Supplementary Information
Creativity in temporal social networks: How divergent thinking is impacted by one's choice of peers

Raiyan Abdul Baten[1], Daryl Bagley[2], Ashely Tenesaca[2], Famous Clark[2], James P. Bagrow[3], Gourab Ghoshal[4], Ehsan Hoque[2,*]
[1]Department of Electrical and Computer Engineering, University of Rochester, NY, USA
[2]Department of Computer Science, University of Rochester, NY, USA
[3]Department of Mathematics & Statistics, University of Vermont, VT, USA
[4]Department of Physics and Astronomy, University of Rochester, NY, USA
*mehoque@cs.rochester.edu

Published in the Journal of the Royal Society Interface, September 2020

Contents

List of Figures

List of Tables

1 Demographic information

Among the 288 participants we recruited from Amazon Mechanical Turk, 167 were male and 121 were female. Their ages ranged from 18 to 55+ (18y-24y: 30, 25y-34y: 129, 35y-44y: 81, 45y-54y: 23, 55y+: 25). The racial distribution was: White: 224, Asian: 15, Black or African American: 22, American Indian or Alaska Native: 15, other: 12. Among them, 15 participants belonged to Hispanic or Latino ethnicity.

2 Supplementary figures

Figures S1 through S7 present additional results from the analysis, as referred to from the main manuscript.

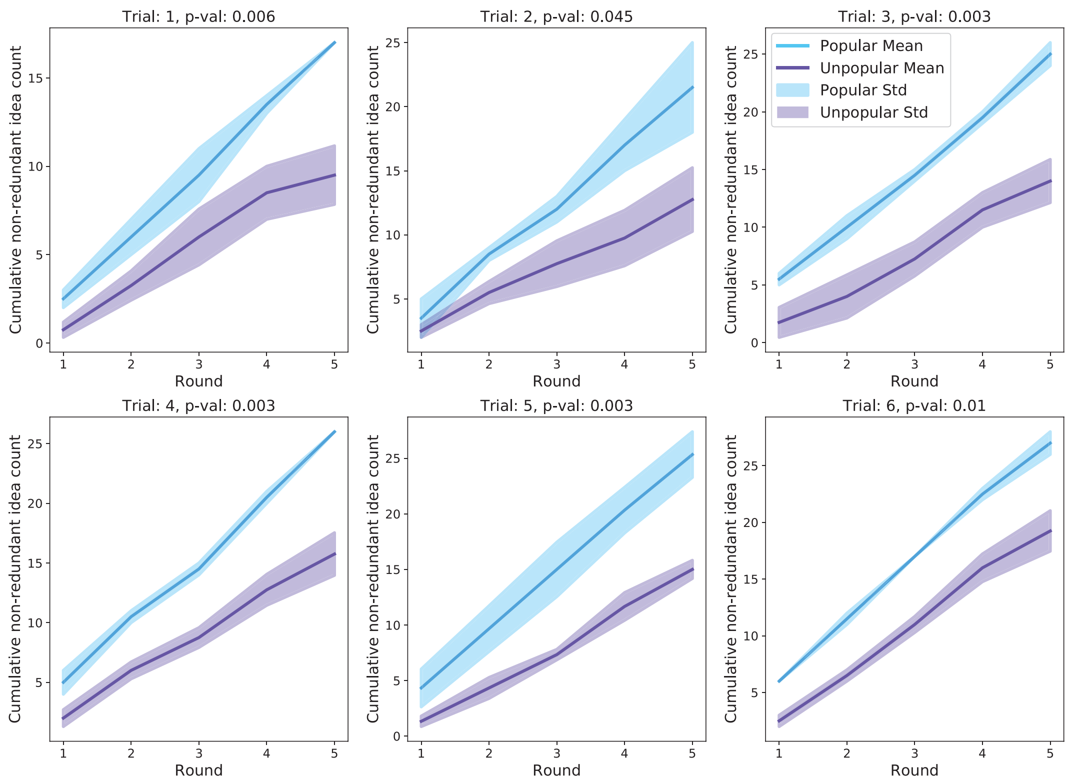


Figure S1: Trial-wise comparisons of cumulative non-redundant idea counts between popular and unpopular alters. 2-tailed tests show the popular alters (p) to have significantly higher cumulative counts over all rounds than unpopular alters (u) in all 6 trials, detailed as follows. Trial 1: $m_p = 17.0$, $m_u = 9.5$, $t(4) = 5.222$, $p = 0.0064$, 95% C.I. for $m_p - m_u = [4.0, 11.0]$; Trial 2: $m_p = 21.5$, $m_u = 12.8$, $t(4) = 2.879$, $p = 0.045$, 95% C.I. for $m_p - m_u = [2.1, 15.4]$; Trial 3: $m_p = 25.0$, $m_u = 14.0$, $t(4) = 6.351$, $p = 0.0031$, 95% C.I. for $m_p - m_u = [6.9, 15.1]$; Trial 4: $m_p = 26.0$, $m_u = 15.8$, $t(4) = 6.629$, $p = 0.0027$, 95% C.I. for $m_p - m_u = [6.5, 14.0]$; Trial 5: $m_p = 25.3$, $m_u = 15.0$, $t(4) = 6.609$, $p = 0.0027$, 95% C.I. for $m_p - m_u = [6.8, 13.9]$; Trial 6: $m_p = 27.0$, $m_u = 19.3$, $t(4) = 4.66$, $p = 0.0096$, 95% C.I. for $m_p - m_u = [3.8, 11.7]$.

