doi:10.1038/nature22332

Table of Contents

Methods

1. Experiment setting

1.1 Recruitment procedure

A total of 4,000 unique subjects (plus a further 340 for the secondary experiment regarding bot visibility, described below) participated in our incentivized economic game experiments. Subjects were recruited using Amazon Mechanical Turk (AMT)[1-6]. AMT is an online labor market in which employers contract with workers to complete short tasks for relatively small amounts of money. Workers often receive a baseline payment, plus an additional bonus depending on their performance. Thus, incentivized experiments are easy to conduct using AMT: the baseline payment corresponds to the traditional show-up fee, and the bonus payment, here, is determined by the solution time during the experimental session.

Issues exist when running experiments online that do not arise in the traditional laboratory. For example, running experiments online naturally implies some loss of control, since the workers cannot be directly monitored as in the traditional lab; experimenters cannot be certain that each observation is the result of a single person (as opposed to multiple people making joint decisions at the same computer), or that one person does not participate multiple times (although AMT goes to great lengths to try to prevent this, and, based on IP address monitoring, it seems to happen very infrequently); and the sample of subjects in AMT experiments is restricted to people who participate in online labor markets (although most physical lab studies are restricted to college undergraduates, who are also far from representative). A number of studies have demonstrated the validity of behavioral experiment data gathered using AMT.[5] It has also been shown that AMT subjects are as attentive as undergraduates[3], as consistent in their answers to a range of survey questions[2], and significantly more nationally representative[6]; and that a range of classic psychological manipulations and biases are apparent among AMT subjects[1,6].

1.2 Experimental setup

Our participants interacted anonymously over the Internet using customized software playable in a browser window (available at http://breadboard.yale.edu). We prohibited subjects from participating in more than one session of the experiment by using unique identifications for each subject on AMT. The experiments were conducted from March to August 2015 and from September to October 2016. To clearly observe the effects of different behaviors and geodesic locations of the autonomous agents ("bots") while keeping other initial conditions the same, we completed 30 sessions for the only-human condition (control) and 20 sessions for each bot-treated condition (treatment). Each session lasted no longer than thirty minutes. In each session, the subjects were paid a $2 show-up fee and a declining bonus of up to $3 depending on speed to a global solution in which every player in a group had chosen a different color than their connected neighbors. When they did not reach a global solution within five minutes, the game was stopped and the subjects earned no bonus. This research was approved by the Yale University Committee of the Use of Human Subjects.

At the start, subjects were required to pass color-matching tests. They were asked to click the same color button as a picture on the screen with five options: green, orange, purple, pink, and yellow (these colors were selected from http://colorbrewer2.org in order to be colorblind-safe, and the first three colors were used in the real game). If the subjects failed to select the correct color in three trials, they were dropped from the game.

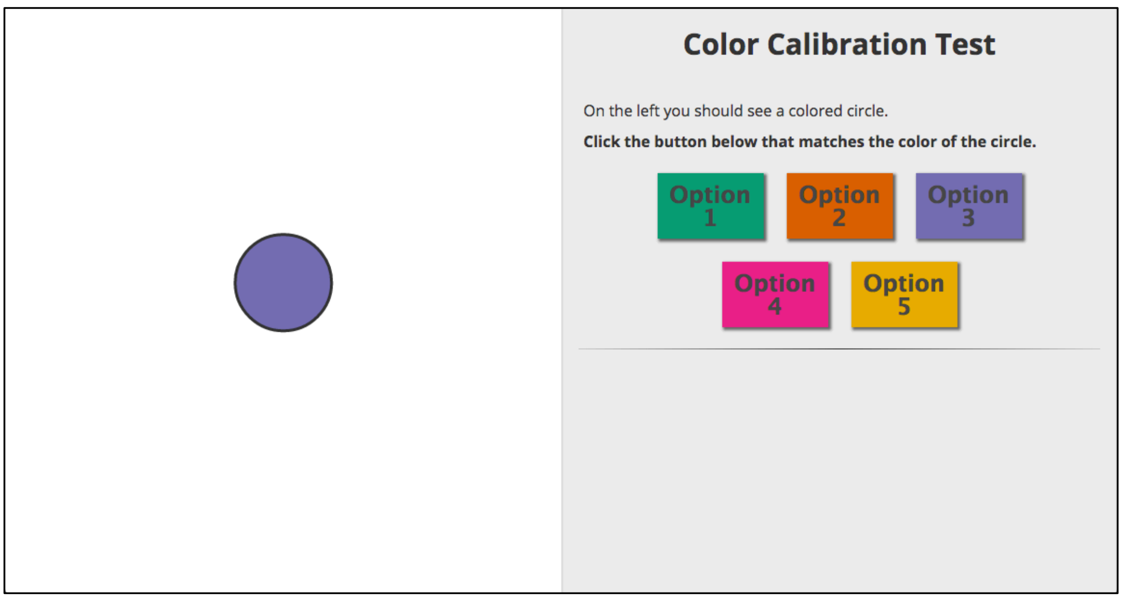
After passing the color-matching tests, each subject was asked to take a tutorial before the actual game would begin. In the tutorial, each subject separately interacted with three dummy players in a one-minute practice game. After the practice game, subjects were assessed for their comprehension of the game rules and payment structure using three multiple-choice questions each with two options. If they failed to select the correct answer in any of the questions, they were dropped from the game. At 690 seconds after the tutorial beginning, a "Ready" button became visible simultaneously to all the subjects who completed the tutorial and passed the comprehension tests. The real games started 30 seconds after the "Ready" button showed up. If subjects did not click the button before the game started, they were dropped. The game required an exact number of subjects (20 for only-human sessions and 17 for bots-treated sessions). When the subjects who successfully clicked the button were more than the required number, surplus subjects, who were randomly selected, were dropped from the game. When the number of qualified subjects was less than the required number, the game did not start.

Each session lasted for a maximum of five minutes. If the players reached a global solution within five minutes, the session was finished at that point. After the game, each subject was asked about his or her satisfaction with behaviors of him- or herself, their neighbors, and unseen others with a five-level rating system (very satisfied, satisfied, neither, dissatisfied, and very dissatisfied). The exact questions asked were: "How satisfied were you with your actions?" "How satisfied were you with the actions of your neighbors you were connected with?" and "How satisfied were you with the actions of other players you could not see?"

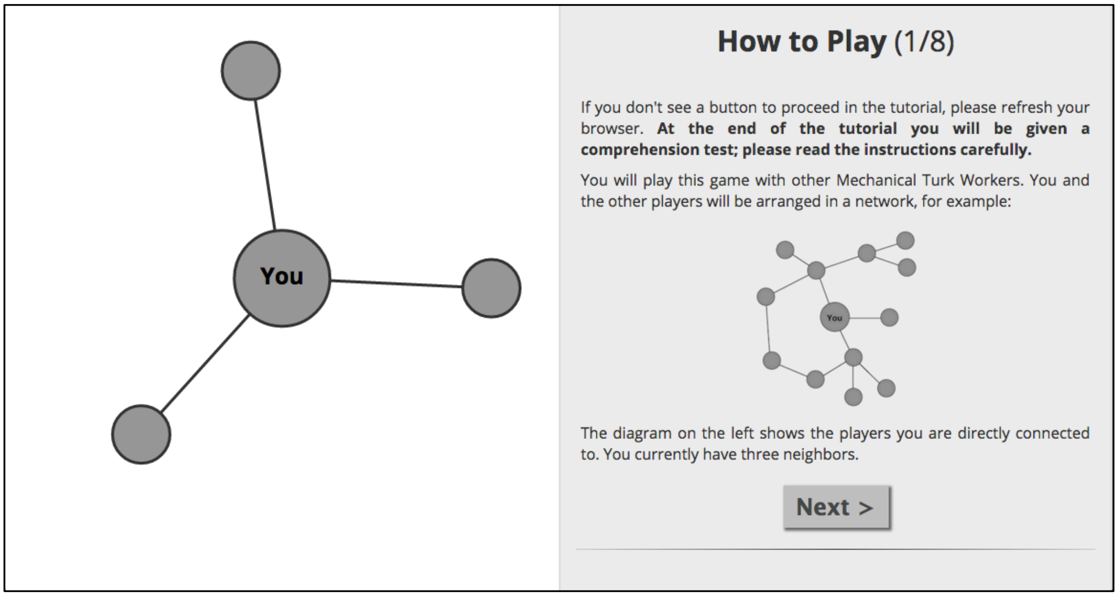
Except for the control group sessions, the networks had 3 bots in addition to 17 human subjects. These bots were allocated to node positions based on a pre-set network degree preference ("location"). In the game, they were controlled programmatically with a simple, greedy algorithm incorporating a random element; we drew a random number from a uniform distribution between 0.0 and 1.0; if the random number was less than a preset threshold ("behavioral noise"), the bot picked a color among the three color options at random; otherwise, it behaved based on the colors of its neighbors; if the bot's current color was not the least common among its neighbors, it changed to the least common color; otherwise, it maintained the current color. Subjects were not informed that they were playing with bots (except for the additional treatment of making bots visible – see Section 2.4).

