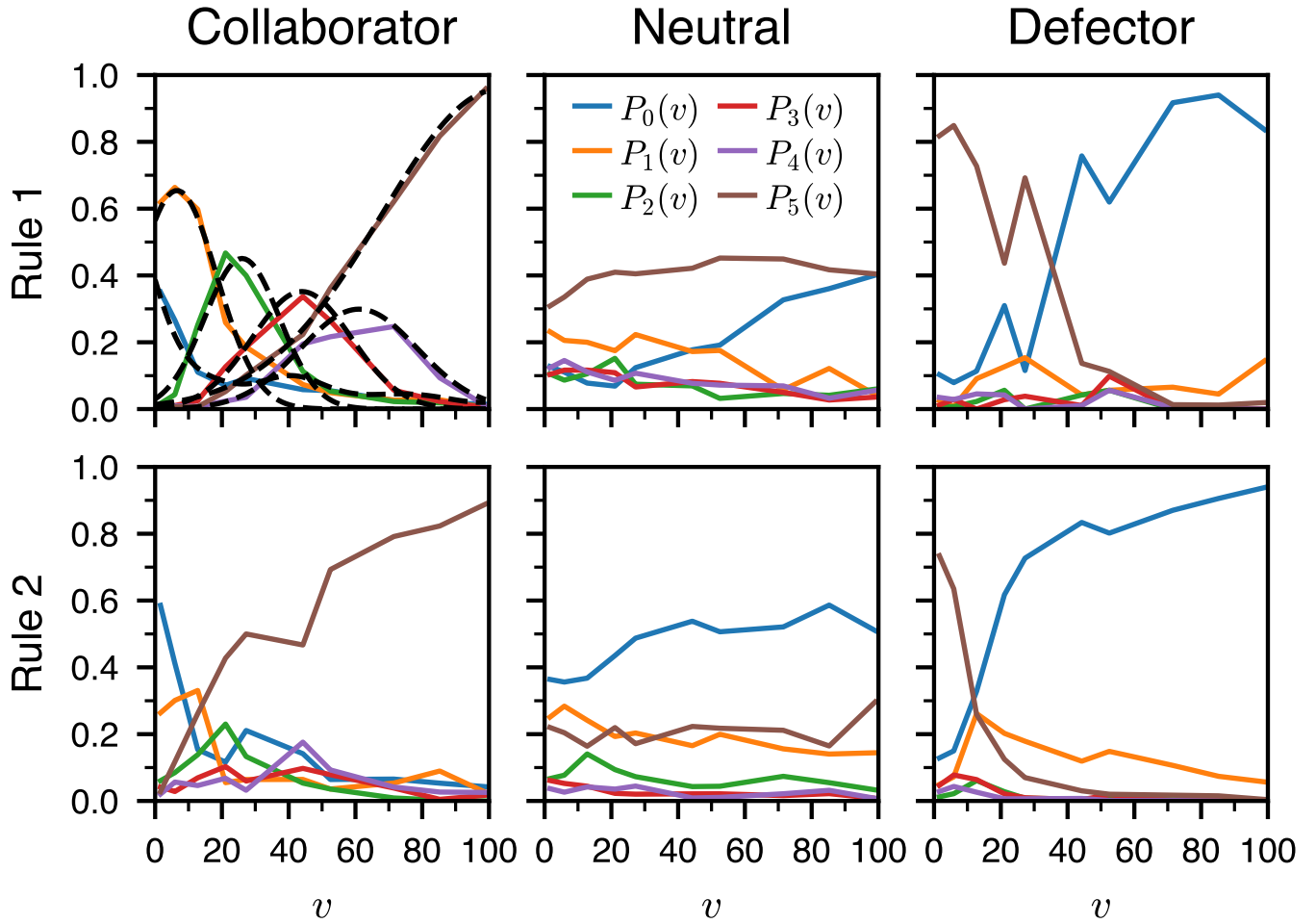
Note: Although the individuals' behavior has been defined on each experimental run in Fig. 4 of the main text, we chose to represent the aggregate behavior of each individual averaged over the 10 runs they played in a session, in order to limit the number of displayed graphs (75 instead of 750 if all runs were shown). Therefore, the proportions of each behavioral profile slightly differ from those shown in Fig. 4 (see SI-Appendix, Table S3).



**Fig. S8.** Behavioral profiles of individuals in Rule 1 (A) and Rule 2 (B). For each subfigure: (Bottom-left) Scatter plot of the values of the two parameters  $u_0$  and  $u_1$  of the linear function used to fit each subject's ratings as a function of the value of the visited cells. The color of the symbols corresponds to the behavioral profile of the individuals: collaborator (green), neutral (brown), and defector (red). The two horizontal lines at  $u_{\text{def-neu}} = -0.5$  and  $u_{\text{neu-col}} = 0.5$  are the delimitations between the profiles. (Top-left) Histogram of the values of  $u_0$ . (Bottom-right) Histogram of the values of  $u_1$ . (Top-right) The table gives the percentage of individuals for each of the behavioral profiles.