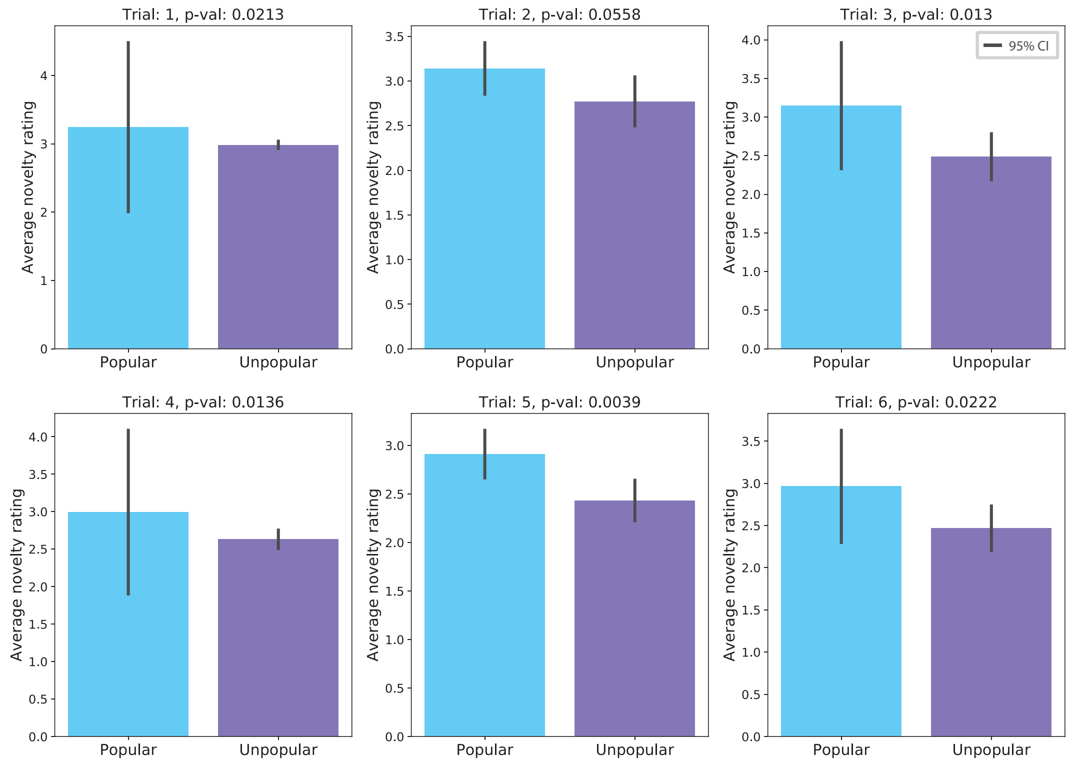


Figure S2: Trial-wise comparisons of average novelty ratings between popular and unpopular alters. 2-tailed tests show the popular alters (p) to have significantly higher average novelty ratings over all rounds than unpopular alters (u) in 5 out of 6 trials, detailed as follows. Trial 1: $m_p = 3.2$, $m_u = 3.0$, $t(4) = 3.675$, $p = 0.021$, 95% C.I. for $m_p - m_u = [0.1, 0.4]$; Trial 2: $m_p = 3.1$, $m_u = 2.8$, $t(4) = 2.67$, $p = 0.0558$, 95% C.I. for $m_p - m_u = [0.04, 0.7]$; Trial 3: $m_p = 3.2$, $m_u = 2.5$, $t(4) = 4.264$, $p = 0.013$, 95% C.I. for $m_p - m_u = [0.3, 1.0]$; Trial 4: $m_p = 3.0$, $m_u = 2.6$, $t(4) = 4.207$, $p = 0.0136$, 95% C.I. for $m_p - m_u = [0.2, 0.6]$; Trial 5: $m_p = 2.9$, $m_u = 2.4$, $t(4) = 5.98$, $p = 0.0039$, 95% C.I. for $m_p - m_u = [0.3, 0.7]$, Trial 6: $m_p = 3.0$, $m_u = 2.5$, $t(4) = 3.63$, $p = 0.022$, 95% C.I. for $m_p - m_u = [0.2, 0.8]$.

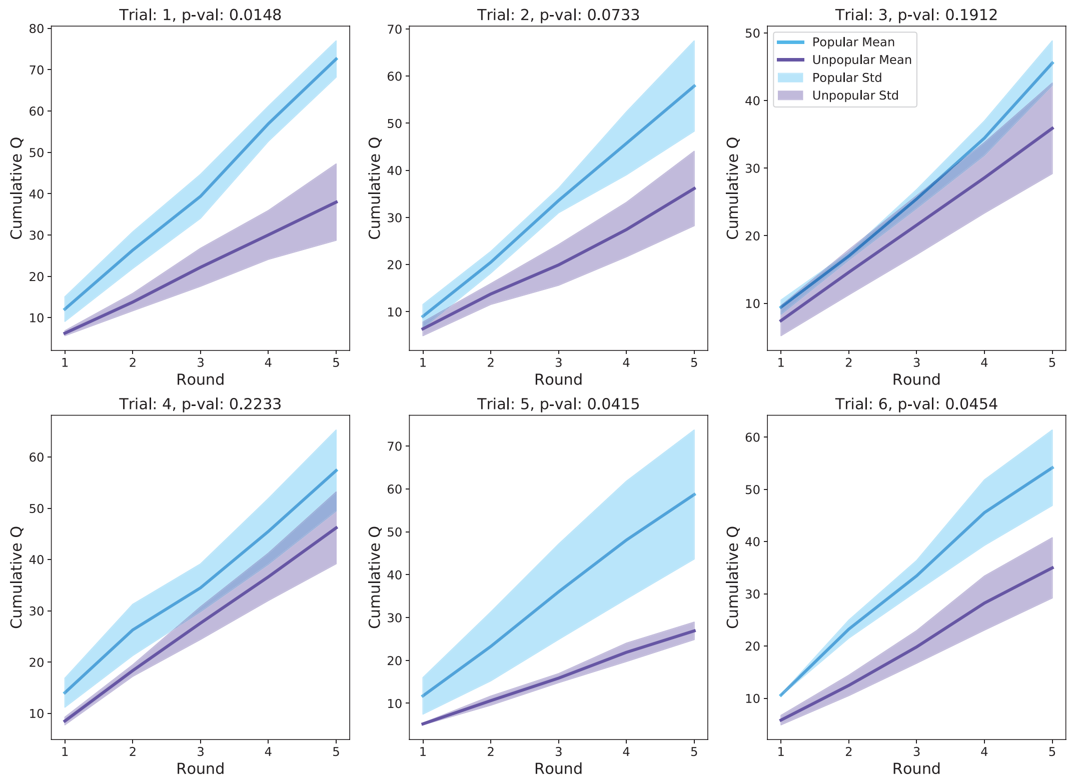


Figure S3: Trial-wise comparisons of cumulative Q between popular and unpopular alters. 2-tailed tests show the popular alters (p) to have significantly higher total Q scores over all rounds than unpopular alters (u) in 3 of the trials, detailed as follows. Trial 1: $m_p = 72.6$, $m_u = 38$, $t(4) = 4.102$, $p = 0.015$, 95% C.I. for $m_p - m_u = [14.7, 54.6]$; Trial 2: $m_p = 57.9$, $m_u = 36.1$, $t(4) = 2.41$, $p = 0.073$, 95% C.I. for $m_p - m_u = [1.7, 41.8]$; Trial 3: $m_p = 45.5$, $m_u = 35.9$, $t(4) = 1.572$, $p = 0.19$, 95% C.I. for $m_p - m_u = [-4.9, 24.2]$; Trial 4: $m_p = 57.4$, $m_u = 46.2$, $t(4) = 1.44$, $p = 0.223$, 95% C.I. for $m_p - m_u = [-6.2, 28.6]$; Trial 5: $m_p = 58.7$, $m_u = 26.9$, $t(4) = 2.962$, $p = 0.041$, 95% C.I. for $m_p - m_u = [7.5, 56.2]$; Trial 6: $m_p = 54.1$, $m_u = 35$, $t(4) = 2.872$, $p = 0.045$, 95% C.I. for $m_p - m_u = [4.3, 34.0]$.

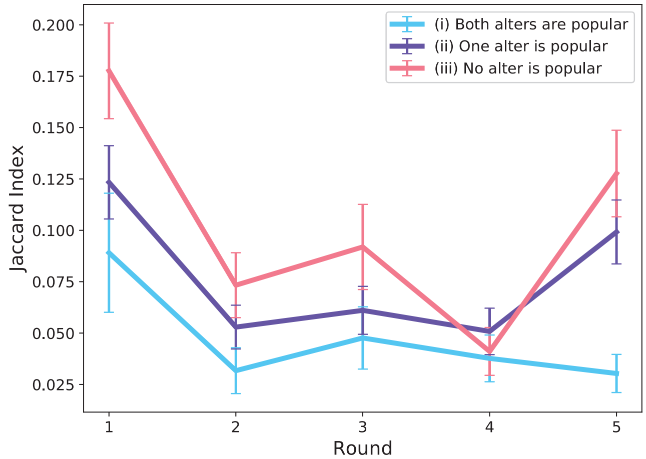


Figure S4: Average overlap (measured with Jaccard Index) between idea-sets of egos' turn-1 ideas and their alters in various rounds. Comparisons are made among three cases of egos: those with (i) both, (ii) only one and (iii) no alter(s) who are round-wise popular. As can be seen, egos who follow 2 popular alters consistently show a lower overlap compared to the other two cases. 2-tailed test results on the fifth round is given below. (i) vs (ii): $m_1 = 0.03$, $m_2 = 0.1$, $t(145) = -7.03$, Bonferroni-corrected $p < 0.001$, 95% C.I. for $m_1 - m_2 = [-0.088, -0.05]$; (i) vs (iii): $m_1 = 0.03$, $m_3 = 0.13$, $t(131) = -8.223$, Bonferroni-corrected $p < 0.001$, 95% C.I. for $m_1 - m_3 = [-0.121, -0.074]$.