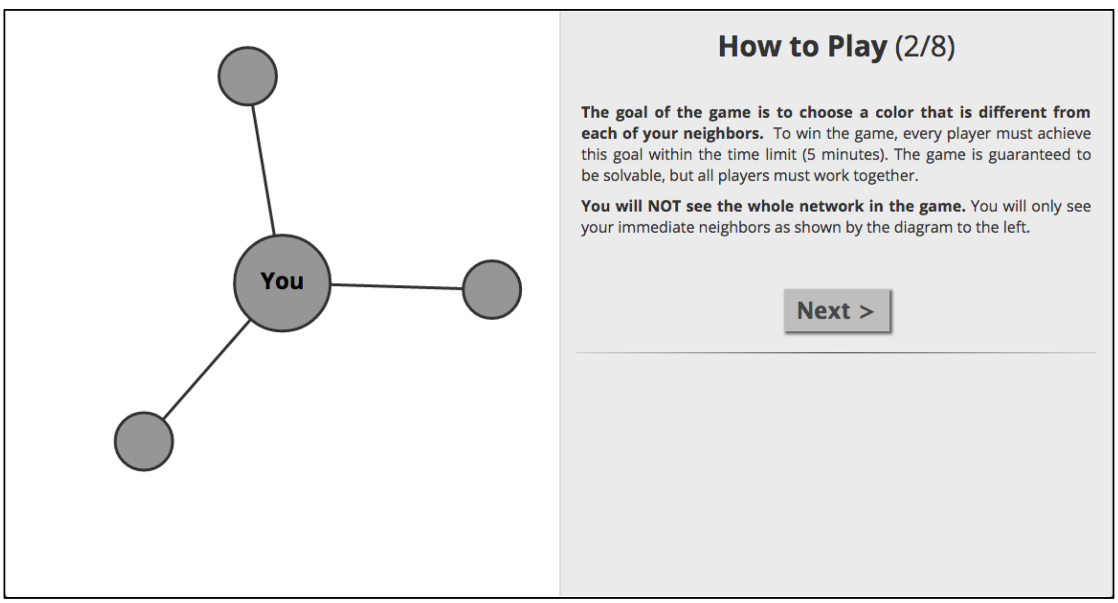
1.3 Instructions / Tutorial

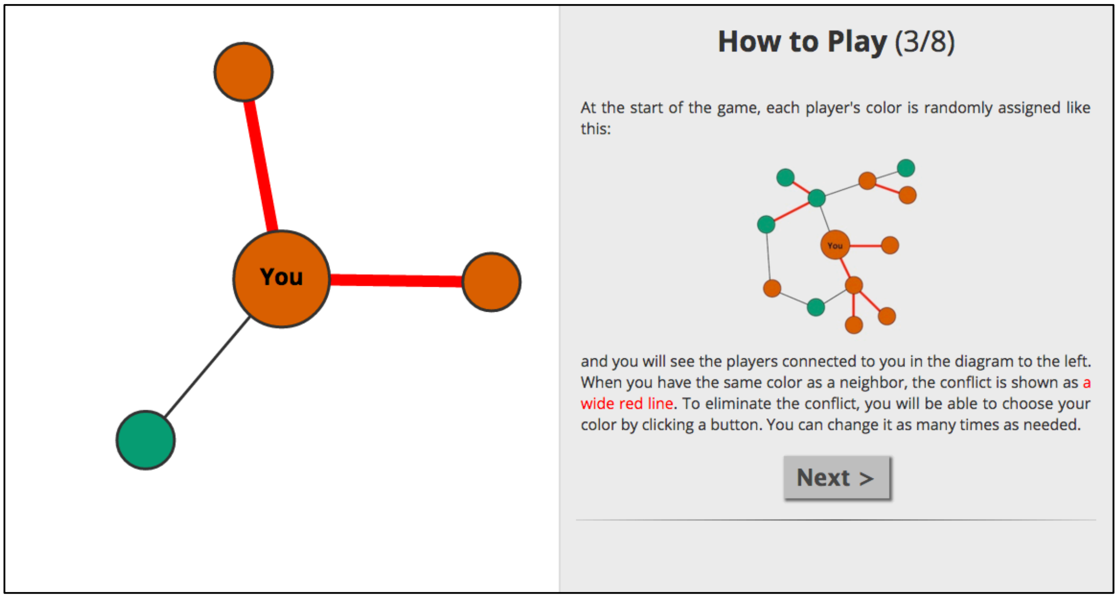
Below are screenshots for the initial description of the tutorial and the confirmation tests. We also show some sample screenshots of the real game.