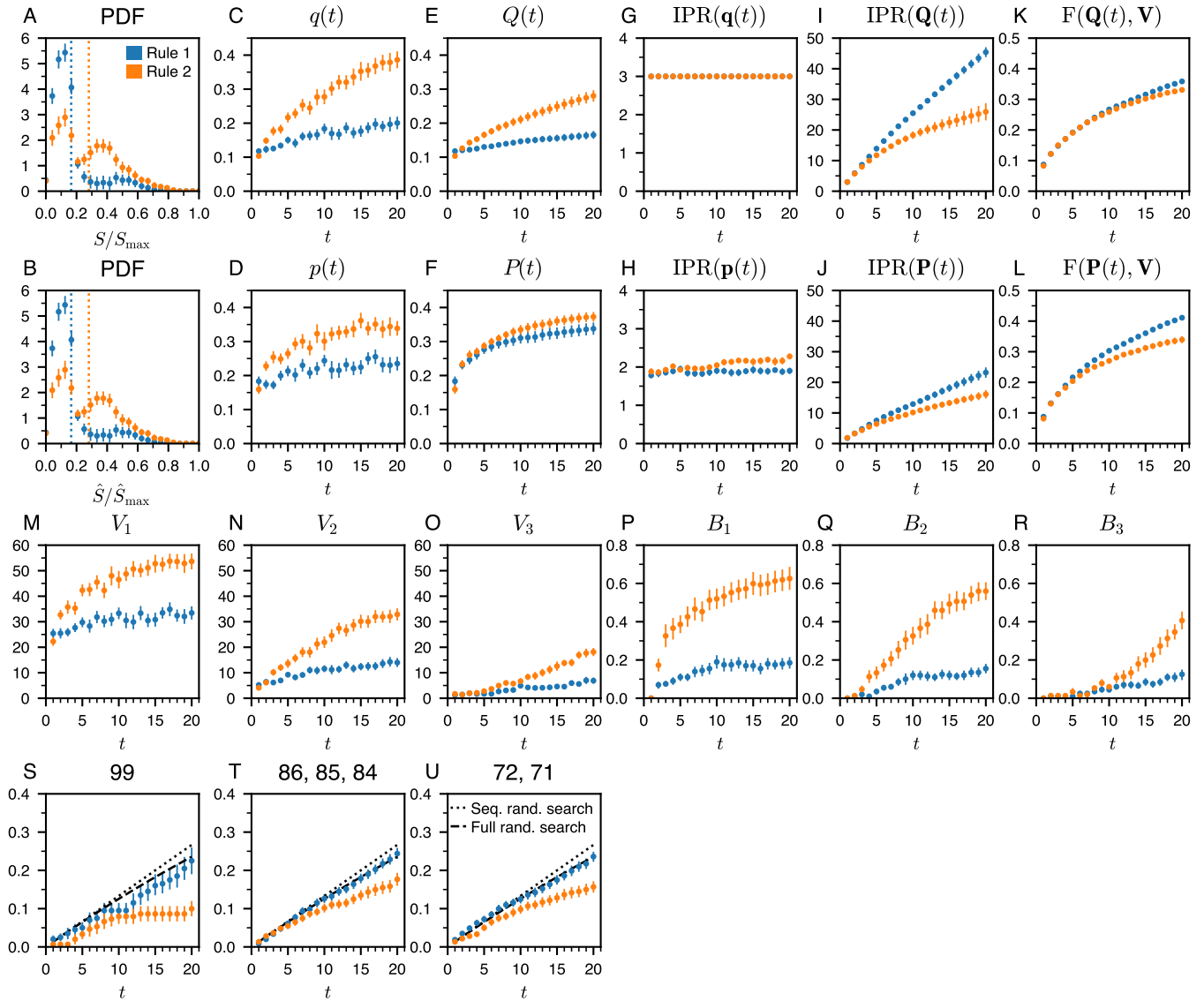


**Fig. S9.** Fraction of individuals with each behavioral profile (collaborator, neutral, and defector) found at ranks  $r = 1, 2, \dots, 5$  (rank determined by their score at the end of the experiment) in Rule 2. The colored bars correspond to experimental data for each behavioral profile: collaborator (green), neutral (brown), and defector (red). The black horizontal lines are the predictions of the model, and the horizontal dashed lines are the proportion of individuals of each behavioral profile in all experiments (null model). The graph shows that collaborators are less likely to be ranked 1st and more likely to be ranked 5th than expected by the null model, and the opposite is true for defectors. This illustrates the advantage of defectors over collaborators in the competitive Rule 2.



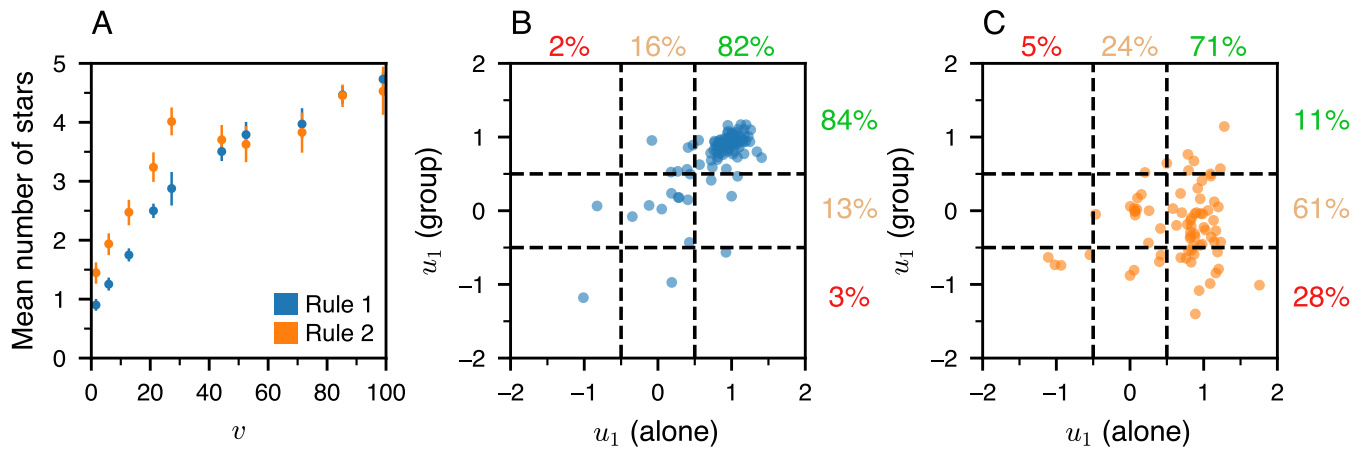
**Fig. S10.** Probability of rating a cell with  $s = 0, 1, \dots, 5$  stars,  $P_s(v)$  for the collaborators, neutrals, and defectors, and for the two rules. The solid lines correspond to the experimental data, and the black dashed lines correspond to the fitted Gaussians (Eq. 6) used in the model for collaborators in Rule 1. Note that  $P_0(v)$  and  $P_5(v)$  have slightly different values in this figure compared to Fig. 5 D–I in the main text. Here,  $P_0(v)$  and  $P_5(v)$  are the actual experimental values, while in Fig. 5 their values have been slightly adjusted to keep the average number of stars put in a cell of value  $v$  unchanged while using the condition  $P_1(v) = P_2(v) = P_3(v) = P_4(v) = P_{1234}(v)$ .