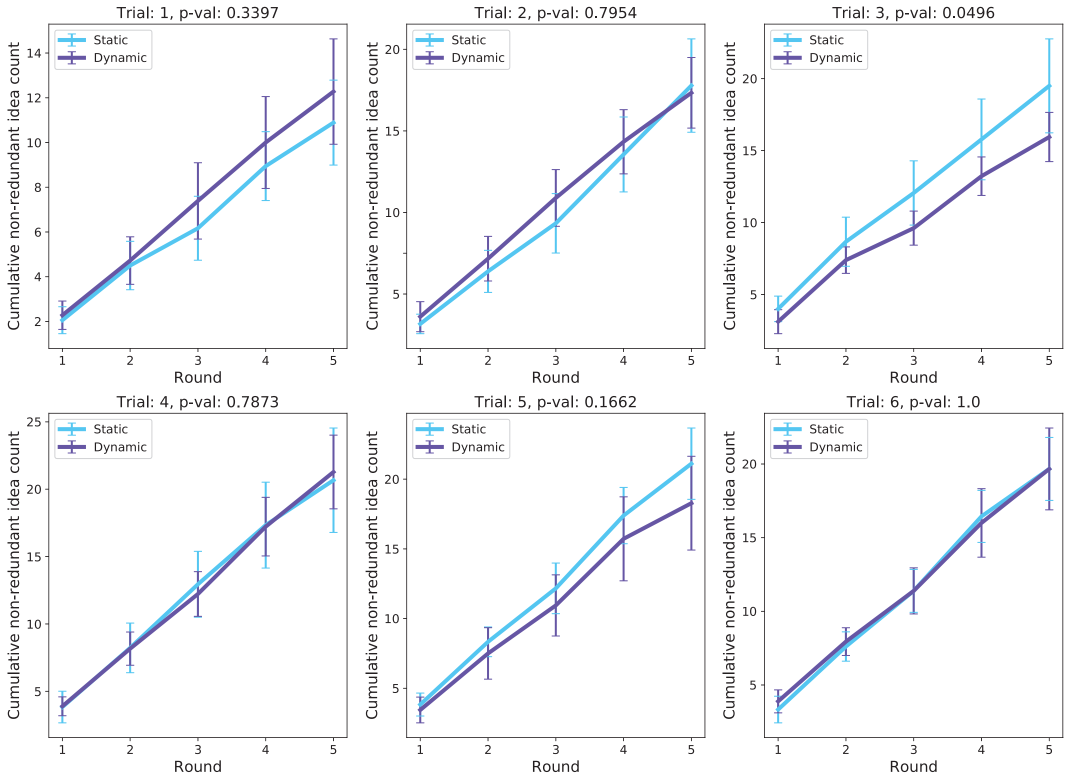


Figure S5: Trial-wise comparisons of non-redundant idea counts between static and dynamic egos. 2-tailed tests are performed between the cumulative counts of static (s) and dynamic (d) conditions at the end of all 5 rounds, as detailed in the following: Trial 1: $m_s = 10.89$, $m_d = 12.28$, $t(34) = -0.968$, $p = 0.3397$, 95% C.I. for $m_s - m_d = [-4.221, 1.444]$; Trial 2: $m_s = 17.78$, $m_d = 17.33$, $t(34) = 0.261$, $p = 0.7954$, 95% C.I. for $m_s - m_d = [-2.914, 3.803]$; Trial 3: $m_s = 19.5$, $m_d = 15.94$, $t(34) = 2.036$, $p = 0.0496$, 95% C.I. for $m_s - m_d = [0.106, 7.005]$; Trial 4: $m_s = 20.67$, $m_d = 21.28$, $t(34) = -0.272$, $p = 0.7873$, 95% C.I. for $m_s - m_d = [-5.050, 3.828]$; Trial 5: $m_s = 21.11$, $m_d = 18.28$, $t(34) = 1.415$, $p = 0.1662$, 95% C.I. for $m_s - m_d = [-1.122, 6.789]$; Trial 6: $m_s = 19.67$, $m_d = 19.67$, $t(34) = 0.0$, $p = 1.0$, 95% C.I. for $m_s - m_d = [-3.280, 3.280]$. Whiskers represent 95% C.I.

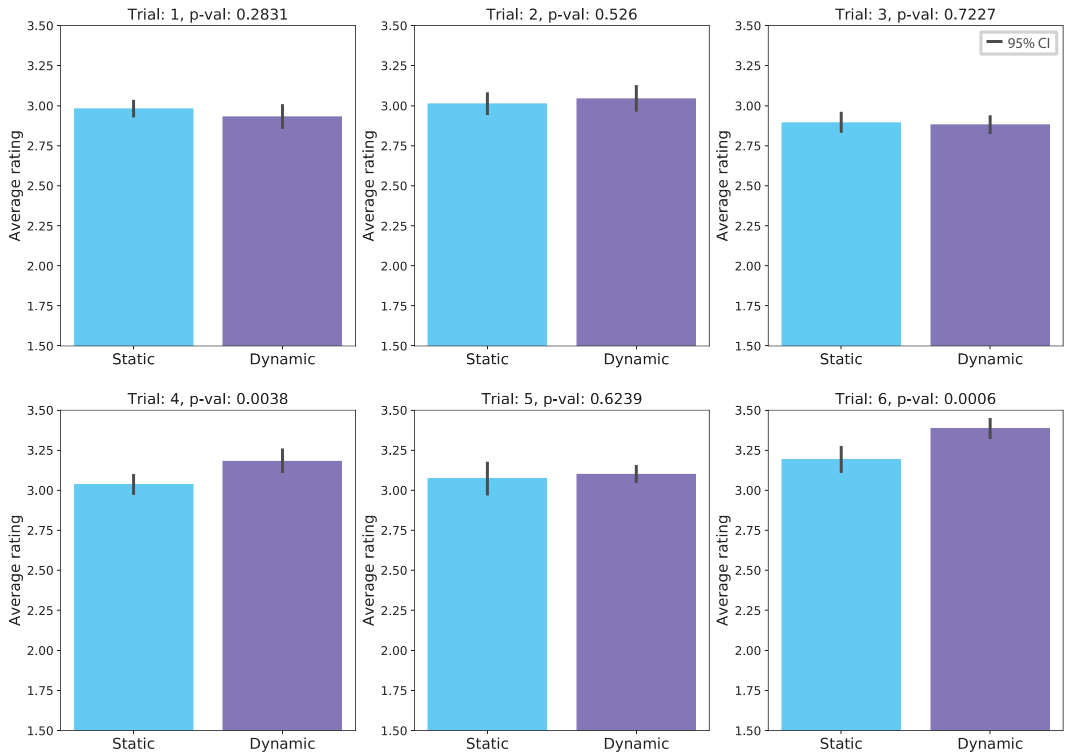


Figure S6: Trial-wise comparisons of average novelty ratings between dynamic and static egos. 2-tailed tests are performed between the average novelty ratings of dynamic (d) and static (s) conditions over all 5 rounds, as detailed in the following: Trial 1: $m_d = 2.93$, $m_s = 2.98$, $t(34) = -1.091$, $p = 0.283$, 95% C.I. for $m_d - m_S = [-0.137, 0.04]$; Trial 2: $m_d = 3.05$, $m_s = 3.01$, $t(34) = 0.641$, $p = 0.526$, 95% C.I. for $m_d - m_s = [-0.069, 0.136]$; Trial 3: $m_d = 2.88$, $m_s = 2.9$, $t(34) = -0.358$, $p = 0.723$, 95% C.I. for $m_d - m_s = [-0.097, 0.067]$; Trial 4: $m_d = 3.18$, $m_s = 3.04$, $t(34) = 3.107$, $p = 0.0038$, 95% C.I. for $m_d - m_s = [0.054, 0.241]$; Trial 5: $m_d = 3.1$, $m_s = 3.07$, $t(34) = 0.495$, $p = 0.624$, 95% C.I. for $m_d - m_s = [-0.084, 0.14]$; Trial 6: $m_d = 3.38$, $m_s = 3.19$, $t(34) = 3.801$, $p = 0.00057$, 95% C.I. for $m_d - m_s = [0.092, 0.292]$.