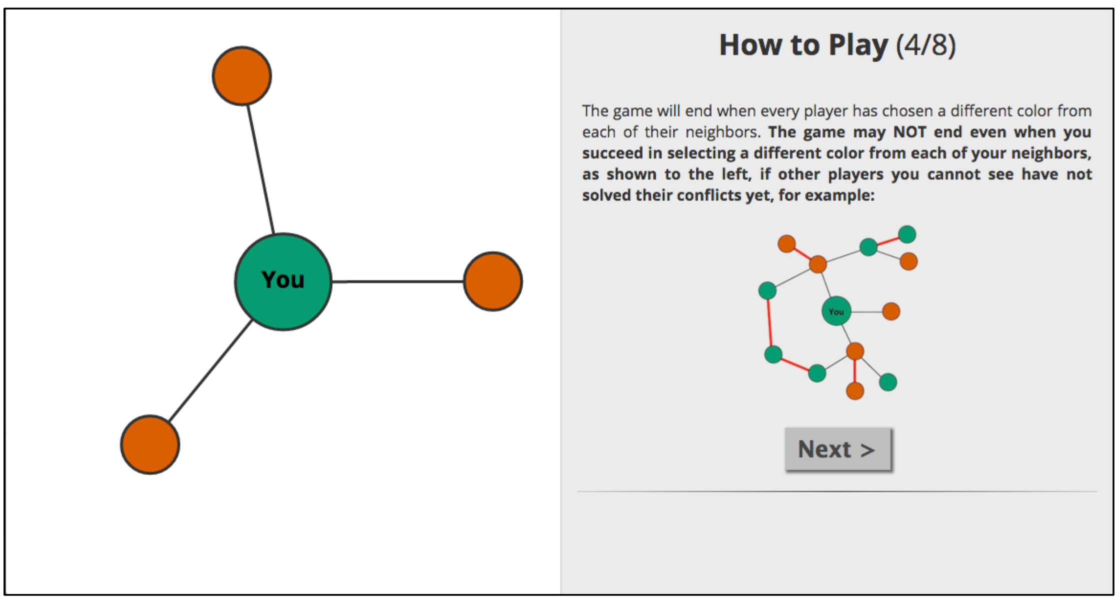


doi:10.1038/nature22332

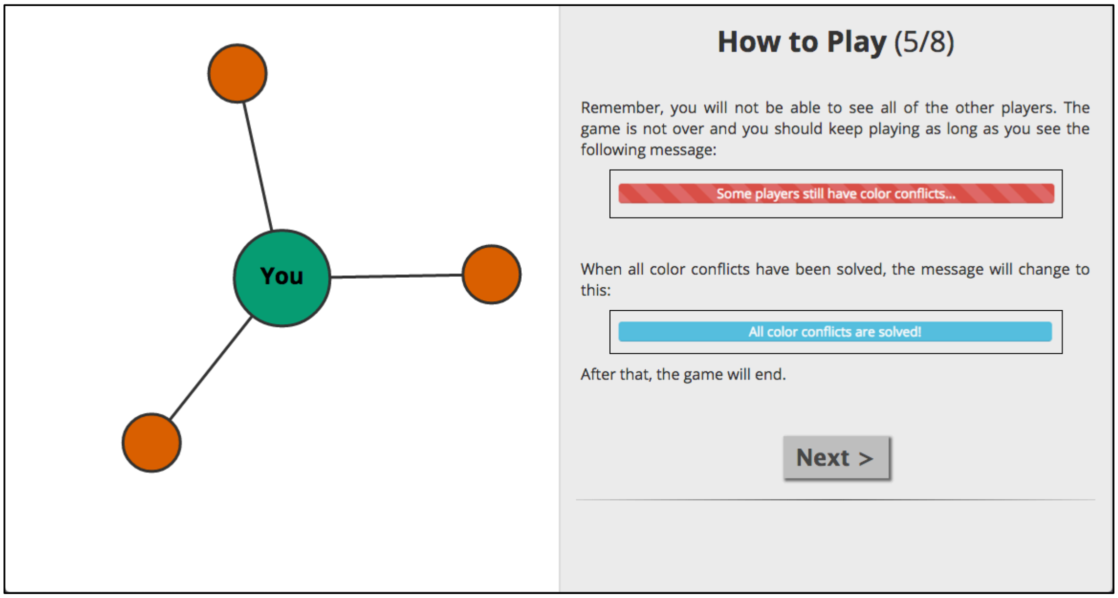


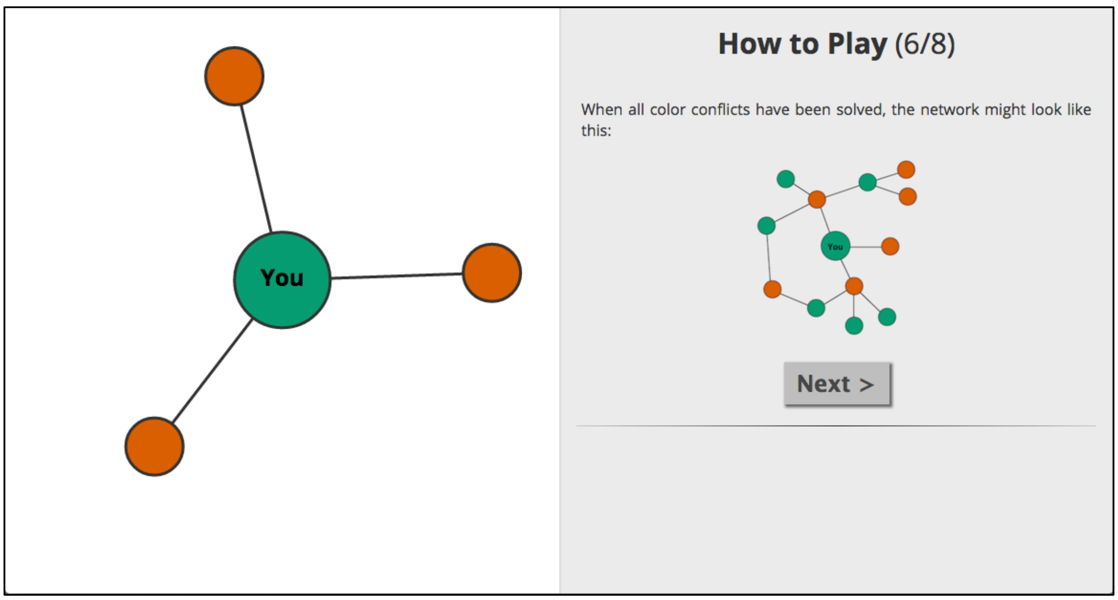


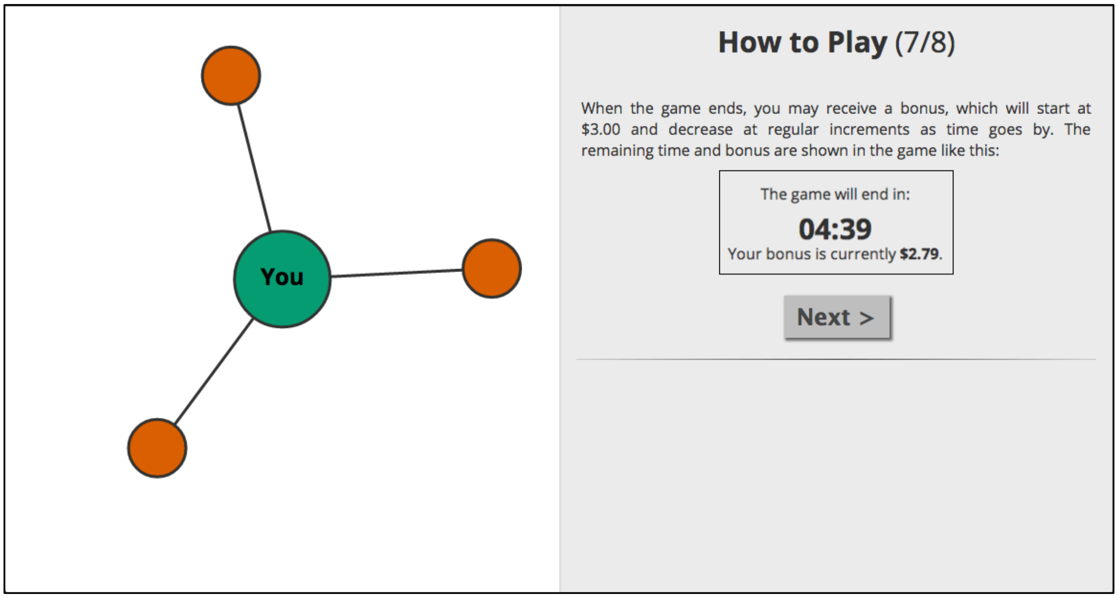

You
How to Play (3/8)
At the start of the game, each player's color is randomly assigned like this:
You
and you will see the players connected to you in the diagram to the left. When you have the same color as a neighbor, the conflict is shown as a wide red line. To eliminate the conflict, you will be able to choose your color by clicking a button. You can change it as many times as needed.
Next >

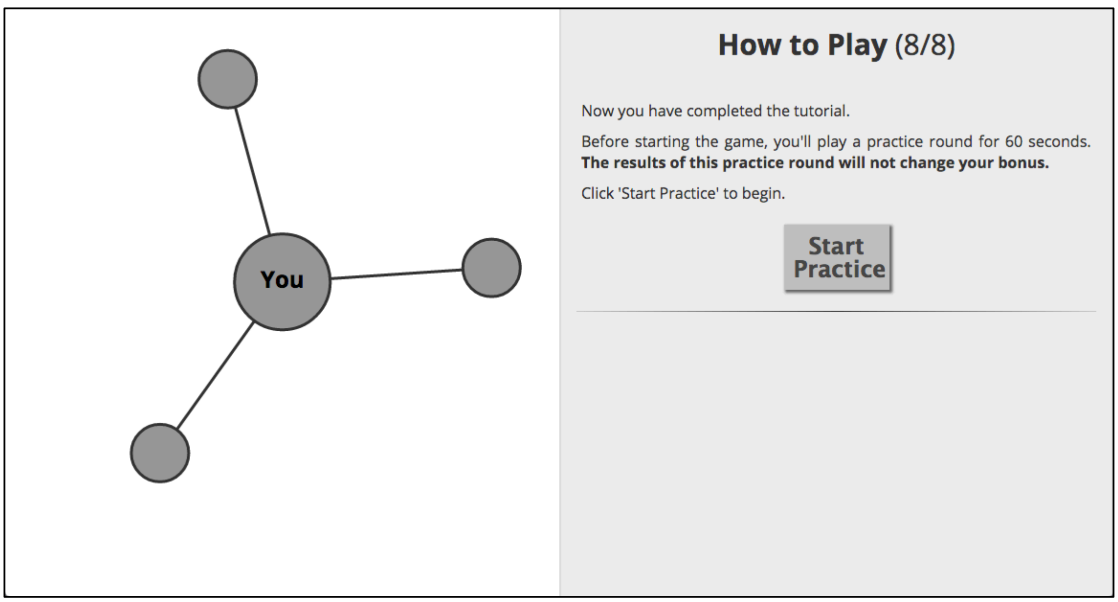

You
How to Play (4/8)
The game will end when every player has chosen a different color from each of their neighbors. The game may NOT end even when you succeed in selecting a different color from each of your neighbors, as shown to the left, if other players you cannot see have not solved their conflicts yet, for example:
You
Next >