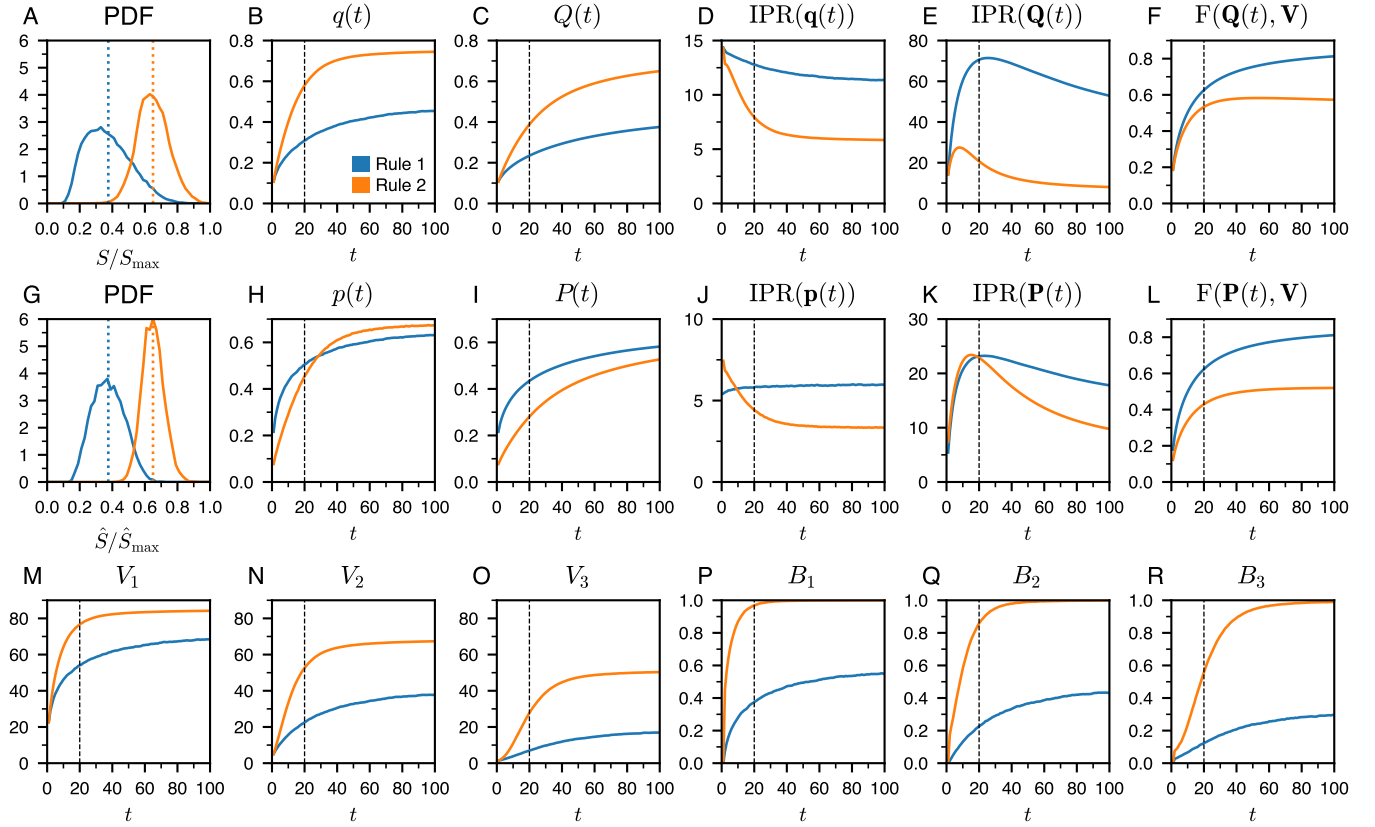


**Fig. S11.** Collective performance and dynamics of collective exploration and ratings for the experiment in which individuals play alone for the non-competitive Rule 1 (blue) and the competitive Rule 2 (orange). (A) Probability distribution function (PDF) of the scores of individuals  $S$ , and (B) of the groups  $\hat{S}$ , respectively normalized by their theoretical maxima  $S_{\max}$  and  $\hat{S}_{\max} = \hat{S}_{\max}$ . The dotted vertical lines are the mean score in the experiment, and the dashed vertical lines are the mean scores in the model. (C) Average value of the cells visited at round  $t$ ,  $q(t)$  and (E) up to round  $t$ ,  $Q(t)$ . (D) Average value of the cells visited weighted by their ratings at round  $t$ ,  $p(t)$  and (F) up to round  $t$ ,  $P(t)$ . (G) and (I) Inverse participation ratio of the visits,  $\text{IPR}(\mathbf{q}(t))$  and  $\text{IPR}(\mathbf{Q}(t))$ . (H) and (J) Inverse participation ratio of the ratings,  $\text{IPR}(\mathbf{p}(t))$  and  $\text{IPR}(\mathbf{P}(t))$ . (K) Fidelity to the cell value distribution of the distribution of visits,  $F(\mathbf{Q}(t), \mathbf{V})$ , and, (L) of ratings,  $F(\mathbf{P}(t), \mathbf{V})$ . (M–O)  $V_1(t)$ ,  $V_2(t)$ ,  $V_3(t)$  are respectively the value of the first-best cell, second-best cell, and third-best cell visited by the participants, as a function of the round  $t > 1$ . (P–R) Probability  $B_1(t)$ ,  $B_2(t)$ ,  $B_3(t)$  to revisit the first-best cell, the second-best cell, and the third-best cell of the previous round, as a function of the round  $t > 1$ . (S) Probability to find the best cell, of value 99. (T) Probability to find one of the four cells whose values are 86 ( $\times 2$ ), 85, or 84. (U) Probability to find one of the four cells whose values are 72 ( $\times 2$ ) or 71 ( $\times 2$ ).

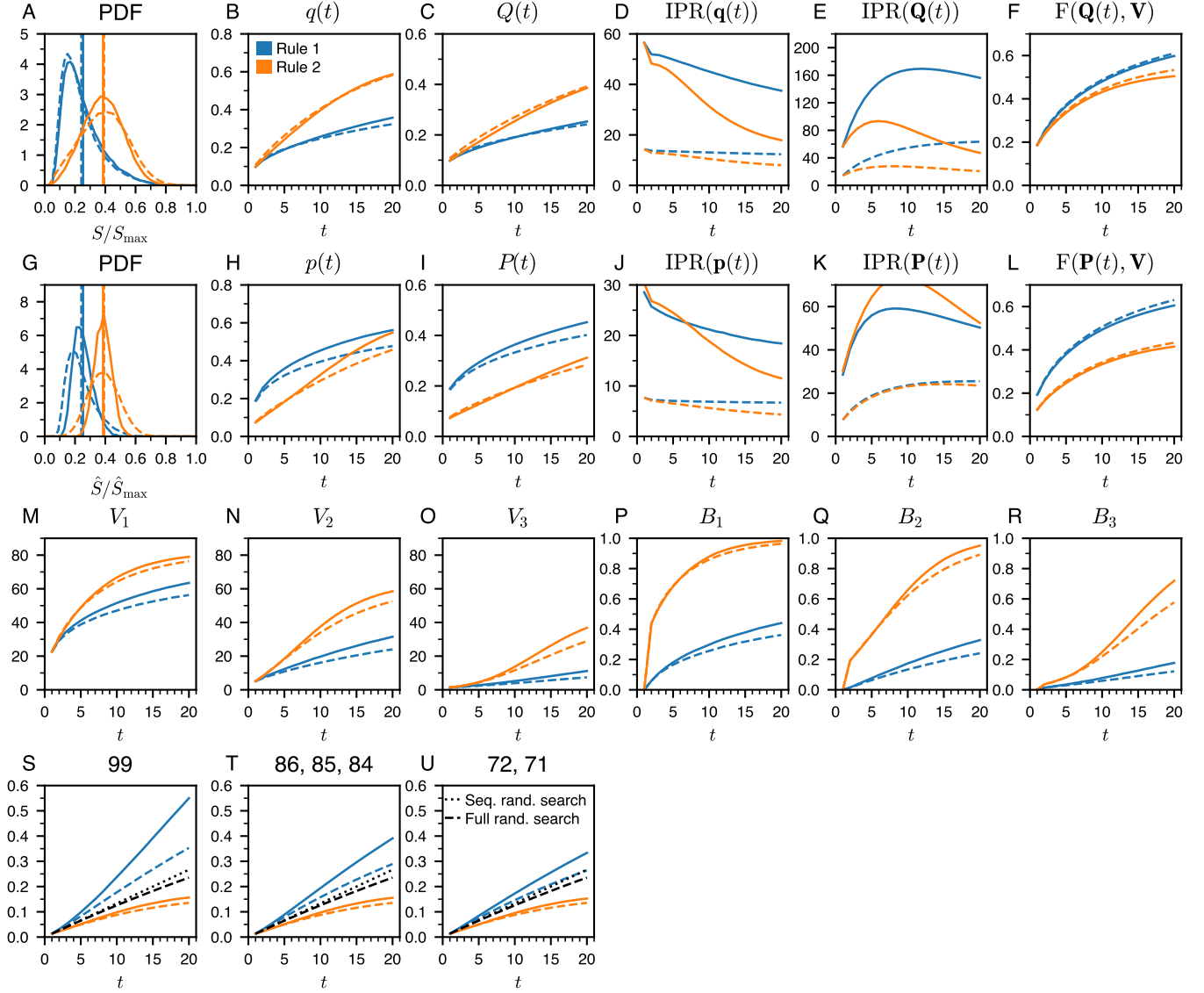
It is worth noting that there are two peaks in the PDF of scores in Rule 2 (A). This phenomenon results from the fact that the probability for an individual alone to find a cell with a high-value cell is very low. As a result, their final score is based solely on exploration.