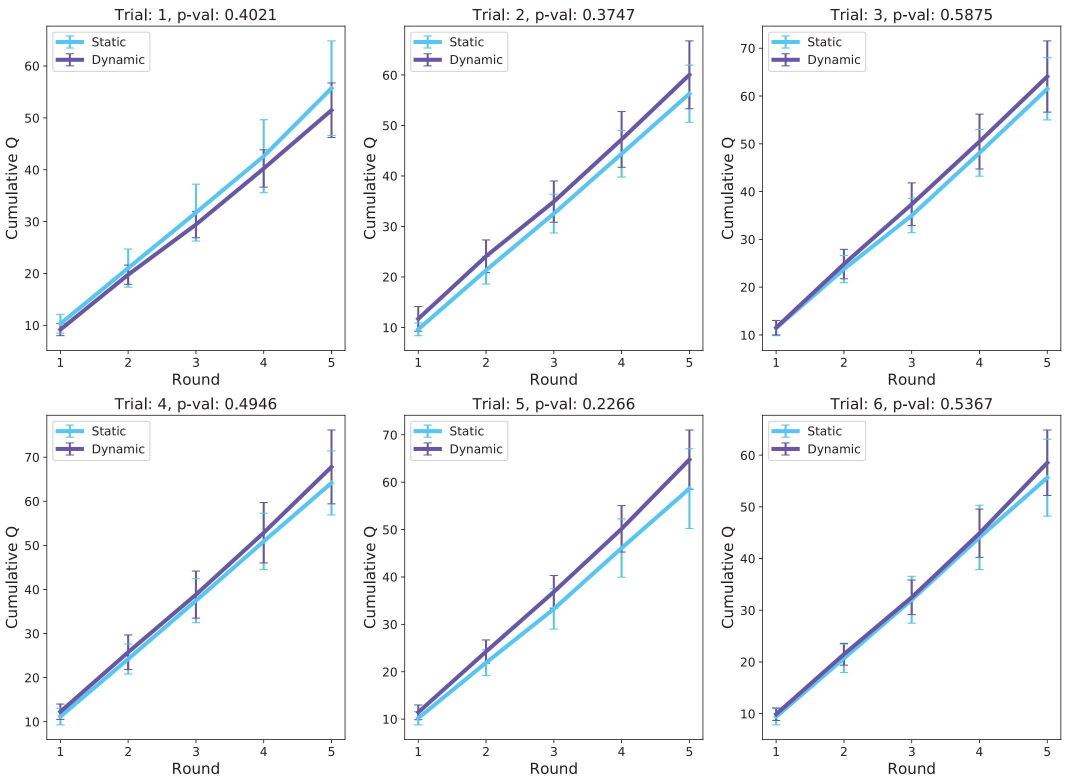
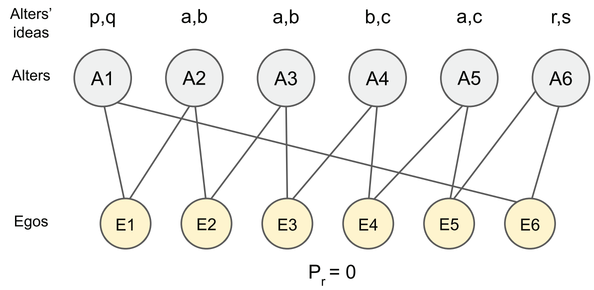
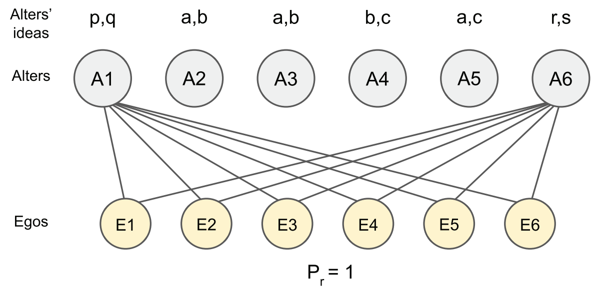


Figure S7: Trial-wise comparisons of creativity quotients between static and dynamic egos. 2-tailed tests results between the cumulative Q counts of the static (s) and dynamic (d) conditions at the end of all 5 rounds is given in the following: Trial 1: $m_s = 55.71$, $m_d = 51.47$, $t(34) = 0.848$, $p = 0.402$, 95% C.I. for $m_s - m_d = [-5.628, 14.104]$; Trial 2: $m_s = 56.28$, $m_d = 60.03$, $t(34) = -0.9$, $p = 0.375$, 95% C.I. for $m_s - m_d = [-11.976, 4.481]$; Trial 3: $m_s = 61.52$, $m_d = 64.08$, $t(34) = -0.548$, $p = 0.588$, 95% C.I. for $m_s - m_d = [-11.833, 6.695]$; Trial 4: $m_s = 64.17$, $m_d = 67.8$, $t(34) = -0.69$, $p = 0.495$, 95% C.I. for $m_s - m_d = [-14.01, 6.752]$; Trial 5: $m_s = 58.65$, $m_d = 64.76$, $t(34) = -1.232$, $p = 0.227$, 95% C.I. for $m_s - m_d = [-15.912, 3.689]$; Trial 6: $m_s = 55.64$, $m_d = 58.53$, $t(34) = -0.624$, $p = 0.537$, 95% C.I. for $m_s - m_d = [-12.033, 6.254]$. Whiskers denote 95% C.I.



Ego	Alters	Exposure set *E*
E_1	A_1, A_2	{a,b,p,q}
E_2	A_2, A_3	{a,b}
E_3	A_3, A_4	{a,b,c}
E_4	A_4, A_5	{a,b,c}
E_5	A_5, A_6	{a,c,r,s}
E_6	A_6, A_1	{p,q,r,s}



Ego	Alters	Exposure set *E*
E_1	A_1, A_6	{p,q,r,s}
E_2	A_1, A_6	{p,q,r,s}
E_3	A_1, A_6	{p,q,r,s}
E_4	A_1, A_6	{p,q,r,s}
E_5	A_1, A_6	{p,q,r,s}
E_6	A_1, A_6	{p,q,r,s}

Figure S8: (*Top row*) Simulation of the initial condition of the bipartite network (rewiring probability $P_r = 0$). One realization of the stimuli idea set is shown here, where alters A1 and A6 generated non-redundant ideas (p, q and r, s respectively). Alters A2 through A5 generated ideas a, b and c, which are not unique and were submitted by multiple alters. Thus, A1 and A6 are the top-performing alters here. The egos are connected to the alters in the same pattern as used in the original experiment. 6 egos are shown for demonstration purposes. The table to the left shows the computation of the exposure sets of the egos. (*Bottom row*) The evolved network for $P_r = 1$, where all the egos follow the same top-performing alters. This results in making all of the egos' exposure sets the same, as shown in the table on the left.

3 Simulation model

We simulate the study outcomes using three key building blocks: (A) the network rewiring dynamics, (B) the cognitive stimulation mechanisms, and (C) the inter-ego similarities. In (A), we generate the initial network condition, the alters' ideas, the egos' exposure sets and the evolution of those exposure sets that stem from network rewiring. For generating the stimulated ideas based on these exposure sets, in (B), we abstract the cognitive mechanisms using linear, sub-linear and super-linear stimulation functions. Finally, in (C), we explore the outcomes in two corner cases of inter-ego similarities: full similarity and no similarity. We describe each block in detail below. We make our code available for easy replication of the model.

