S1. MODEL DETAILS

The Fig. S1 illustrates the stability rule implemented in the Model (main text). The Fig. S2 shows the statistics of simultaneous requests and the nature of acceptances.

FIG. S1. The effect of the stability rule on the average collective progress (left) and the fraction of games completed (right). The parameter $f$ allows us to scan between the limits of having no stability rule ($f = 0$) and having absolute implementation of the rule ($f = 1$).

S2. TESTING FOR LEARNING DURING GAMES

The model is able to describe (provide probabilities on) the choices made by the players in terms of the three variables of the system – (i) cluster size of the focal player, $s_i$, (ii) cluster size of the neighbour to whom the request is made or whose request is received, $s_j$, and (iii) the average of the cluster sizes of the number of neighbours $n_i(c_j)$ of player $i$ that have the same colour as $j$, $\langle s(c_j) \rangle$. 

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To investigate whether the subjects were learning and changing their preferences over the span of the 9 games, we utilize the aforementioned information and first categorize the observed decisions in terms of the three variables $s_i$, $s_j$, and $\langle s(c_j) \rangle$. We divide the 3-dimensional decision space into octants ($s_i \geq 0.5, s_j \geq 0.5, \langle s(c_j) \rangle \geq 0.5$) and count the number of choices in each of these 8 octants (categories) in a given game. We then compare the distribution of the choices across the 9 different games. The distribution of choices for requesters and acceptors are shown in Fig. S3 and Fig. S4, respectively. We compare the distribution of counts using the Pearson’s chi-squared test. We also clustered the games into three (games 1 to 3, 4 to 6, and 7 to 9) and two (games 1 to 5, and 6 to 9) sets by aggregating the counts of the individual games. In Table S1 we show the results the test with the strategy being the categorical variable and the null hypothesis being that there is no difference between the distribution of strategy across the groups (games) [1]. We find that $p$-values are not small enough to reject the null hypothesis. Therefore, we conclude that no significant learning behaviour was observed.

**S3. TESTING FOR BEHAVIOURAL HETEROGENEITY**

Below we provide a method to study and model the aspect of heterogeneity among agents. In the basic modelling scheme (refer to the main text, Model section) we cast the model in the form of a logistic regression that learn the parameters $\alpha$, $\beta$ and $\delta$ from the data. We extend the scheme to consider mixed effects logistic regression [2], where an additional variable for subjects account
FIG. S3. Requesting decisions of the subjects on each one of the 9 games. The decisions are categorized into 8 different strategies and the fraction of cases in each strategy is shown for each game. The counts for the decisions in a given game is normalized using the total decisions in the game.

for random effects (heterogeneity). We consider the following four models with different levels of complexity that we implement using the \textit{tlme4} R-programming package for generalized linear mixed models [3]:

Model-0: \( \text{logit}(P_{\omega}(m,k)/P_0(m,k)) = \lambda + \alpha s_i^{(m,k)} + \beta s_j^{(m,k)} + \delta(s(c_j))^{(m,k)} \)

Model-1: \( \text{logit}(P_{\omega}(m,k)/P_0(m,k)) = (\lambda + \lambda_m) + \alpha s_i^{(m,k)} + \beta s_j^{(m,k)} + \delta(s(c_j))^{(m,k)} \)

Model-2: \( \text{logit}(P_{\omega}(m,k)/P_0(m,k)) = (\lambda + (\alpha + \alpha_m)s_i^{(m,k)} + (\beta + \beta_m)s_j^{(m,k)} + (\delta + \delta_m)(s(c_j))^{(m,k)} \)

Model-3: \( \text{logit}(P_{\omega}(m,k)/P_0(m,k)) = (\lambda + \lambda_m) + (\alpha + \alpha_m)s_i^{(m,k)} + (\beta + \beta_m)s_j^{(m,k)} + (\delta + \delta_m)(s(c_j))^{(m,k)}. \)

In the above equations the superscript \((m,k)\) refers to the \(k\)-th observation for the \(m\)-th subject in a game. Model-0 is the basic model used without random effects. The intercept \(\lambda_m\) and the
coefficients $\alpha_m$, $\beta_m$ and $\delta_m$ account for random effects due to the subjects. Model-1 is the random intercept model assuming that different subjects tend to have different intercepts and that slopes do not differ. Model-2 ignores random effects in the intercept and considers the slopes. Model-3 is a combination of Model-1 and Model-2. Using the data from the requesters’ decisions we fit the models. In table S2 we provide the intercepts, coefficients and their standard deviations obtained from the models (all the coefficients are significant with, $p$-value $\leq 0.001$). An Anova test shows that out of the 4 models, Model-1 and Model-3 are the best candidates ($AIC \simeq 572$ and $p < 0.001$). We also considered models of higher complexity, for instance, with correlated intercepts and slopes, but on these the optimization method failed to converge. Using this scheme we are able to obtain the standard deviations of the intercepts and coefficients that quantify the heterogeneity of the subjects.

In principle, the standard deviations can be used for generating randomly distributed intercepts and coefficients in the agent-based model. In the case of the acceptors the sparseness of the data (accepting instances are much lower than requesting instances) the fits could not be performed. However, from

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**FIG. S4.** Accepting decisions of the subjects during the 9 games. The decisions are categorized into 8 different strategies and the fraction of cases in each strategy is shown for the different games.
TABLE S1. Distribution of strategies in different sets of games are tested for difference using the Pearson’s chi-squared test.