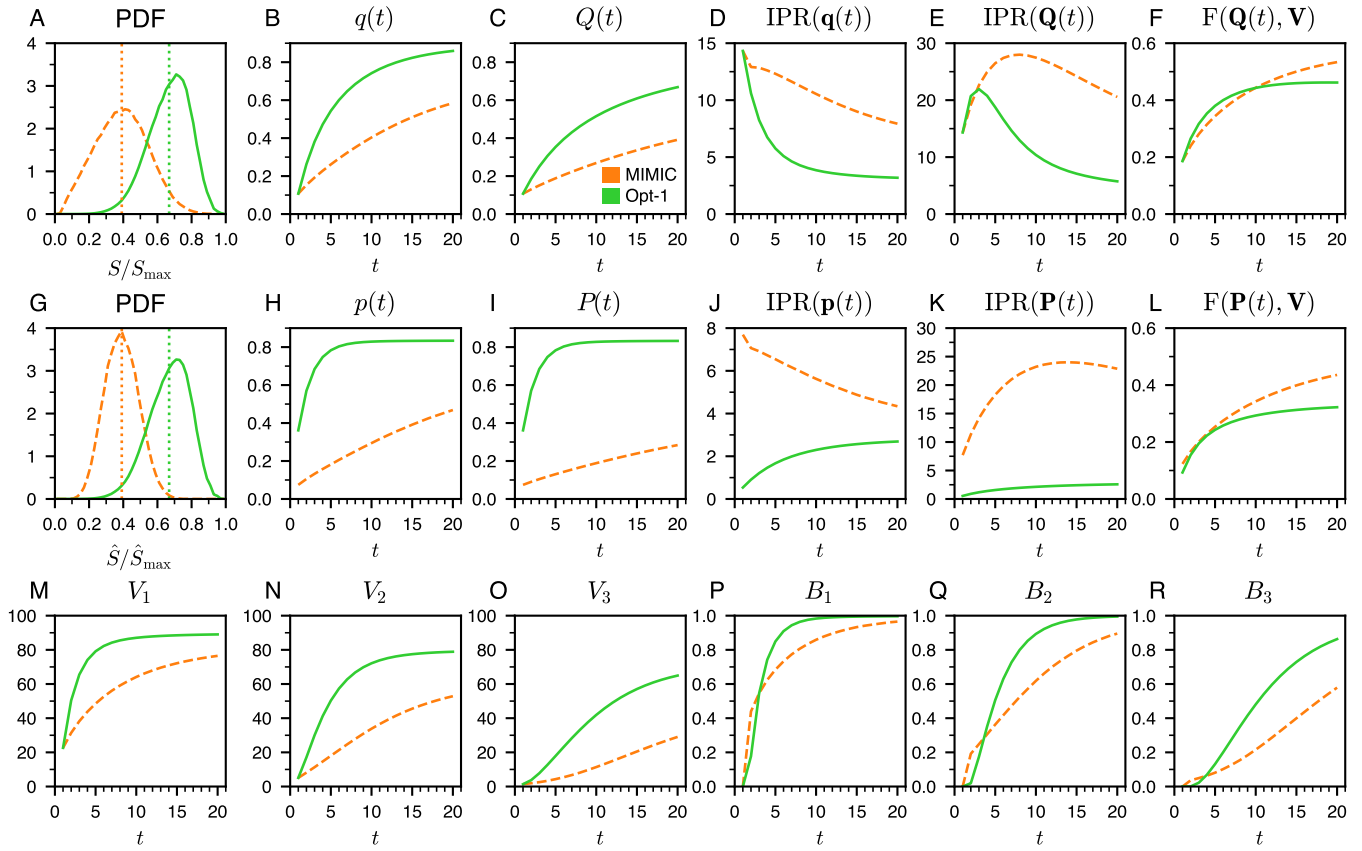
**Fig. S12.** (A) Mean number of stars as a function of the cell value  $v$  for the experiments in which individuals play alone, for Rule 1 (blue) and Rule 2 (orange), which shows that most participants are “collaborating with themselves” (compare this figure to Fig. S5). (B, C) Change in individuals’ behaviors between the single-player and five-player experiments, for Rule 1 (B; blue dots) and Rule 2 (C; orange dots). The x-axis represents the average slope  $u_1$  of individuals over the two experiments in which they play alone, while the y-axis represents the average slope  $u_1$  of individuals over the ten experiments in which they play in groups of five. The two horizontal lines at  $u_{\text{def-neu}} = -0.5$  and  $u_{\text{neu-col}} = 0.5$  are the delimitations between the profiles. The percentages indicate the fraction of each behavioral profile: collaborators (green), neutrals (brown), and defectors (red). For Rule 1, we find a strong correlation between the behavioral profiles of a participant alone or in a group, in particular, for the vast majority of collaborators, and the few neutrals. For Rule 2, this correlation is mostly lost, and many collaborators while playing alone become defectors or neutrals when confronted with 4 other participants.



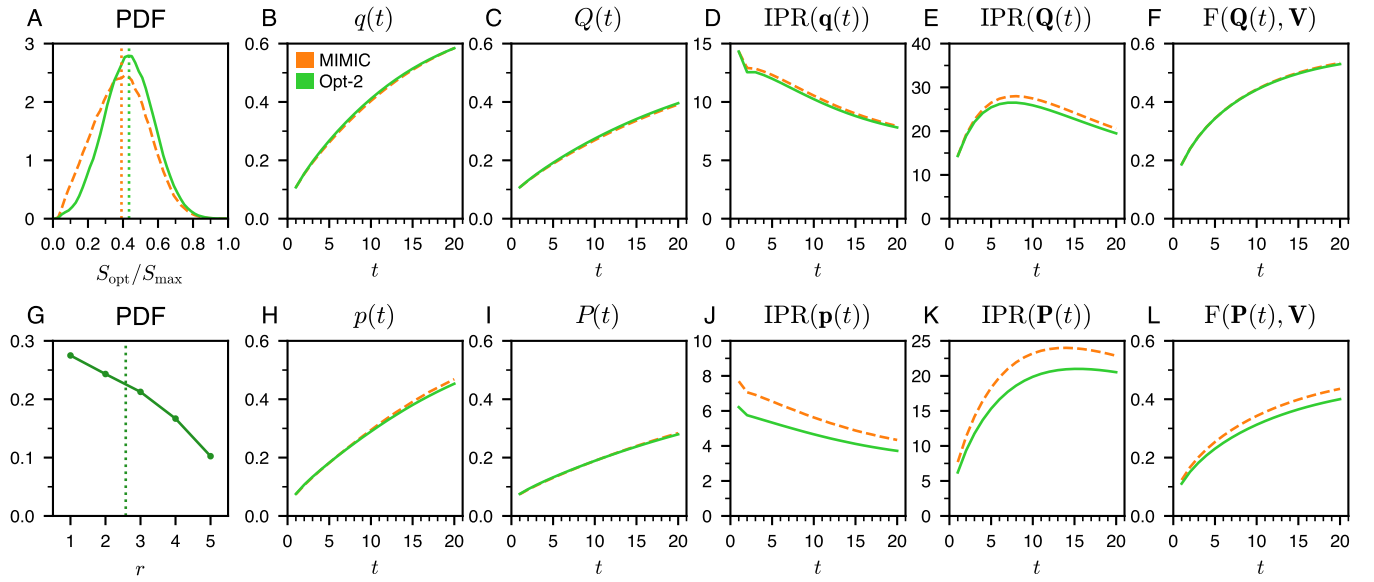
**Fig. S13.** Collective performance and dynamics of collective exploration and ratings in simulations with five MIMIC agents over 100 rounds in Rule 1 (blue), and in Rule 2 (orange). The dotted line at  $t = 20$  corresponds to the final round used in the experiments with humans. (A) Probability distribution function (PDF) of the scores of agents  $S$ , and (G) of the groups  $\hat{S}$ , respectively normalized by their theoretical maxima  $S_{\max}$  and  $\hat{S}_{\max} = 5S_{\max}$ . The dotted vertical lines are the mean score in the experiment, and the dashed vertical lines are the mean scores in the model. (B) Average value of the cells visited at round  $t$ ,  $q(t)$  and (C) up to round  $t$ ,  $Q(t)$ . (H) Average value of the cells visited weighted by their ratings at round  $t$ ,  $p(t)$  and (I) up to round  $t$ ,  $P(t)$ . (D) and (E) Inverse participation ratio of the visits,  $\text{IPR}(\mathbf{q}(t))$  and  $\text{IPR}(\mathbf{Q}(t))$ . (J) and (K) Inverse participation ratio of the ratings,  $\text{IPR}(\mathbf{p}(t))$  and  $\text{IPR}(\mathbf{P}(t))$ . (F) Fidelity to the cell value distribution of the distribution of visits,  $F(\mathbf{Q}(t), \mathbf{V})$ , and, (L) of ratings,  $F(\mathbf{P}(t), \mathbf{V})$ . (M–O)  $V_1(t)$ ,  $V_2(t)$ ,  $V_3(t)$  are respectively the value of the first-best cell, second-best cell, and third-best cell visited by the participants, as a function of the round  $t$ . (P–R) Probability  $B_1(t)$ ,  $B_2(t)$ ,  $B_3(t)$  to revisit the first-best cell, the second-best cell, and the third-best cell of the previous round, as a function of the round  $t > 1$ .