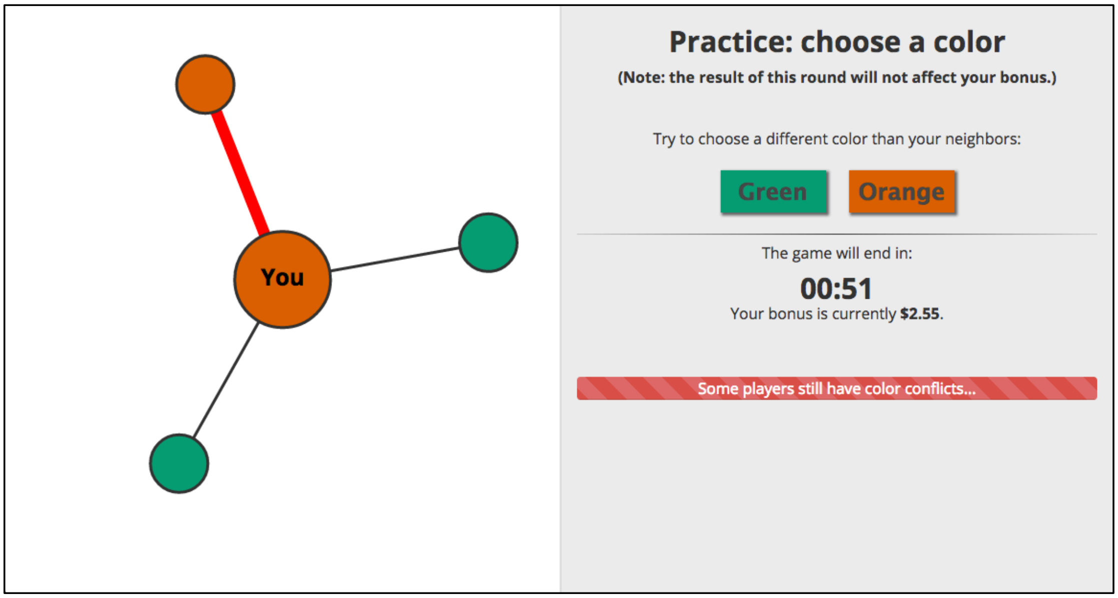
doi:10.1038/nature22332

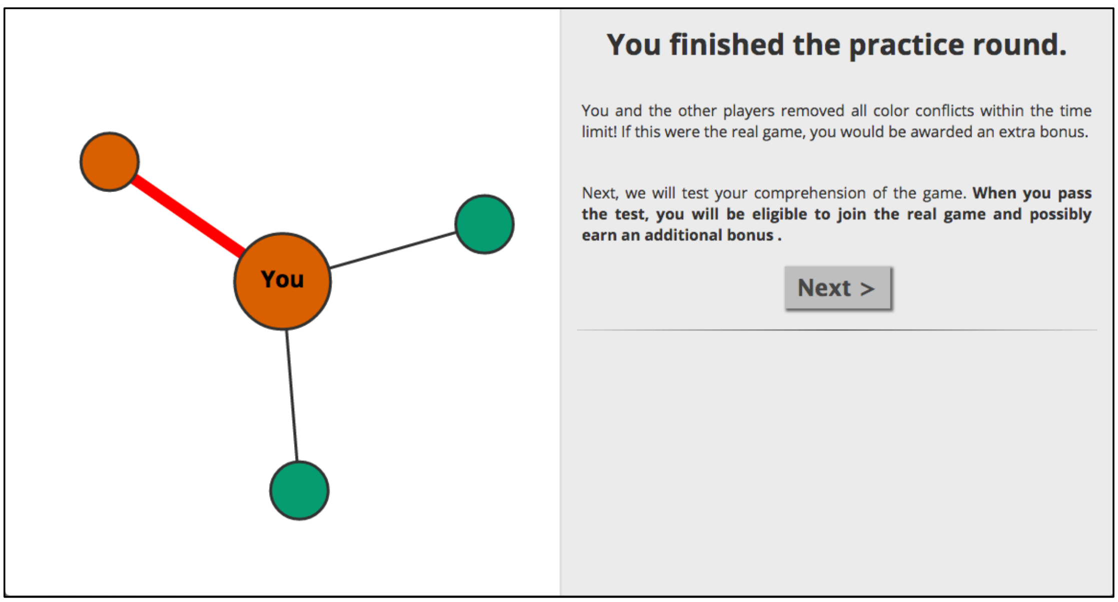


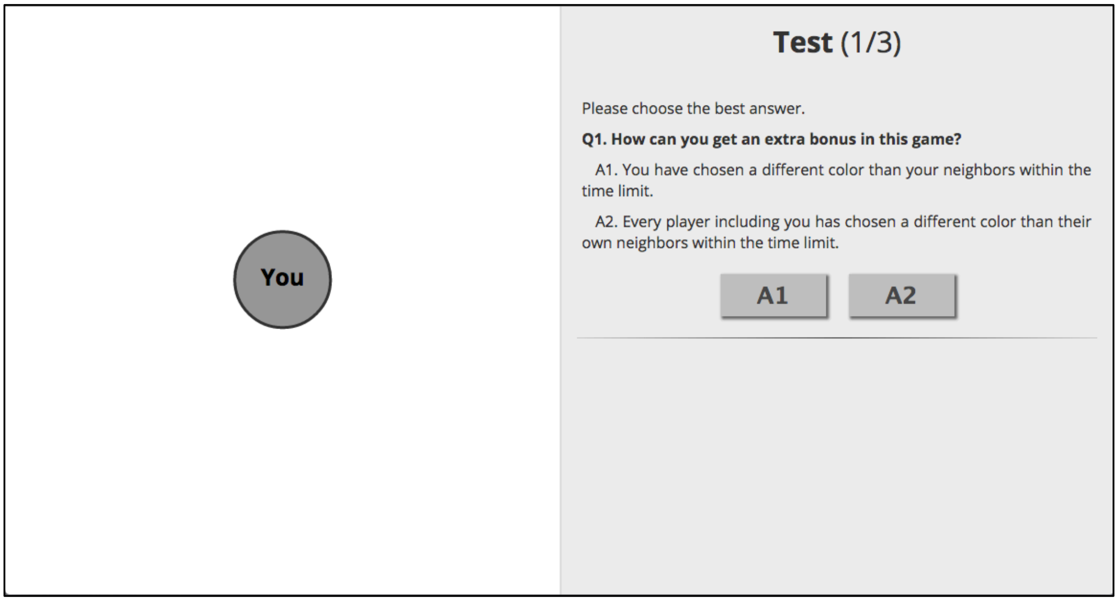


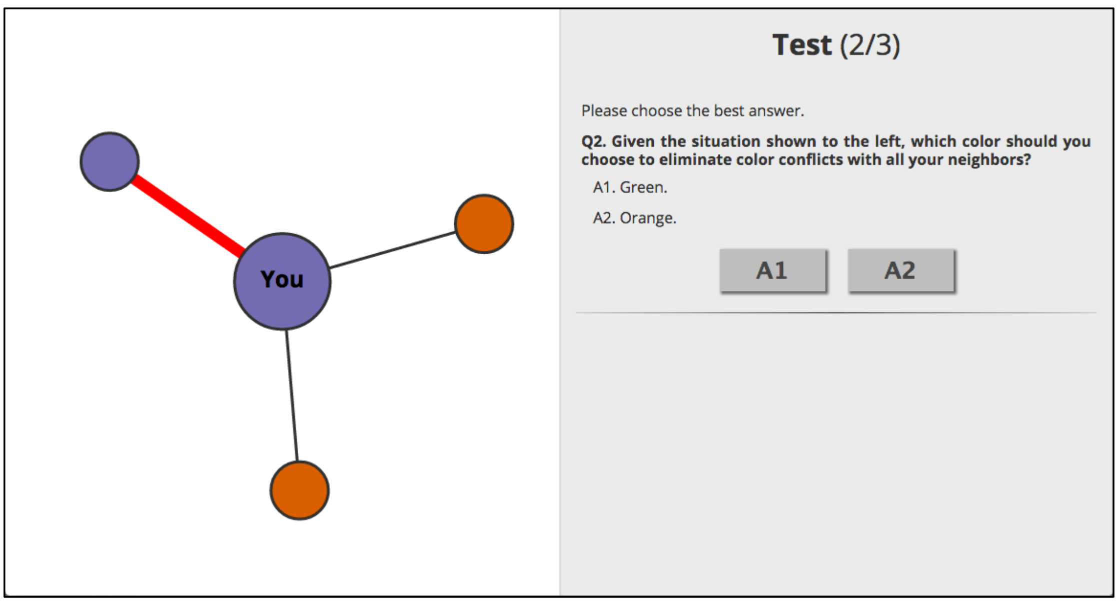

You
How to Play (7/8)
When the game ends, you may receive a bonus, which will start at $3.00 and decrease at regular increments as time goes by. The remaining time and bonus are shown in the game like this:
The game will end in:
04:39
Your bonus is currently $2.79.
Next >