(A) Capturing the network dynamics

Network initialization. Here, we adopt the same bipartite network settings as used in the empirical explorations. We first consider $m = 6$ alters and $n = 18$ egos, and initialize their connections in the same initial pattern as the original experiment. Each of the alters i has an idea set A_i, which is used as the stimuli for the egos. Later, we experiment with larger networks that have $m = 18$, 60, and 600, with $n = 3m$ for each of those. We connect each ego to 2 alters.

Stimuli set generation. Following the empirical observations in our study, we generate idea-sets A_i for alters i such that some of the alters have larger unique idea counts than others (popular and unpopular alters, respectively). To simulate this, we start with two pools (sets) of symbols representing unique ideas: U_1 and U_2. By having $|U_1| << |U_2|$, we ensure that ideas sampled with replacement from U_1 will be more common than those from U_2. In other words, we simulate U_1 to include ideas that occur to people with a high probability, and U_2 to consist of rare ideas.

We assume that each alter i generates a fixed number of $|A|$ ideas. Each idea in A_i comes from pool U_1 with probability α_i, or from U_2 with probability $1-\alpha_i$. For a random one-third of the alters, we take $0 \leq \alpha_i \leq 0.5$ (high-performing alters), and for others $0.5 < \alpha \leq 1$ (low-performing alters). This makes the idea sets A_i non-uniform, with the high-performing alters having a higher unique idea count than the low-performing alters, as shown in the top row of Figure S8.

Exposure set calculation. For each ego j, we take the set of ideas they are exposed to as the exposure set $E_j = A_{i_1} \cup A_{i_2}$, where alters i_1 and i_2 are ego j's peers.

Evolution of exposure set. With time (e.g., with rounds in our study), the egos in the dynamic condition can rewire their connections to the alters, which the static egos cannot. In the empirical results, we saw that the connection changes per ego dropped with time ($p < 1e-4$ for the negative slope) as more egos followed the high-performing popular alters. We define a rewiring probability P_r that captures how much the network deviates from its initial configuration ($P_r = 0$) to the extreme case where two popular alters win the attention of all the egos ($P_r = 1$). Therefore, instead of simulating the dynamic network through time to explore its temporal effects, we can equivalently sweep over the rewiring probability P_r and explore its effects on the exposure sets of the egos. Figure S8 shows the idea. With higher P_r, the exposure sets of the egos become more uniform, as even the rare stimuli ideas from pool U_2 become common due to increased exposure.

(B) Capturing cognitive stimulation

Given the exposure set E_j, an ego j can generate the following: with probability p_1, s/he can generate ideas that are substantially inspired/stimulated by ideas from the exposure set, with probability p_2 s/he can generate ideas with negligible or no stimulation from the exposure set ideas, and with probability p_3 s/he can generate ideas that are inspired by the exposure set but do not fulfill the study requirements of being substantially different than the stimuli and also feasible. For our purposes of exploring the effects of the network dynamics, we can set $p_2 = p_3 = 0$, which makes $p_1 = 1$. In other words, we are assuming that an ego only generates ideas that are inspired by the exposure set. Any effect from p_2 and p_3 should occur similarly in both static and dynamic conditions as the participants are randomly placed, and therefore act as mere random noise that we set to 0. This leads to the set of stimulated ideas for ego j, $S_j = \{e'_1\} \cup \{e'_2\} \cup ... \cup \{e'_k\}$ where each idea in the exposure set $e_k \in E_j$ leads to a set of ideas $S^{(e_k)} = \{e'_k\}$, and the union of all such idea sets from all $e_k \in E_j$ are contained in S_j.

The empirical results show a positive stimulation of ideas in the dynamic and static conditions compared to the solo condition (no stimuli). Therefore we can reasonably ignore the possibility that a stimulus can hurt the ideation process (negative association between $|E|$ and $|S|$). Also, our choice of having $p_1 = 1$ in the previous paragraph gets rid of the possibility of no association between $|E|$ and $|S|$. This leaves a positive stimulation effect, captured by a positive association between $|E|$ and $|S|$.

As argued in the main manuscript, less overlap between an ego's own ideas and his/her alters' ideas can help in stimulating further novel ideas in the ego. Again, the rarer a stimulus idea e is, the less overlap can be expected to exist between e and the ego's own ideas, which can lead to a higher chance of stimulation. We measure the rarity of each stimulus idea as $R_e = 1 - \frac{\text{Number of times the idea was submitted by the alters}}{\text{total number of alters' ideas}}$. Therefore, we have the number of ideas stimulated by e, $|S^{(e)}| \propto f(R_e)$, where f is a stimulation function. We consider three cases of this stimulation relation: (1) linear: $|S^{(e)}| = kR_e$, (2) sub-linear: $|S^{(e)}| = k\sqrt{R_e}$, (3) super-linear: $|S^{(e)}| = kR_e^2$, where k is a proportionality constant.

(C) Capturing inter-ego similarity

Every ego j generates stimulated ideas S_j independently of other egos. However, when the network evolves such that the high-performing alters become highly popular (high rewiring probability P_r), the exposure sets of the egos can become similar. We consider two extreme cases in this regard: (1) No similarity: every ego j with the same stimulus idea e generates completely different stimulated ideas in $S^{(e)}$, and (2) Full similarity: every ego j with the same stimulus idea e generates exactly the same stimulated ideas in $S^{(e)}$.

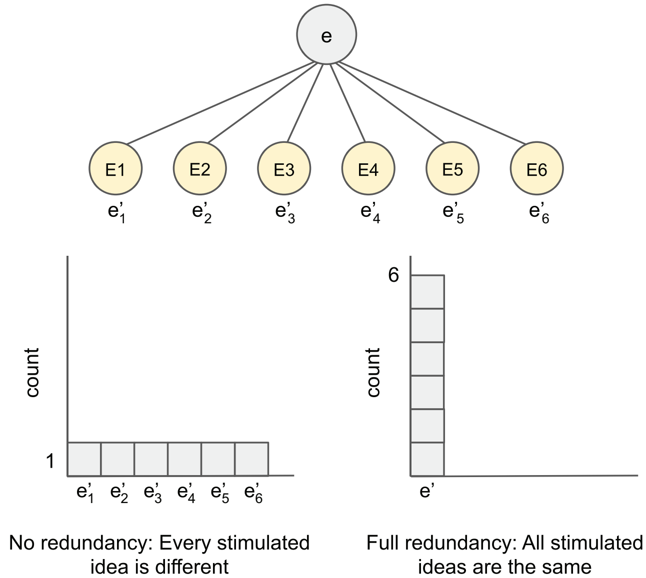


Figure S9: (*Top row*) An illustration of one stimulus e being shown to 6 independent egos, where the egos generate one stimulated idea each. (*Bottom row*) Two extreme cases: (1) No similarity/redundancy, where each stimulated idea is unique, and (2) Full similarity/redundancy, where all the stimulated ideas turn out to be the same. The dynamic network suffers in case of increased similarity, since the rewiring process exposes an increased number of people to the same stimulus e.

The first case will have the least network effect due to the complete uniqueness of every stimulated idea. But in the second case, the dynamic network will suffer from generating more redundant ideas among the participants. An example is shown in Figure S9.

To evaluate performance of the alters, we set a non-redundancy threshold of 1, as explained in the main manuscript. In other words, any idea that is generated by at most one alter is considered non-redundant. For the egos, we take an idea to be non-redundant if it is generated by at most 15% of the number of egos on the simulation.

Experiments

We explore the following cases in our simulation:

Network size. We experiment with bipartite networks consisting of $m = \{6, 18, 60, 600\}$ alters and $n = 3m$ egos. Each ego is connected to 2 alters using the same initial configuration pattern as the original experiment. The results of the four cases are shown in Figures S10-S13 respectively.

Inter-ego similarity. For each network size, we consider both of the cases of no inter-ego similarity and full similarity. In each of the Figures S10-S13, the left column and right columns respectively show the two cases.