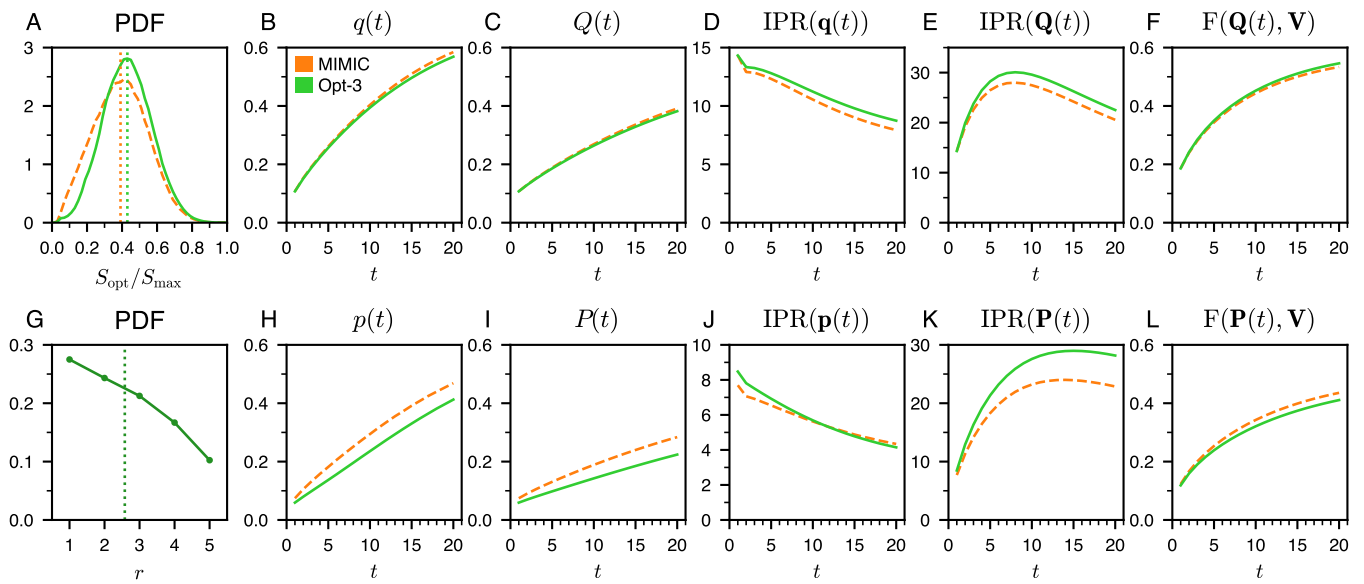
**Fig. S14.** Impact of the group size on the collective performance and the dynamics of collective exploration and ratings in simulations of MIMIC agents for Rule 1 (blue) and Rule 2 (orange). Dashed lines correspond to simulations with five MIMIC agents exploring a table with 225 ( $15 \times 15$ ) cells, as used in the experiments with humans. Solid lines correspond to simulations with twenty MIMIC agents exploring a table 4 times larger, with 900 ( $30 \times 30$ ) cells. (A) Probability distribution function (PDF) of the scores of agents  $S$ , and (G) of the groups  $\hat{S}$ , respectively normalized by their theoretical maxima  $S_{\max}$  and  $\hat{S}_{\max} = 5S_{\max}$  for the dashed line and  $\hat{S}_{\max} = 20S_{\max}$  for the solid line. The dotted vertical lines are the mean score in the experiment, and the dashed vertical lines are the mean scores in the model. (B) Average value of the cells visited at round  $t$ ,  $q(t)$  and (C) up to round  $t$ ,  $Q(t)$ . (H) Average value of the cells visited weighted by their ratings at round  $t$ ,  $p(t)$  and (I) up to round  $t$ ,  $P(t)$ . (D) and (E) Inverse participation ratio of the visits,  $\text{IPR}(q(t))$  and  $\text{IPR}(Q(t))$ . (J) and (K) Inverse participation ratio of the ratings,  $\text{IPR}(p(t))$  and  $\text{IPR}(P(t))$ . (F) Fidelity to the cell value distribution of the distribution of visits,  $F(Q(t), \mathbf{V})$ , and, (L) of ratings,  $F(P(t), \mathbf{V})$ . (M–O)  $V_1(t)$ ,  $V_2(t)$ ,  $V_3(t)$  are respectively the value of the first-best cell, second-best cell, and third-best cell visited by the participants, as a function of the round  $t$ . (P–R) Probability  $B_1(t)$ ,  $B_2(t)$ ,  $B_3(t)$  to revisit the first-best cell, the second-best cell, and the third-best cell of the previous round, as a function of the round  $t > 1$ . (S) Probability to find the best cell, of value 99. (T) Probability to find one of the four cells whose values are 86 ( $\times 2$ ), 85, or 84. (U) Probability to find one of the four cells whose values are 72 ( $\times 2$ ) or 71 ( $\times 2$ ).



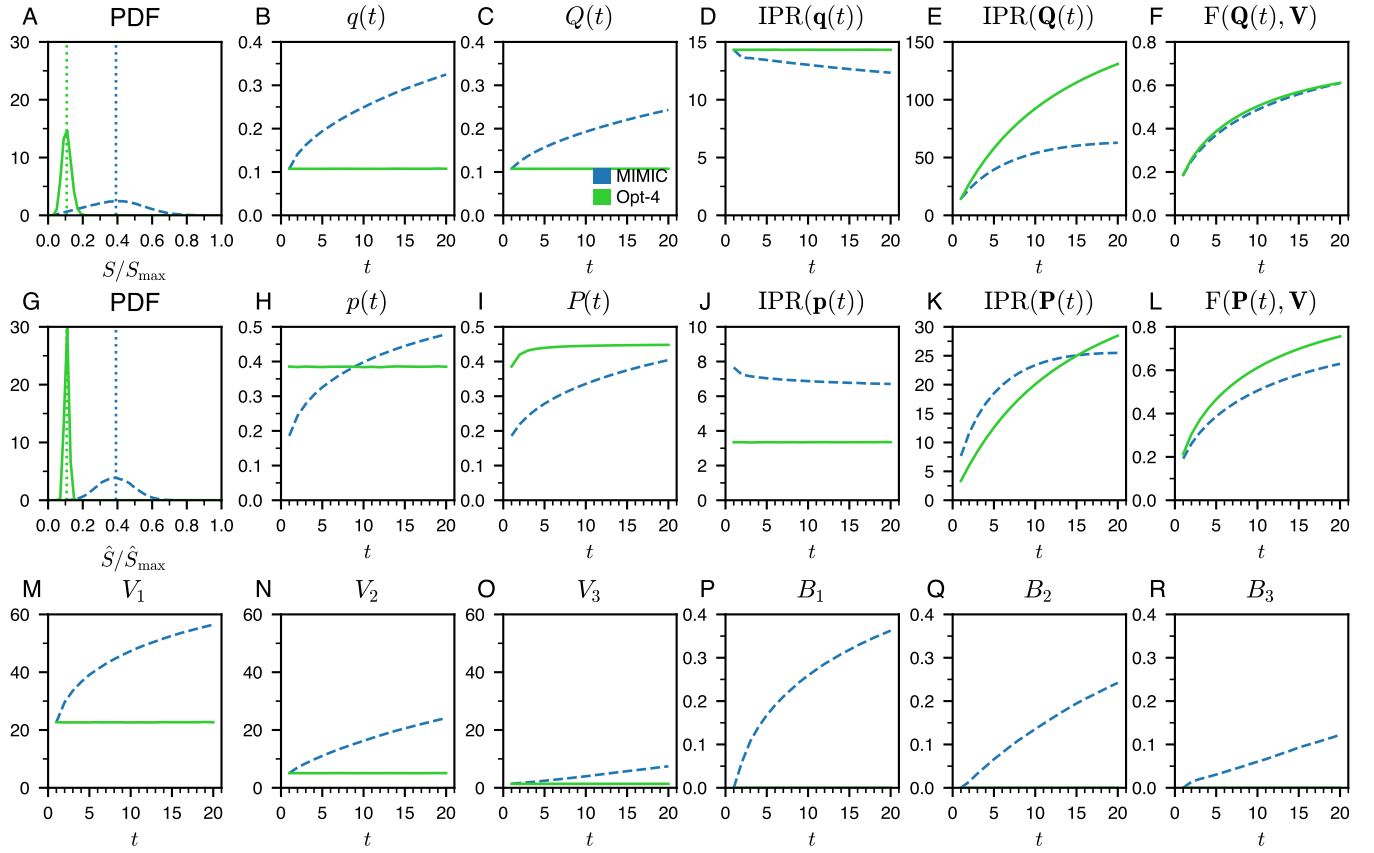
**Fig. S15.** Collective performance and dynamics of collective exploration and ratings in simulations with five Opt-1 agents optimizing the score  $S$  (green solid lines) compared to the simulation results with five MIMIC agents (Rule 2, orange dashed lines) which are in good agreement with the experimental results (see Fig. 2 in the main text). (A) Probability distribution function (PDF) of the scores of agents  $S$ , and (G) of the groups  $\hat{S}$ , respectively normalized by their theoretical maxima  $S_{\max}$  and  $\hat{S}_{\max} = 5S_{\max}$ . The dotted vertical lines are the mean score in the experiment, and the dashed vertical lines are the mean scores in the model. (B) Average value of the cells visited at round  $t$ ,  $q(t)$  and (C) up to round  $t$ ,  $Q(t)$ . (H) Average value of the cells visited weighted by their ratings at round  $t$ ,  $p(t)$  and (I) up to round  $t$ ,  $P(t)$ . (D) and (E) Inverse participation ratio of the visits,  $\text{IPR}(\mathbf{q}(t))$  and  $\text{IPR}(\mathbf{Q}(t))$ . (J) and (K) Inverse participation ratio of the ratings,  $\text{IPR}(\mathbf{p}(t))$  and  $\text{IPR}(\mathbf{P}(t))$ . (F) Fidelity to the cell value distribution of the distribution of visits,  $F(\mathbf{Q}(t), \mathbf{V})$ , and, (L) of ratings,  $F(\mathbf{P}(t), \mathbf{V})$ . (M–O)  $V_1(t)$ ,  $V_2(t)$ ,  $V_3(t)$  are respectively the value of the first-best cell, second-best cell, and third-best cell visited by the participants, as a function of the round  $t$ . (P–R) Probability  $B_1(t)$ ,  $B_2(t)$ ,  $B_3(t)$  to revisit the first-best cell, the second-best cell, and the third-best cell of the previous round, as a function of the round  $t > 1$ .