You
How to Play (8/8)
Now you have completed the tutorial.
Before starting the game, you'll play a practice round for 60 seconds.
The results of this practice round will not change your bonus.
Click 'Start Practice' to begin.
Start Practice

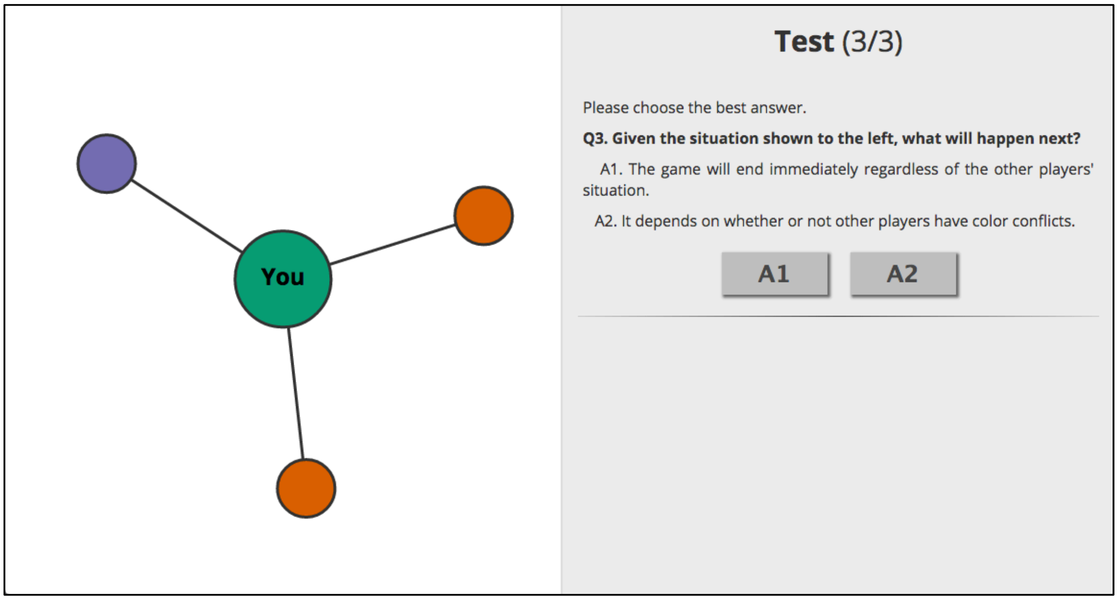

You
Practice: choose a color
(Note: the result of this round will not affect your bonus.)
Try to choose a different color than your neighbors:
Green
Orange
The game will end in:
00:51
Your bonus is currently $2.55.
Some players still have color conflicts...


You
You finished the practice round.
You and the other players removed all color conflicts within the time limit! If this were the real game, you would be awarded an extra bonus.
Next, we will test your comprehension of the game. When you pass the test, you will be eligible to join the real game and possibly earn an additional bonus .
Next >


You
Test (1/3)
Please choose the best answer.
Q1. How can you get an extra bonus in this game?
A1. You have chosen a different color than your neighbors within the time limit.
A2. Every player including you has chosen a different color than their own neighbors within the time limit.
A1
A2

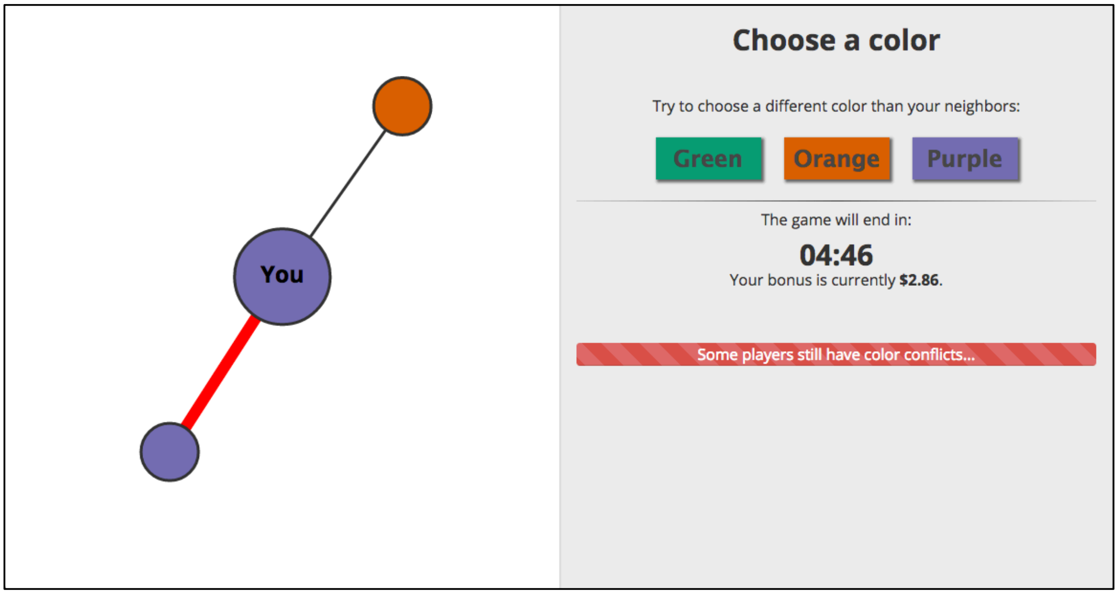

You
Test (2/3)
Please choose the best answer.
Q2. Given the situation shown to the left, which color should you choose to eliminate color conflicts with all your neighbors?
A1. Green.
A2. Orange.
A1
A2