Cognitive stimulation functions. For each of the inter-ego similarity cases, we experiment with three stimulation functions, relating the rarity of the stimulus ideas to the number of novel ideas in sub-linear, linear and super-linear ways. These results are shown in the top, middle and bottom rows of the Figures S10-S13.

Rewiring probabilities. For the dynamic condition, we sweep through the rewiring probability P_r from 0 (initial condition) to 1 (all of the egos follow only the two most popular alters). For the static control, we keep P_r fixed at 0.

Results and Discussion

The results are shown in Figures S10-S13. When there is no similarity/redundancy among the egos' ideas generated in response to the same stimuli, the dynamic condition enjoys an advantage over the static condition as the rewiring probability P_r increases. The network's performance maximizes at $P_r = 1$. But when there is full redundancy, none of the ideas in the dynamic condition remains unique anymore as P_r approaches 1, thereby hurting the creative outcomes. This result is robust to various stimulation functions we chose, and also to network size.

The simulation highlights the roles played by the network dynamics and the cognitive stimulation mechanism in the creative ideation process. First, the rewiring process makes the stimuli set similar with time for the egos in the dynamic condition, which is a purely network-driven process. Second, the redundancy among the egos' ideas in response to the same stimulus also becomes a manifestation of the network dynamics, as the redundancy is initiated/facilitated by the egos' similar choices of peers. These two factors, taken together, negatively impact the creative outcomes in the dynamic condition. On the other hand, the stimulation process of the egos' ideas is driven by cognitive mechanisms. The various stimulation functions we experimented with (f) benefit the creative outcomes in varying degrees. However, as the simulation demonstrates, sufficient redundancy in the egos' ideas has the ability to overpower the cognitive stimulation benefits. In our empirical data, we find evidence of both of the network and cognitive factors to be present concurrently, which are captured by this simulation model.

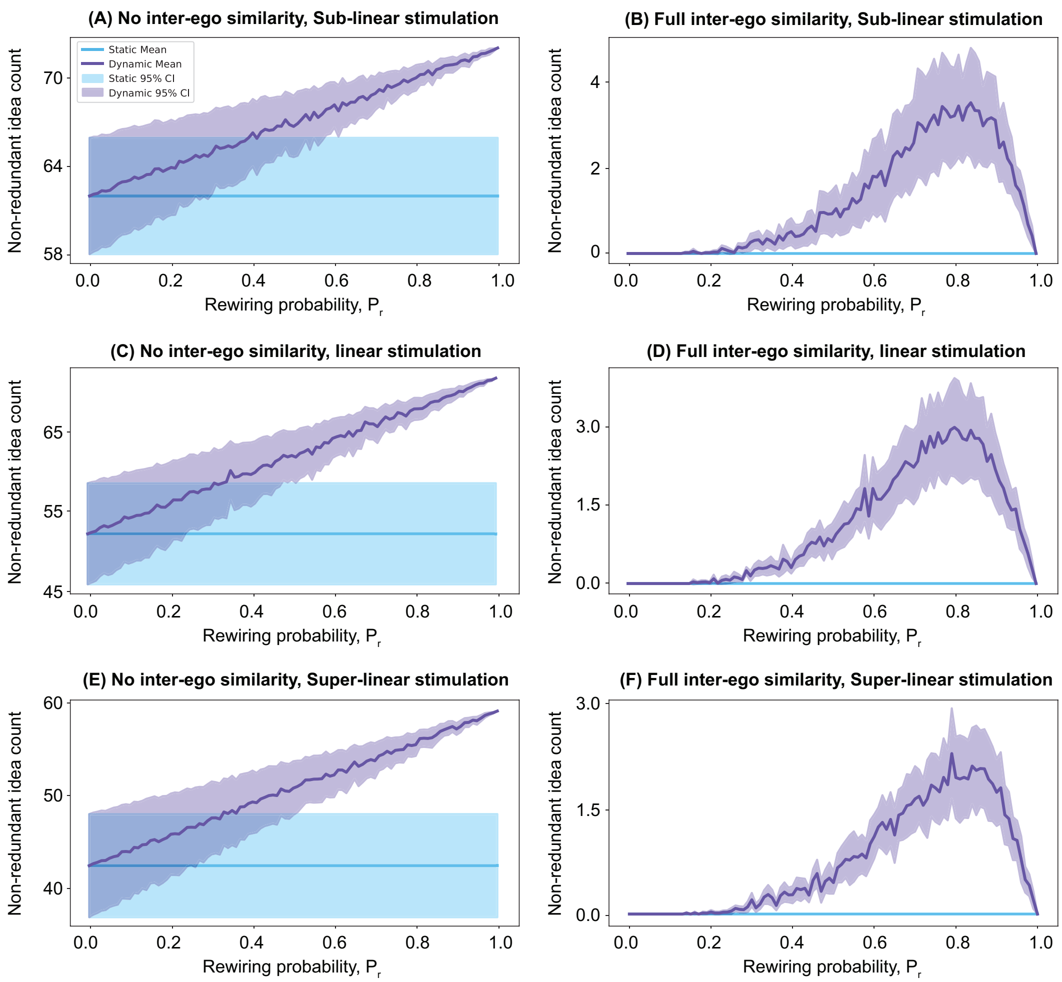


Figure S10: Simulation results for $m = 6$ alters and $n = 18$ egos, computed for each of the three stimulation functions. The x-axis denotes rewiring probability P_r, where $P_r = 0$ denotes the initial network structure and $P_r = 1$ denotes the extreme case where all the egos follow the same two popular alters. The left column panels (A, C and E) show the simulation results for the case of no redundancy among the ideas generated by different egos in response to the same stimulus. The right column panels (B, D and F) show results for full redundancy cases. The top row, middle row and bottom row are the simulation results for the sub-linear, linear and super-linear stimulation functions, respectively. As can be seen, when there is no redundancy, the dynamic networks outperform the static ones as P_r increases. However, when there is redundancy, the dynamic network suffers as more egos follow the same alters at higher P_r, eventually making all the stimulated ideas redundant and therefore not creative. Slope parameter $k = 20$ has been used in the stimulation functions.