**Fig. S16.** Collective performance and dynamics of collective exploration and ratings in simulations with one Opt-2 agent optimizing its score  $S$  playing with four MIMIC agents (green solid lines) compared to the simulations results with five MIMIC agents (Rule 2, orange dashed lines) which are in good agreement with the experimental results (see Fig. 2 in the main text). (A) Probability distribution function (PDF) of the scores of agents  $S$  normalized by its theoretical maxima  $S_{\max}$ . The dotted vertical lines are the mean score in the experiment and the model. (G) Probability distribution function (PDF) of the rank  $r$  of the optimized agent. The dotted vertical lines correspond to the mean rank. (B) Average value of the cells visited at round  $t$ ,  $q(t)$  and (C) up to round  $t$ ,  $Q(t)$ . (H) Average value of the cells visited weighted by their ratings at round  $t$ ,  $p(t)$  and (I) up to round  $t$ ,  $P(t)$ . (D) and (E) Inverse participation ratio of the visits,  $\text{IPR}(\mathbf{q}(t))$  and  $\text{IPR}(\mathbf{Q}(t))$ . (J) and (K) Inverse participation ratio of the ratings,  $\text{IPR}(\mathbf{p}(t))$  and  $\text{IPR}(\mathbf{P}(t))$ . (F) Fidelity to the cell value distribution of the distribution of visits,  $F(\mathbf{Q}(t), \mathbf{V})$ , and, (L) of ratings,  $F(\mathbf{P}(t), \mathbf{V})$ .

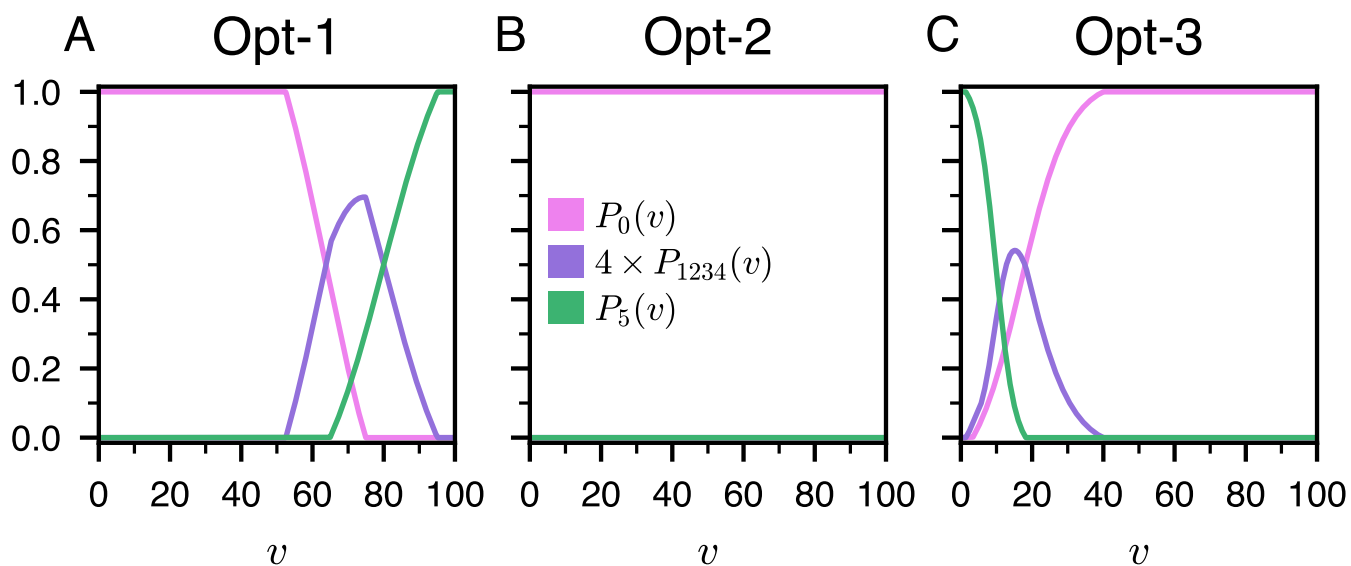


**Fig. S17.** Collective performance and dynamics of collective exploration and ratings in simulations with one Opt-3 agent optimizing its rank  $r$  while playing against four MIMIC agents (green solid lines) compared to the simulations results with five MIMIC agents (Rule 2, orange dashed lines) which are in good agreement with the experimental results (see Fig. 2 in the main text). (A) Probability distribution function (PDF) of the scores of agents  $S$  normalized by its theoretical maxima  $S_{\max}$ . The dotted vertical lines are the mean score in the experiment and the model. (G) Probability distribution function (PDF) of the rank  $r$  of the optimized agent. The dotted vertical line corresponds to the mean rank. (B) Average value of the cells visited at round  $t$ ,  $q(t)$  and (C) up to round  $t$ ,  $Q(t)$ . (H) Average value of the cells visited weighted by their ratings at round  $t$ ,  $p(t)$  and (I) up to round  $t$ ,  $P(t)$ . (D) and (E) Inverse participation ratio of the visits,  $\text{IPR}(\mathbf{q}(t))$  and  $\text{IPR}(\mathbf{Q}(t))$ . (J) and (K) Inverse participation ratio of the ratings,  $\text{IPR}(\mathbf{p}(t))$  and  $\text{IPR}(\mathbf{P}(t))$ . (F) Fidelity to the cell value distribution of the distribution of visits,  $F(\mathbf{Q}(t), \mathbf{V})$ , and, (L) of ratings,  $F(\mathbf{P}(t), \mathbf{V})$ .