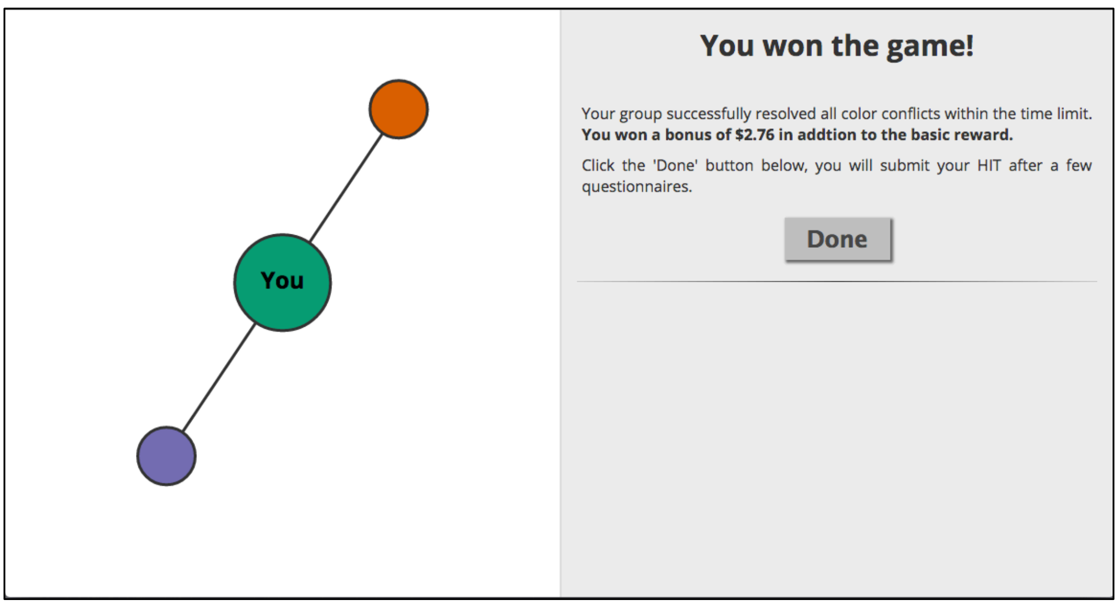
doi:10.1038/nature22332



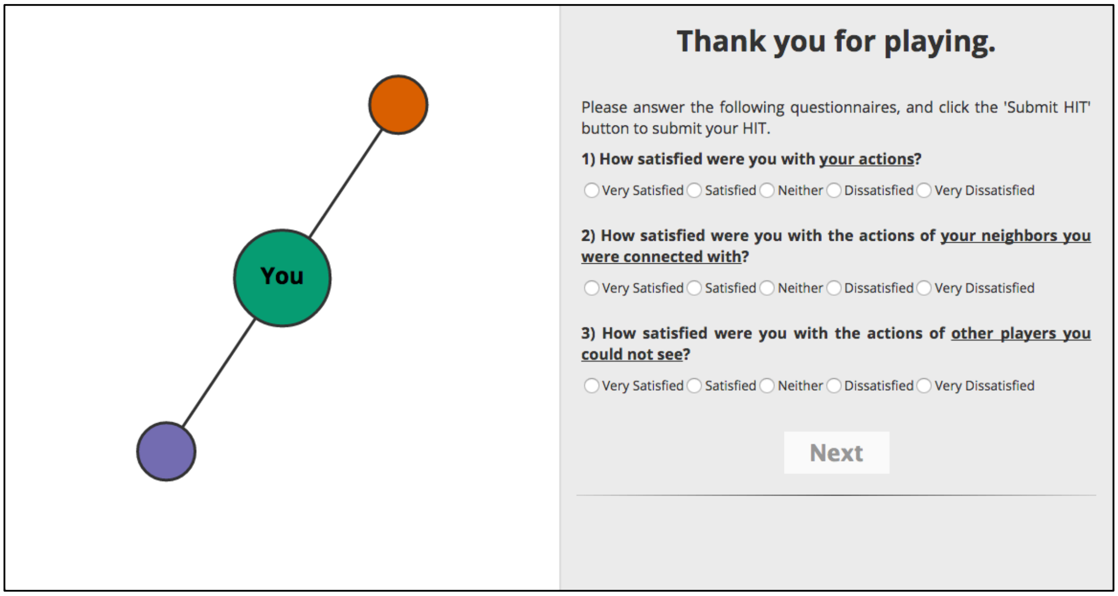

You
Please wait...
You are now ready to join the game. Please wait for the other players to complete the tutorial steps.
Please do not leave your computer. When the timer elapses, click the "Ready" button to begin.
Ready

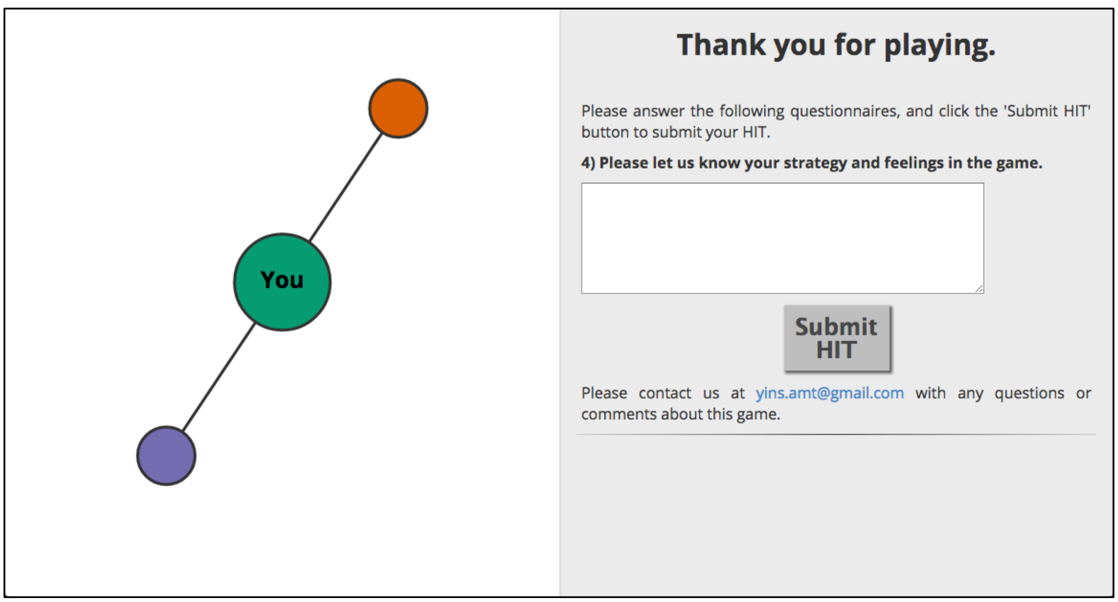

You
Please wait...
You are now ready to join the game. Please wait for the other players to complete the tutorial steps.
Please do not leave your computer. When the timer elapses, click the "Ready" button to begin.
Please wait... the game will start within 30 seconds.


You
Choose a color
Try to choose a different color than your neighbors:
Green
Orange
Purple
The game will end in:
04:46
Your bonus is currently $2.86.
Some players still have color conflicts...


You
You won the game!
Your group successfully resolved all color conflicts within the time limit.
You won a bonus of $2.76 in addtion to the basic reward.
Click the 'Done' button below, you will submit your HIT after a few questionnaires.
Done

doi:10.1038/nature22332





2. Statistical analysis

All analyses were performed using R version 3.1.2.

2.1 Analysis of game solvability with autonomous agents

Given the multiple comparisons here, before performing pairwise comparisons of the treated groups with the control group (as shown in **Fig. 2**), we performed a log-rank test of the null hypothesis that all the survival curves are identical; that hypothesis was rejected ($P = 0.024$), indicating that at least two of the survival curves are different from each other. We confirmed the robustness of this analysis using other statistical tests (other than the aforementioned log-rank test), including a Cox regression model incorporating the intrinsic difficulty of network structure (the logarithm of number of solutions sets – the chromatic polynomial of the graph) (**Table S2**).

Then, we implemented similar statistical tests (**Table S2**) and show a significant pairwise improvement, compared to control, only for the sessions having bots with 10% noise and central locations, compared to the sessions having only humans (**Fig. 2**).

To evaluate the difference in effectiveness between the various bot treatments, we analyzed the solution time of the sessions using Cox proportional hazard models (**Table S3**). The sessions that were not solved within 300 seconds were regarded as censored. Note that each network session has a distinct level of complexity with respect to finding a coloring solution because it is generated *de novo*; some networks turn out to be much easier to color than others. Thus, we controlled for the number of possible color combinations of the network (known as the "solution set" or "chromatic polynomial" in graph coloring) in the statistical analysis. **Table S3** shows that the bots affect the solution time only when they behave with 10% randomness and are placed in the central location in the network; moreover, when the network structure affords many solutions, the beneficial impact of bots decreases (**Fig. 3**).

We used mean convergence steps with linear probabilities as another measure of the complexity of solution space (in addition to the number of possible color combinations). The linear probability algorithm is to repeat the following sequence until it finds a global solution: a node is randomly selected and changes its color to one that is different from its random neighbor. This algorithm offers the advantage of allowing us to evaluate the landscape of the solution space starting from an arbitrary initial value. We calculated the mean convergence steps for 100 iterations of each experimental network with its initial colorings. As expected, we found a strong negative correlation between the logarithm of the solution set and the logarithm of mean convergence steps (correlated coefficient = -0.990; n=180)(**Extended Data Fig. 2**) and got similar results from the survival analysis (**Table S4**).

To assess the effect of the bots intervention, we compared the bots-treated sessions with those having three nodes with fixed (constant) colors in a configuration known in advance to be compatible with global solution (**Table S1**). There was no significant difference between the sessions with 10%-noise bots and the sessions with fixed colors ($P = 0.675$, log-rank test). We note that specifying a solvable set of nodes with fixed colors requires *prior, global* knowledge of the entire network structure and its solution space. For example, in simulations, if the three colors are randomly assigned in such preferential attachment networks, the network is unsolvable 62% of the time, so the foregoing comparison is actually conservative. Thus, the bots intervention, based on local decision-making alone, is equally as effective as a pre-calculated solution that (in typical circumstances) impractically would impose the heavy information requirement of prior global knowledge.

2.2 Analysis of errant behaviors in human subjects

We examined the impact of bots' behavioral noise on behaviors in human subjects using a statistical approach based on a generalized linear mixed model (GLMM) involving logistic regression (**Table S5A**). The dependent variable is the errant color-change rate evinced by the human players (i.e., choices that deviate from the simple, greedy strategy to minimize local conflicts). The model incorporated fixed effects for the behavioral noise of bots, the number of neighbors, the number of neighboring bots, the session length, and random effects for session. **Figures 4a-c** show estimates of errant color-change rates on the same network depending on bot's noise, using the coefficients in **Table S5A** with the average session length (=189.5 seconds).

As a reference for the bots-treated sessions, we estimated the effects of the number of neighbors and the session length on behaviors in the only-humans sessions, based on GLMM involving logistic regression (**Table S5B**). **Table S5B** shows that both of these independent variables are not statistically significant in only-human sessions. Using the estimated coefficients in **Table S5B**, we calculated the average errant rate in only-human sessions (= 0.041) with the average session length and average number of neighbors (=3.7).

As the dependent variable in the statistical analysis, we calculated the errant color-change rate (that is, color choices that seem to be sub-optimal locally) as the ratio of color selections producing *more* color conflicts divided by the number of opportunities to make such choices. The number of opportunities for the errant color selections was in turn obtained by dividing the accumulated time of locally optimized states (where the player has chosen a color to minimize local conflicts) by the player's decision-making cycle.