<table>
<thead>
<tr>
<th>Groups</th>
<th>df</th>
<th>Requester</th>
<th>Acceptor</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>$\chi^2$</td>
<td>p-value</td>
</tr>
<tr>
<td>All 9 games</td>
<td>56</td>
<td>67.01</td>
<td>0.15</td>
</tr>
<tr>
<td>Grp-1=g1+g2+g3</td>
<td>14</td>
<td>20.37</td>
<td>0.12</td>
</tr>
<tr>
<td>Grp-2=g5+g7+g6</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Grp-3=g7+g8+g9</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Grp-1=g1+g2+g3+g4+g5</td>
<td>7</td>
<td>13.17</td>
<td>0.07</td>
</tr>
<tr>
<td>Grp-2=g6+g7+g8+g9</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

TABLE S2. Results from mixed effects logistic regression models from the data of the requesters. The intercepts, coefficients and their standard deviations obtained from the models are shown. Model-0 does not have any mixed effects. Feature scaling of the input to models have been performed to enhance the optimization.

<table>
<thead>
<tr>
<th>Model</th>
<th>$\lambda$</th>
<th>$\alpha$</th>
<th>$\beta$</th>
<th>$\delta$</th>
<th>$\sigma_\lambda$</th>
<th>$\sigma_\alpha$</th>
<th>$\sigma_\beta$</th>
<th>$\sigma_\delta$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model-0</td>
<td>-0.97</td>
<td>-1.36</td>
<td>-1.55</td>
<td>1.05</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model-1</td>
<td>-1.12</td>
<td>-1.65</td>
<td>-1.65</td>
<td>1.13</td>
<td>1.08</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model-2</td>
<td>-1.05</td>
<td>-1.72</td>
<td>-1.71</td>
<td>1.07</td>
<td>0.86</td>
<td>0.41</td>
<td>0.61</td>
<td></td>
</tr>
<tr>
<td>Model-3</td>
<td>-1.21</td>
<td>-1.99</td>
<td>-1.93</td>
<td>1.17</td>
<td>1.17</td>
<td>0.87</td>
<td>0.47</td>
<td>0.52</td>
</tr>
</tbody>
</table>

the similarity between requesting and accepting coefficients, as observed in Table-1 of the main text, we may consider the standard deviations in the accepting coefficients to be of similar magnitude.
**S4. VISUAL PRESENTATION GIVEN TO PARTICIPANTS BEFORE THE EXPERIMENT**

**Game: Group formation**
- Each player has one of 3 colors and occupies a node in the network (3×10=30 players).
- Players can move on the network by exchanging places with players of different color.
- Goal: All nodes of the same color get connected (to form groups or clusters)
- Game ends after 21 rounds, or when every player is in a group of size 10.

**Network**

**Network: Clusters**

**End of game**

FIG. S5. Slides 1-6 of the visual material (presentation) given to the participants before the experiment to introduce them to rules, goal and dynamics of the game on which they participated.
End of game

What you see
- You occupy a node and you see:
  1. Your position
  2. Your cluster's size (group size).
  3. Neighbours: Players connected to you - denoted by their place and clustersize in brackets (example: 6(3))
  4. Dark gray lines are links to nodes of your own color. These nodes cannot be requested by you.
  5. Pink lines are links to nodes with other colors. These nodes can be requested by you.

Gameplay
- Each round consists of 3 phases:
  - Requesting (A color, e.g. BLUE sends requests to exchange places)
  - Accepting (Other colors, RED & GREEN)
  - End of round (Network after the round)
- Each different round begins by a different colour getting chance to send requests.
- Players can request only to their neighbors to exchange places.
- Requested players can accept any received request to exchange OR keep their place.

Requesting stage
- Make a request OR keep your place.
- Different nodes to request. After choosing you can confirm your choice.

FIG. S6. Slides 13-18 of the visual material (presentation) given to the participants.
Accepting stage

- Time to make a choice, otherwise keeps place
- Different requests are shown. After choosing you can confirm your choice and proceed onward.

Accepting stage

- Limited time to make a choice, otherwise you keep your place
- Different requests are shown. After choosing you can confirm your choice and proceed onward.

End of round

Other information you have

- The size of the biggest cluster of each color
- Progress: average of these three biggest clusters divided by 10

Maximum cluster sizes: red: 8, yellow: 7, blue: 4

FIG. S7. Slides 19-22 of the visual material (presentation) given to the participants.
Rewarding

- You get 1 ticket for attending the session
- Additional tickets are calculated from the performance:
  - The final progress of a game is compared to the progress of AI playing with random logic on the same network (49.03%) and added to the sum.
  - The sum is then divided by the maximum performance and multiplied by 4.

The experiment

- Communication is not allowed during the game.
- Do not look at other screens!
- Do not close your browser/tab!
- 2 short breaks during the session.

The experiment

- Take your time to make your choices, but remember the time limit.
- REMEMBER: This game is a team effort! The progress is collective!
- Follow the instructions and have fun!

Questions?

- We’ll start by playing a short practice game with longer timeouts.
- This game will not affect the rewards.
- Please read and sign the consent form on your table.

FIG. S8. Slides 7-12 of the visual material (presentation) given to the participants.