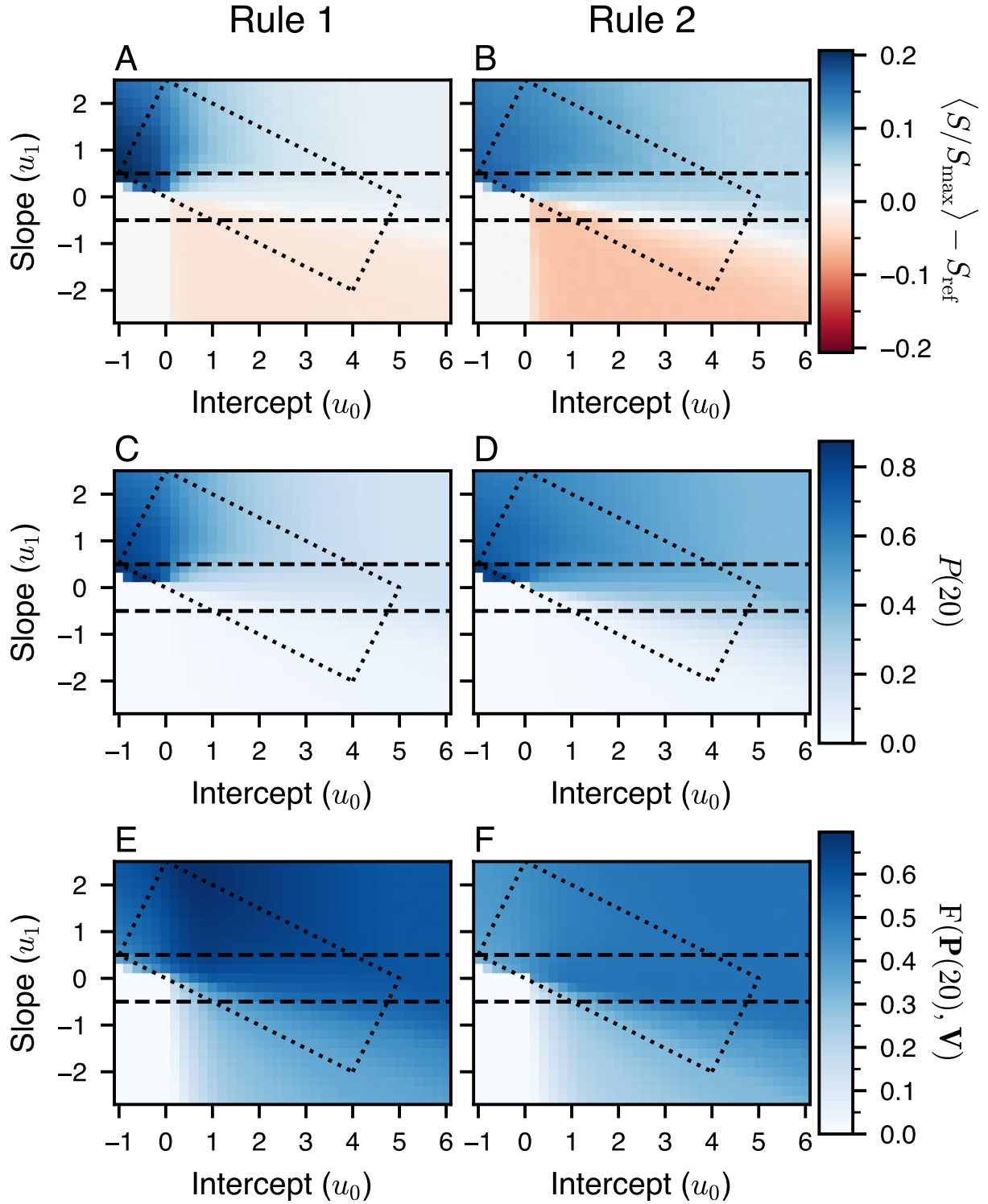


**Fig. S18.** Collective performance and dynamics of collective exploration and ratings in simulations with five Opt-4 agents optimizing the fidelity of ratings with respect to cell values at the end of the experiment  $F(\mathbf{P}(t = 20), \mathbf{V})$  (green solid lines) compared to the simulations results with five MIMIC agents (Rule 1, blue dashed lines) which are in good agreement with the experimental results (see Fig. 2 in the main text). (A) Probability distribution function (PDF) of the scores of agents  $S$ , and (G) of the groups  $\hat{S}$ , respectively normalized by their theoretical maxima  $S_{\max}$  and  $\hat{S}_{\max} = 5S_{\max}$ . The dotted vertical lines are the mean score in the experiment, and the dashed vertical lines are the mean scores in the model. (B) Average value of the cells visited at round  $t$ ,  $q(t)$  and (C) up to round  $t$ ,  $Q(t)$ . (H) Average value of the cells visited weighted by their ratings at round  $t$ ,  $p(t)$  and (I) up to round  $t$ ,  $P(t)$ . (D) and (E) Inverse participation ratio of the visits,  $\text{IPR}(\mathbf{q}(t))$  and  $\text{IPR}(\mathbf{Q}(t))$ . (J) and (K) Inverse participation ratio of the ratings,  $\text{IPR}(\mathbf{p}(t))$  and  $\text{IPR}(\mathbf{P}(t))$ . (F) Fidelity to the cell value distribution of the distribution of visits,  $F(\mathbf{Q}(t), \mathbf{V})$ , and, (L) of ratings,  $F(\mathbf{P}(t), \mathbf{V})$ . (M–O)  $V_1(t)$ ,  $V_2(t)$ ,  $V_3(t)$  are respectively the value of the first-best cell, second-best cell, and third-best cell visited by the participants, as a function of the round  $t$ . (P–R) Probability  $B_1(t)$ ,  $B_2(t)$ ,  $B_3(t)$  to revisit the first-best cell, the second-best cell, and the third-best cell of the previous round, as a function of the round  $t > 1$ .





**Fig. S19.** Probability of rating a cell with 0 stars ( $P_0(v)$ ; magenta), 1 to 4 stars ( $P_{1234}(v)$ ; violet) and 5 stars ( $P_5(v)$ ; green) as a function of its value  $v$ , for the different kinds of optimized agents. The Opt-1 agents (maximizing their score in a group of 5 identical agents) are strong collaborators, also suggesting that a competition between groups should favor intragroup collaboration. The Opt-2 agents (maximizing their score against 4 MIMIC agents) are neutrals always giving a rating of 0 star, and hence not participating at all in the coloring of the table. Finally, the Opt-3 agents (optimizing their rank against 9 MIMIC agents in 2 groups of 5) are strong defectors, illustrating that deception naturally emerges from our competitive payment structure.



**Fig. S20.** Heatmap for Rule 1 (left column) and Rule 2 (right column) and for different combinations of values of intercept  $u_0$  and slope  $u_1$  of: (A) and (B) the average value of the score  $S/S_{\max} - S_{\text{ref}}$ , (B) and (C) the average value of the cells visited weighted by their ratings at the end of the experiment  $P(t = 20)$ , and (E) and (F) the average value of the fidelity of ratings with respect to cell values at the end of the experiment  $F(\mathbf{P}(t = 20), \mathbf{V})$ . Each data point on the heatmap corresponds to the average over 10,000 simulations with five identical agents, defined by their intercept  $u_0$  and slope  $u_1$ . In (A) and (B),  $S_{\text{ref}}$  is the normalized score obtained with simulations done with  $u_0 = 0$  and  $u_1 = 0$ . Blue (resp. red) corresponds to positive (resp. negative) values, see color bars. The two horizontal lines at  $u_{\text{def-neu}} = -0.5$  and  $u_{\text{neu-col}} = 0.5$  are the delimitation between the behavioral profiles, and the rectangle represents the rough location of the agents in the experiments.