We approximated the players' decision-making time to be roughly 1.5 seconds, based on the behaviors of human subjects in the color matching tests in our preliminary experiments. We measured time from when a color in question showed up on screen until when a subject clicked a button. **Extended Data Fig. 1** shows the histogram of the response time of 142 subjects. Because most subjects clicked the correct button in 1.0 to 2.0 seconds, we used 1.5 seconds for the standard decision-making time not only in the estimation of player's errant color-change rate but also in the bot programming.

2.3 Analysis of satisfaction in human subjects

After each session was completed, subjects rated their satisfaction with the actions of their neighbors on a five-point scale: very satisfied, satisfied, neither, dissatisfied, and very dissatisfied (the specific question asked was: "How satisfied were you with the actions of your neighbors you were connected with?"). We analyzed the satisfaction level according to bots' behavioral noise and number of bots among a subject's neighbors while controlling for the number of neighbors and whether the game was solved, using a proportional odds logistic regression model. **Extended Data Fig. 4** shows the coefficients for the number of bots among neighbors, according to bots' behavioral noise. According to **Extended Data Fig. 4**, noisier bots are less likely to satisfy their neighbors. Although 10%-noise bots were the most likely to lead to a global solution, human subjects actually preferred to interact with 0%-noise bots. Behavioral noise in bots or individuals can improve collective performance of the entire social network, even though, at the same time, it might reduce the satisfaction of people around them.

2.4 Analysis of game solvability with visibility of autonomous agents

To further explore the beneficial effect of low levels of noise, we conducted a separate experiment involving a further 340 subjects (in addition to the 4,000 subjects in the core experiments), and examined the impact of making the bots visible. In addition to the basic setting used before (the bots in the "invisible" condition), the human players were informed that they were interacting with bots and which nodes were played by bots, by labeling the relevant nodes "B" in their local network diagram. Hence, in the visible condition, before the session began, the human players knew both the existence and the identity of bots in their local neighbors. That is, they could make a decision with knowledge that they had both bot neighbors and human neighbors, but they were not informed of how exactly the bots would behave (i.e., just as in the core experiments).

We tested the visible bots condition only with the bots having 10% noise and high degree, which we had established had a beneficial effect on group coordination in the invisible-bots condition (**Fig. 2 and 3**). We used the same exact network sets (i.e. the same randomly generated topology) as the sessions of invisible bots having 10% noise and high degree (*n*=20), and did pairwise statistical tests.

We find that making bots identifiable may slow the game solution, compared to identical circumstances where bots are not identified (**Extended Data Fig. 5**; mean time = 153.4 seconds for bots-visible sessions versus 103.1 seconds for the invisible-bots sessions). The difference, however, is not statistically significant (P = 0.435, log-rank test; P = 0.507, Wilcoxon signed-rank test, with paired data).

The human players had variable responses to having bots in their network neighborhood. One left a comment saying “I tried to work with the non-bots more so since I suspected that the bots knew what they were somewhat doing.” But another player seemed to have a different idea regarding the bots, saying, “At first I just tried to stay a different color, but then I realized I needed to continuously change it so the bots would be able to find a color that would satisfy conflicts between their other neighbors.”

Likewise, we find no significant difference in the accumulated time of unresolvable conflicts for each geodesic location in which the bots were placed (**Extended Data Fig. 6**). Therefore, the results show that, even when the bots’ identity is revealed to human players, the bots have the same effect in this experimental setting (with bots placed in the center, with low levels of noise).

doi:10.1038/nature22332

Table S1. Full experimental results. Solved sessions are sessions whose solution time is within 300.0 seconds.

Treatment		Only humans (control)	Random-zero noise	Random-small noise	Random-large noise	Central-zero noise	Central-small noise	Central-large noise	Peripheral-zero noise	Peripheral-small noise	Peripheral-large noise	Cenral-fixed color
Bots location		-	Random	Random	Random	High degree	High degree	High degree	Low degree	Low degree	Low degree	High degree
Bots noise		-	0%	10%	30%	0%	10%	30%	0%	10%	30%	-
# humans		20	17	17	17	17	17	17	17	17	17	17
# bots		0	3	3	3	3	3	3	3	3	3	3
# sessions		30	20	20	20	20	20	20	20	20	20	20
# solved sessions		20	9	11	10	12	17	10	10	13	14	18
% solved sessions		0.667	0.450	0.550	0.500	0.600	0.850	0.500	0.500	0.650	0.700	0.900
Solution time (s)	Median	232.4	300.0	269.1	297.3	170.6	103.1	298.1	267.2	159.3	70.6	133.1
	Q1	143.7	130.3	104.5	145.1	76.4	49.5	133.2	79.8	82.5	33.7	85.2
	Q3	300.0	300.0	300.0	300.0	300.0	170.1	300.0	300.0	300.0	300.0	240.5
	Actual data	8.9	24.9	14.9	32.9	9.1	10.8	35.5	11.2	27.1	20.8	13.1
		33.6	30.7	16.5	43.3	10.4	20.9	35.6	34.6	29.6	24.0	39.9
		35.1	37.2	27.4	60.7	16.9	23.8	46.9	40.3	53.5	33.0	53.0
		41.7	67.3	58.1	64.6	34.0	30.9	48.7	45.1	54.9	33.1	68.0
		83.7	129.2	74.1	89.9	69.7	40.4	60.4	72.0	71.0	33.2	73.3
		116.3	130.6	114.6	163.5	78.7	52.5	157.5	82.4	86.3	33.8	89.2
		129.5	139.1	128.0	173.0	99.4	58.5	175.0	125.1	90.1	36.0	95.6
		141.3	228.7	201.9	179.2	102.0	70.5	216.9	148.7	97.6	50.6	99.6
		150.9	255.8	255.1	181.9	110.5	78.0	225.7	156.0	103.1	62.3	116.3
		151.9	300.0	268.5	294.6	169.4	92.5	296.2	234.5	136.5	68.9	127.8
		158.5	300.0	269.8	300.0	171.9	113.8	300.0	300.0	182.2	72.3	138.4
		186.4	300.0	300.0	300.0	187.1	120.4	300.0	300.0	194.3	87.1	163.6
		222.6	300.0	300.0	300.0	300.0	126.4	300.0	300.0	220.6	243.4	189.4
		228.5	300.0	300.0	300.0	300.0	141.0	300.0	300.0	300.0	279.7	235.3
		231.2	300.0	300.0	300.0	300.0	147.4	300.0	300.0	300.0	300.0	238.4
		233.6	300.0	300.0	300.0	300.0	238.1	300.0	300.0	300.0	300.0	246.7
		246.1	300.0	300.0	300.0	300.0	272.7	300.0	300.0	300.0	300.0	254.1
		250.9	300.0	300.0	300.0	300.0	300.0	300.0	300.0	300.0	300.0	261.3
		273.3	300.0	300.0	300.0	300.0	300.0	300.0	300.0	300.0	300.0	300.0
		288.9	300.0	300.0	300.0	300.0	300.0	300.0	300.0	300.0	300.0	300.0
		300.0										
		300.0										
		300.0										
		300.0										
		300.0										
		300.0										
		300.0										
		300.0										
		300.0										
		300.0										

doi:10.1038/nature22332

Table S2. The results of various statistical tests regarding the survival curve comparisons. Bold fonts show significant coefficients at the 5% level. “Comprehensive test” here refers a test of the null hypothesis that all the survival curves are identical; that hypothesis was rejected regardless of statistical test used (top row), indicating that at least two of the survival curves are different from each other.

		Log-rank test	Wilcoxon test	Cox regression	Cox regression w\ control. Log (#solution sets)	Parametric (Weibull)
***p*-value with comprehensive test**		**0.024**	**0.041**	**0.044**	**< 0.001**	**0.026**
***p*-value with pairwise test**						
Control	Random-noise0%	0.257	0.460	0.282	0.654	0.270
Control	Random-noise10%	0.560	0.791	0.627	0.663	0.610
Control	Random-noise30%	0.362	0.515	0.408	0.983	0.405
Control	Center-noise0%	0.827	0.433	0.845	0.331	0.833
Control	Center-noise10%	**0.015**	**0.006**	**0.031**	**0.005**	**0.024**
Control	Center-noise30%	0.350	0.489	0.414	0.808	0.398
Control	Periphery-noise0%	0.517	0.869	0.540	0.866	0.534
Control	Periphery-noise10%	0.579	0.313	0.675	0.192	0.646
Control	Periphery-noise30%	0.285	0.079	0.230	0.099	0.231

doi:10.1038/nature22332

Table S3. The results of statistical analysis regarding solution time, by bot treatment and solution set of network (chromatic polynomial), estimated by Cox proportional hazard models (*n*=180). Bold fonts show significant coefficients and hazard ratios (exponentiated values of the coefficients) at the 5% level.