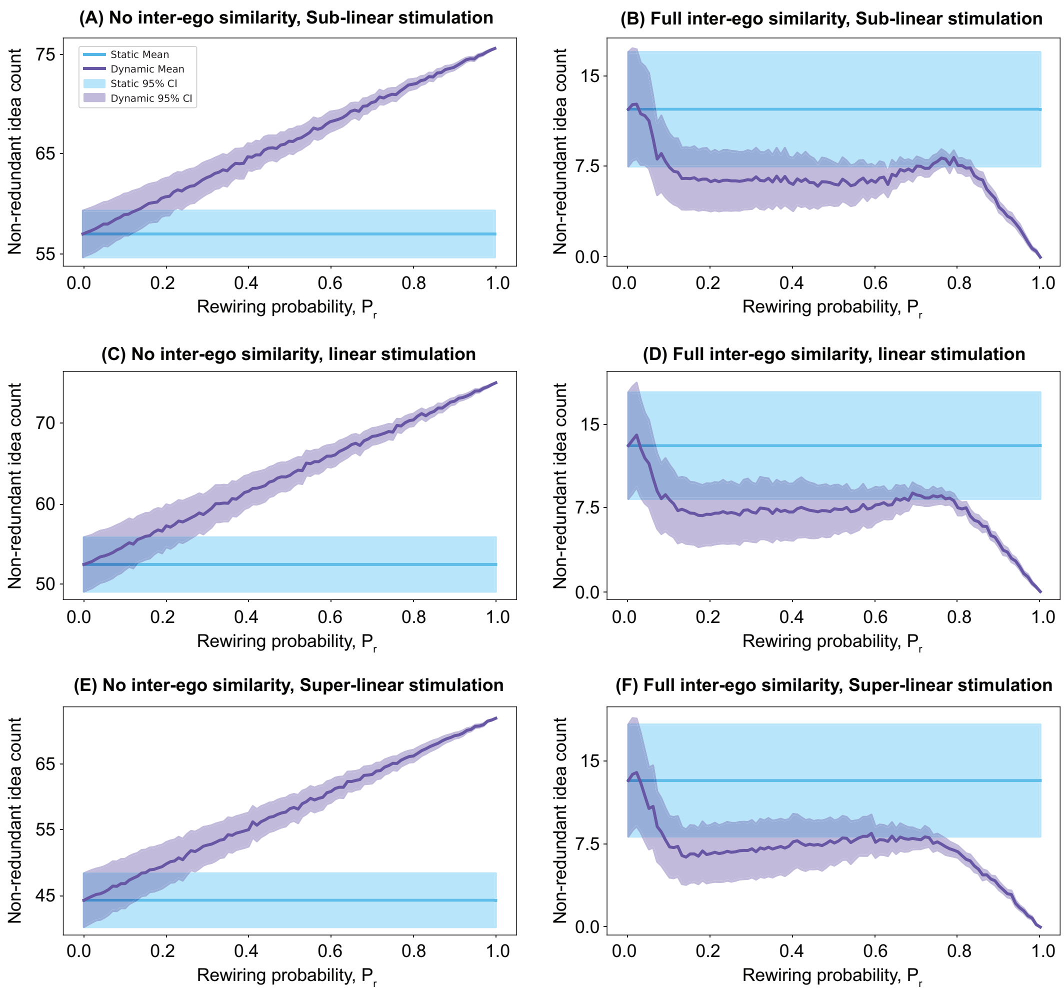


Figure S11: Simulation results for $m = 18$ alters and $n = 54$ egos.

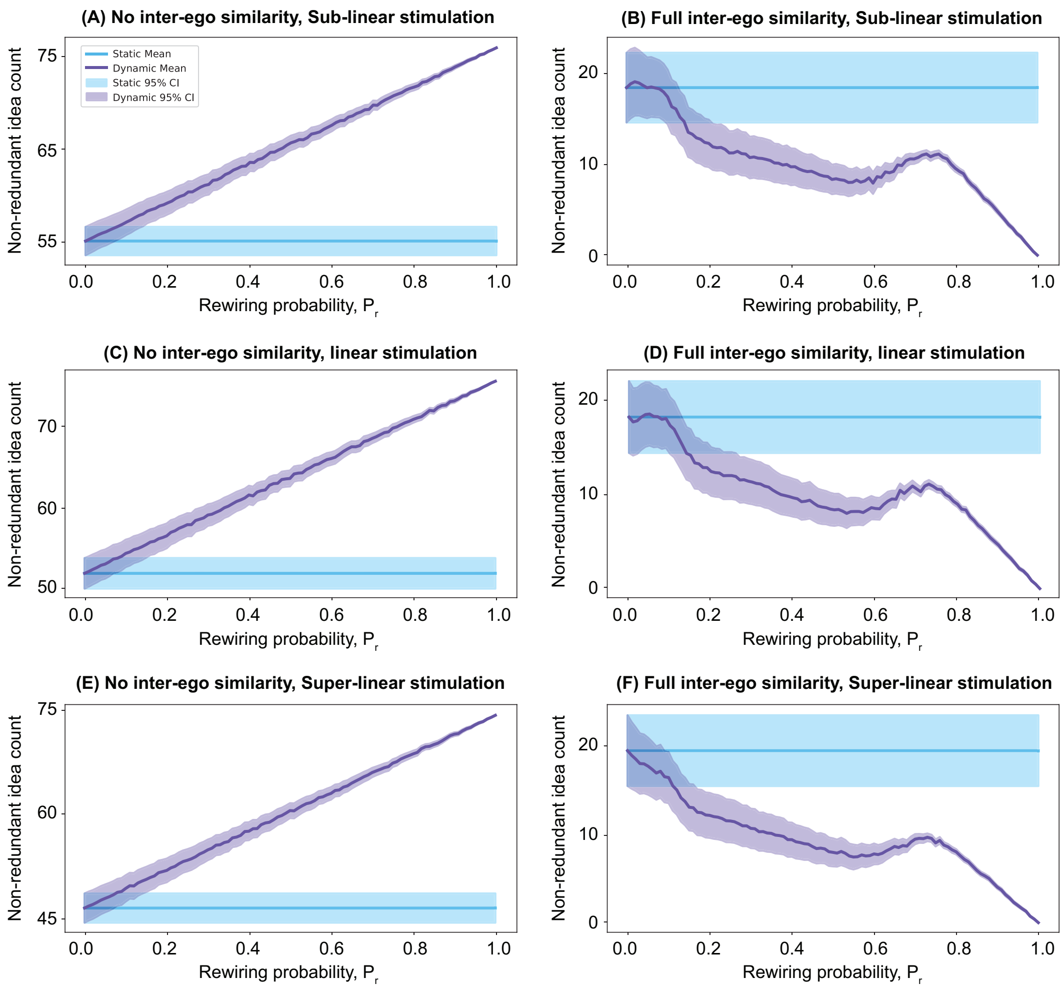


Figure S12: Simulation results for $m = 60$ alters and $n = 180$ egos.

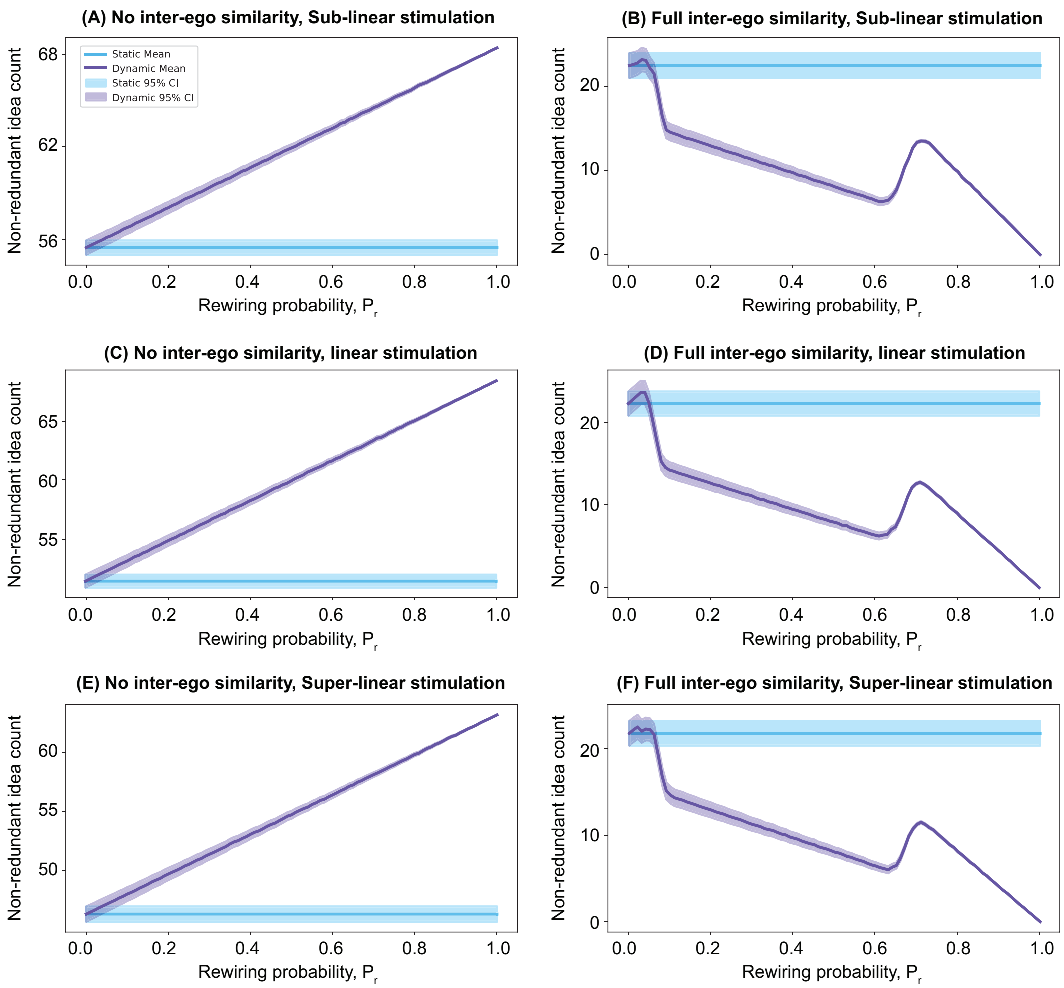


Figure S13: Simulation results for $m = 600$ alters and $n = 1800$ egos.