	$d''_s$	$e''_s$	$f''_s$
$s = 1$	0.65	6.6	5.83
$s = 2$	0.46	25.9	6.30
$s = 3$	0.36	43.8	4.79
$s = 4$	0.30	61.1	4.07
$s = 5$	0.96	102.4	2.01

(a) Collaborator (Rule 1)

	$c_s$	$d_s$	$e_s$	$f_s$
$s = 0$	1113.4	1113.3	-84.5	-4.75
$s = 5$	-1051.9	1052.8	-304.5	1.24

(b) Collaborator (Rule 2)

	$c'_s$	$d'_s$
$s = 0$	0.09	0.30
$s = 5$	0.25	0.30

(c) Neutral (Rule 1)

	$c'_s$	$d'_s$
$s = 0$	0.45	0.17
$s = 5$	0.09	0.17

(d) Neutral (Rule 2)

	$c_s$	$d_s$	$e_s$	$f_s$
$s = 0$	0.50	0.45	39.4	3.86
$s = 5$	0.46	0.52	26.9	-3.11

(e) Defector (Rule 1)

	$c_s$	$d_s$	$e_s$	$f_s$
$s = 0$	0.45	0.46	14.8	7.34
$s = 5$	0.39	0.38	9.8	-18.49

(f) Defector (Rule 2)

	$c_s$	$d_s$	$e_s$	$f_s$
$s = 0$	0.5	0.95	63.7	-5.17
$s = 5$	0.5	0.78	80.1	5.01

(g) Opt-1

	$c'_s$	$d'_s$
$s = 0$	1	0
$s = 5$	0	0

(h) Opt-2

	$c_s$	$d_s$	$e_s$	$f_s$
$s = 0$	0.45	0.59	16.9	7.34
$s = 5$	0.51	0.55	9.8	-18.48

(i) Opt-3

Table S1. Parameters values used for the rating strategy (see Eqs. 5 and 6 in the main text) for MIMIC agents (collaborator, neutral, and defector) in both rules, and for the optimized agents (Opt-1, Opt-2, Opt-3). These values result from the fitting of the probabilities of rating a cell with  $s$  stars described in the main text.

		$P^E(c, t)$		$B_1(t)$		$B_2(t)$		$B_3(t)$	
		$\varepsilon$	$\alpha$	$a_1$	$b_1$	$a_2$	$b_2$	$a_3$	$b_3$
Rule 1	MIMIC	0.78	0.89	57.6	2.19	25.0	2.29	1.4	2.64
	(col, neu, def)	0.69	1.32	-8.4	1.55	-4.1	2.11	-0.2	2.33
Rule 2	Opt-1	1e-5	1.38	25.0	2.00	18.4	2.03	27.1	2.41
	Opt-2	0.58	2.75	-2.4	2.15	4.0	2.54	9.1	2.90
	Opt-3	0.82	4.32	22.3	4.86	13.7	3.54	8.3	3.35
	Opt-4	1	0	0	0	0	0	0	0

**Table S2.** Parameters values used for the visiting strategy (see Eqs. 2 and 3 in the main text) for MIMIC agents (collaborator, neutral, and defector), and optimized agents (Opt-1, Opt-2, Opt-3, and Opt-4). These values result from the optimization procedure described in the Materials and Methods section.

	Col	Neu	Def	
$\overline{\text{Col}}$	96%	4%	0%	84%
$\overline{\text{Neu}}$	9%	72%	8%	13%
$\overline{\text{Def}}$	0%	21%	79%	3%
	84%	13%	3%	

(a) Rule 1

	Col	Neu	Def	
$\overline{\text{Col}}$	70%	28%	1%	11%
$\overline{\text{Neu}}$	9%	69%	22%	61%
$\overline{\text{Def}}$	1%	11%	88%	28%
	13%	49%	38%	

(b) Rule 2

**Table S3. Fractions of behavioral profiles adopted by participants, whether it is calculated on a single experimental run or over the ten experimental runs (average behavioral profile). In the table, col, neu, and def correspond respectively to collaborators, neutrals, and defectors. The lines above col, neu, and def indicate the average profiles.**

Observing the table row-wise reveals that individuals tend to maintain a consistent behavioral profile across the ten experiments. For instance, in Rule 2, an individual who has adopted on average a collaborator profile across the ten experiments was respectively a collaborator 70% of the experiments, a neutral 9% of the experiments, and a defector 1% of the experiments. By examining only the total fractions, shown in the bottom row and right column, one can observe that for each behavioral profile, these fractions remain the same whether they are calculated in single experimental runs or across the ten experiments in Rule 1, and quite similar in Rule 2.

**Movie S1.** Dynamics of the fraction of stars in each cell (in red) and of the fraction of visits in each cell (in blue), as a function of the round  $t$ , for Rule 1. (A) and (C): The first column corresponds to an experiment where the group of 5 participants achieved the mean final normalized score  $\hat{S}(t=20)/\hat{S}_{\max} \approx 0.24$  (where  $\hat{S}_{\max} = 5420 \times 5 = 27100$  is the maximum possible group score). (B) and (D): The second column corresponds to a simulation of the model where a group of 5 MIMIC agents also obtained a normalized score close to 0.24. Note that the participants (and the MIMIC agents in the model) only had access to the dynamics of the fraction of stars.

**Movie S2.** Dynamics of the fraction of stars in each cell (in red) and of the fraction of visits in each cell (in blue), as a function of the round  $t$ , for Rule 2. (A) and (C): The first column corresponds to an experiment where the group of 5 participants achieved the mean final normalized score  $\hat{S}(t=20)/\hat{S}_{\max} \approx 0.40$  (where  $\hat{S}_{\max} = 5420 \times 5 = 27100$  is the maximum possible group score). (B) and (D): The second column corresponds to a simulation of the model where a group of 5 MIMIC agents also obtained a normalized score close to 0.40. Note that the participants (and the MIMIC agents in the model) only had access to the dynamics of the fraction of stars.

**Movie S3.** Dynamics of the fraction of stars in each cell (in red) and of the fraction of visits in each cell (in blue), as a function of the round  $t$ , for Rule 1. (A) and (C): The first column corresponds to an experiment where the group of 5 participants achieved the final normalized score  $\hat{S}(t=20)/\hat{S}_{\max} \approx 0.36$ , which is 50% higher than the mean observed group score. The participants collaborated more than in Movie S1, resulting in a higher score. (B) and (D): The second column corresponds to a simulation of the model where a group of 5 MIMIC agents also obtained a normalized score close to 0.36. Note that the participants (and the MIMIC agents in the model) only had access to the dynamics of the fraction of stars.

**Movie S4.** Dynamics of the fraction of stars in each cell (in red) and of the fraction of visits in each cell (in blue), as a function of the round  $t$ , for Rule 2. (A) and (C): The first column corresponds to an experiment where the group of 5 participants achieved the final normalized score  $\hat{S}(t=20)/\hat{S}_{\max} \approx 0.60$ , which is 50% higher than the mean observed group score. The participants collaborated more than in Movie S2, resulting in a higher score. (B) and (D): The second column corresponds to a simulation of the model where a group of 5 MIMIC agents also obtained a normalized score close to 0.60. Note that the participants (and the MIMIC agents in the model) only had access to the dynamics of the fraction of stars.

**Movie S5.** Dynamics of the fraction of stars in each cell, as a function of the round  $t$  (Rule 1 and Rule 2; experiment only). Compared to Movies S1–S4, we have removed the cell values to enhance the visibility of the different shades of red and to better reflect what the subjects actually saw during the experiment. Panels A–D correspond to panel A of Movie S1–S4, respectively. The first row corresponds to Rule 1 and the second row to Rule 2. The first column corresponds to experiments where the group achieved the mean observed group score, while the second column corresponds to experiments where the group achieved a score 50% higher than the mean group score.

#### SI Dataset S1 (DATA)

All data needed to evaluate and replicate the findings of the article are present in the article, the SI-Appendix, or available at the following online repository: <https://github.com/Thomas-bsnt/Stigmer-article.git>. Additionally, the repository contains the movies mentioned in the article.