A. No interaction model

Variable		Coef.	Exp(Coef.)	95%CI	*p*-value
Bot's noise	0%	-	-	-	Ref.
	10%	**0.545**	**1.725**	**(1.076-2.766)**	**0.024**
	30%	0.124	1.132	(0.694-1.849)	0.619
Bot's location	Random	-	-	-	Ref.
	Center	0.392	1.479	(0.916-2.390)	0.109
	Periphery	0.252	1.286	(0.790-2.094)	0.312
Network	Solution set*	**0.582**	**1.789**	**(1.485-2.157)**	**< 0.001**

B. Full interaction model

Variable		Coef.	Exp(Coef.)	95%CI	*p*-value
Bot's noise	0%	-	-	-	Ref.
	10%	-3.262	0.038	(0.001-1.540)	0.084
	30%	1.190	3.289	(0.073-148.9)	0.541
Bot's location	Random	-	-	-	Ref.
	Center	-3.790	0.023	(0.000-1.803)	0.090
	Periphery	-2.144	0.117	(0.003-4.647)	0.254
Network	Solution set*	0.269	1.308	(0.784-2.183)	0.305
Interaction	10% : Center	**6.969**	**1063**	**(3.150-359000)**	**0.019**
	30% : Center	0.038	1.039	(0.002-670.3)	0.991
	10% : Periphery	4.586	98.09	(0.513-18770)	0.087
	30% : Periphery	0.794	2.213	(0.012-400.3)	0.765
	10% : Solution set*	**0.794**	**2.211**	**(1.028-4.757)**	**0.042**
	30% : Solution set*	-0.253	0.777	(0.319-1.888)	0.577
	Center : Solution set*	**0.943**	**2.567**	**(1.032-6.388)**	**0.043**
	Periphery : Solution set*	0.450	1.569	(0.762-3.272)	0.221
	10% : Center : Solution set*	**-1.476**	**0.229**	**(0.069-0.762)**	**0.016**
	30% : Center : Solution set*	-0.133	0.876	(0.221-3.476)	0.850
	10% : Periphery : Solution set*	-0.922	0.398	(0.138-1.143)	0.087
	30% : Periphery : Solution set*	-0.002	0.998	(0.331-3.008)	0.997

* Logarithmic value

Table S4. The results of statistical analysis regarding solution time, by bot treatment and mean convergence steps with linear probabilities, estimated by Cox proportional hazard models (*n*=180). Bold fonts show significant coefficients and hazard ratios (exponentiated values of the coefficients) at the 5% level. Note that the sign of coefficients in the full interaction model comes out the opposite of Table S2 because mean convergence steps, in contrast to solution set, has a negative impact on game solvability.

A. No interaction model

Variable		Coef.	Exp(Coef.)	95%CI	*p*-value
Bot's noise	0%	-	-	-	Ref.
	10%	**0.566**	**1.762**	**(1.098-2.828)**	**0.019**
	30%	0.140	1.150	(0.704-1.879)	0.577
Bot's location	Random	-	-	-	Ref.
	Center	0.397	1.487	(0.921-2.401)	0.105
	Periphery	0.236	1.266	(0.777-2.063)	0.343
Network	Convergence steps*	**-0.643**	**0.526**	**(0.432-0.640)**	**< 0.001**

B. Full interaction model

Variable		Coef.	Exp(Coef.)	95%CI	*p*-value
Bot's noise	0%	-	-	-	Ref.
	10%	**11.790**	**1.32E+05**	**(1.93E+00 - 9.07E+09)**	**0.038**
	30%	-1.670	1.88E-01	(3.84E-07 - 9.22E+04)	0.803
Bot's location	Random	-	-	-	Ref.
	Center	**13.380**	**6.47E+05**	**(2.11E+00 - 1.98E+11)**	**0.038**
	Periphery	6.352	5.73E+02	(1.76E-02 - 1.87E+07)	0.231
Network	Convergence steps*	-0.286	7.51E-01	(4.30E-01 - 1.31E+00)	0.315
Interaction	10% : Center	**-20.250**	**1.60E-09**	**(6.76E-17 - 3.79E-02)**	**0.019**
	30% : Center	-1.853	1.57E-01	(3.47E-10 - 7.09E+07)	0.855
	10% : Periphery	-12.390	4.18E-06	(1.21E-12 - 1.44E+01)	0.107
	30% : Periphery	-0.593	5.53E-01	(7.13E-08 - 4.29E+06)	0.942
	10% : Convergence steps*	**-0.837**	**4.33E-01**	**(1.90E-01 - 9.85E-01)**	**0.046**
	30% : Convergence steps*	0.131	1.14E+00	(4.46E-01 - 2.92E+00)	0.785
	Center : Convergence steps*	**-0.940**	**3.91E-01**	**(1.54E-01 - 9.93E-01)**	**0.048**
	Periphery : Convergence steps*	-0.475	6.22E-01	(2.85E-01 - 1.36E+00)	0.233
	10% : Center : Convergence steps*	**1.498**	**4.47E+00**	**(1.27E+00 - 1.57E+01)**	**0.020**
	30% : Center : Convergence steps*	0.083	1.09E+00	(2.50E-01 - 4.71E+00)	0.912
	10% : Periphery : Convergence steps*	0.938	2.56E+00	(8.30E-01 - 7.86E+00)	0.102
	30% : Periphery : Convergence steps*	0.098	1.10E+00	(3.44E-01 - 3.54E+00)	0.869

* Logarithmic value

doi:10.1038/nature22332

Table S5. The results of the statistical analysis regarding the errant color change rate of human subjects, by noise level of bot behavior, number of bots in neighbors, number of neighbors, and session length, estimated by GLMM with a logistic regression, incorporating random effects for session.

A. Human subjects in bot-treated sessions (*n*=3,060)

Variable	Coef.	Std. Error	*p*-value
Intercept	-3.362	0.095	< 0.001
Bot's noise 0%	-	-	Ref.
10%	-0.014	0.094	0.879
30%	0.337	0.093	< 0.001
#Neighboring bots	-0.018	0.024	0.443
#Neighbors	0.100	0.007	< 0.001
10% : # Neighboring bots	0.203	0.035	< 0.001
30% : # Neighboring bots	0.148	0.034	< 0.001
10% : #Neighbors	-0.017	0.010	0.081
30% : #Neighbors	-0.067	0.010	< 0.001
Session length	-0.001	0.000	< 0.001

B. Human subjects in only-human sessions (*n*=600)

Variable	Coef.	Std. Error	*p*-value
Intercept	-3.122	0.207	< 0.001
#Neighbors	0.002	0.007	0.767
Session length	0.000	0.001	0.846

doi:10.1038/nature22332

3. Video for network dynamics illustration

To illustrate the dynamics of social coordination on the networked coloring game, we created a video file of a selected session **(Video. S1)**.

- Please refer to the separately submitted video file -

Video Legend

Video, S1. An example of the color coordination game with all human subjects. Each node's color shows the color choice made by assigned human subjects at the time. Wide red edges show that the connected players are in the same color ("color conflicts"). Figure 1a shows the structure snapshots of the session.

4. Code and data availability

The programming codes as well as the experimental data are stored and available upon request at Yale Institute for Network Science Data Archive.

References

1. J. J. Horton, D. G. Rand, R. J. Zeckhauser, The online laboratory: conducting experiments in a real labor market. *Exp Econ* **14**, 399–425 (2011).
2. M. Buhrmester, T. Kwang, S. D. Gosling, Amazon's Mechanical Turk: a new source of inexpensive, yet high-quality, data? *Perspectives on Psychological Science* **6**, 3–5 (2011).
3. W. Mason, S. Suri, Conducting behavioral research on Amazon's Mechanical Turk. *Behav Res* **44**, 1–23 (2011).
4. G. Paolacci, J. Chandler, P. G. Iperirotis, Running experiments on Amazon Mechanical Turk. *Judgement and Decision Making* **5**, 1–9 (2010).
5. D. G. Rand, The promise of Mechanical Turk How online labor markets can help theorists run behavioral experiments. *Journal of Theoretical Biology* **299**, 172–179 (2012).
6. M. Cinyabuguma, T. Page, L. Putterman L, Cooperation under the threat of expulsion in a public goods experiment. *Journal of Public Economics* **89**, 1421–1435 (2005).