4 Study interface

The study was conducted with approval from the University IRB. No personally identifiable information was collected from the participants. The web interfaces used in the experiment are shown below, using pseudo usernames. Some of the materials are redacted to ensure copyright compliance of using materials from Guilford's Alternate Uses test.

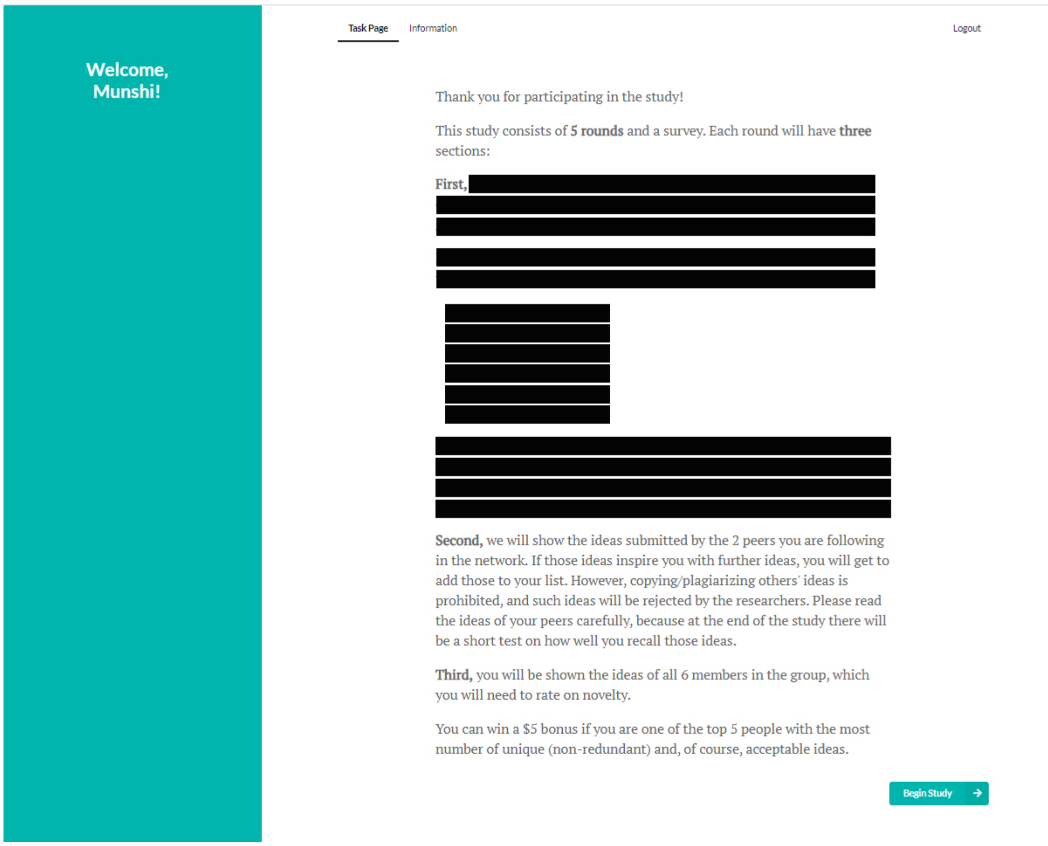
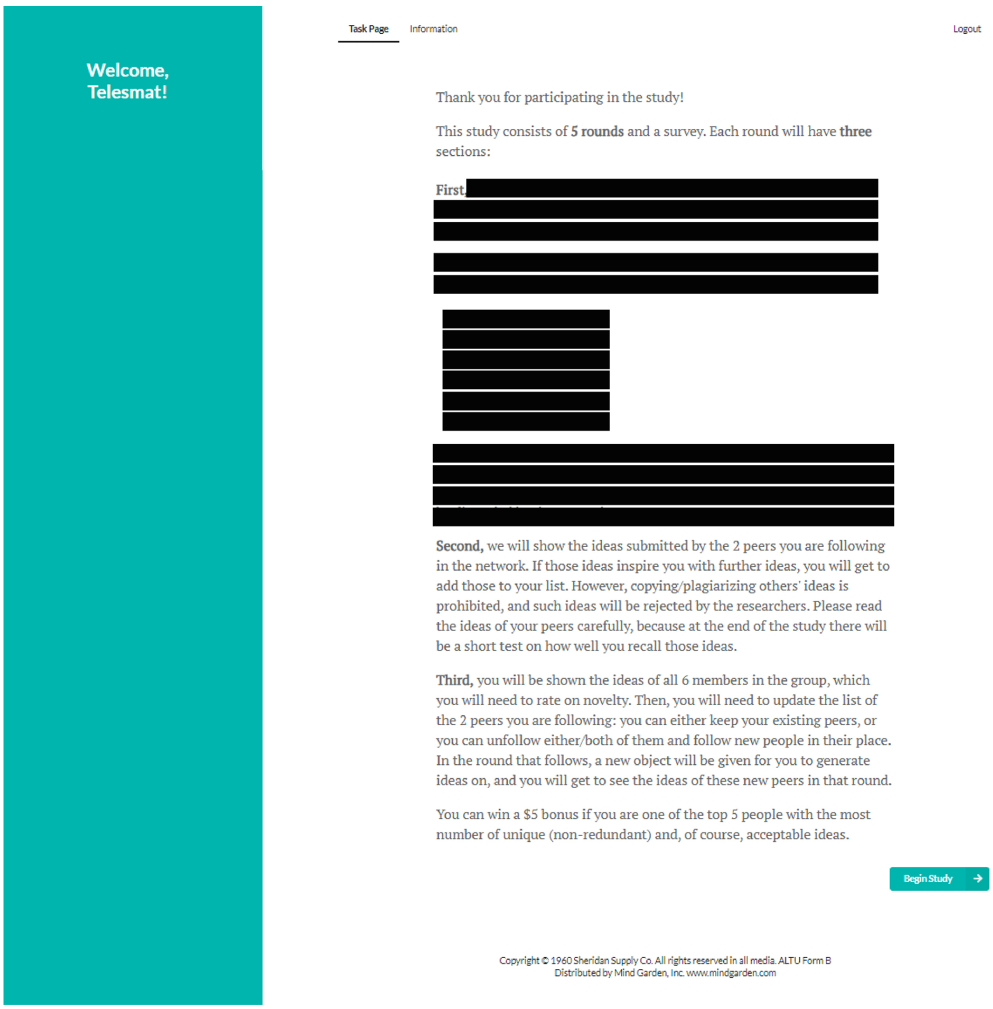


Figure S14: Instruction page for the egos of the static condition. Here, the first point is redacted to ensure copyright compliance of using the Guilford's test. This first point provides instructions for idea generation with examples. For the alters and solo participants, only the first point was shown.



Task Page Information Logout

Welcome, Telesmat!

Thank you for participating in the study!

This study consists of **5 rounds** and a survey. Each round will have **three** sections:

First, [redacted]

[redacted]

[redacted]

Second, we will show the ideas submitted by the 2 peers you are following in the network. If those ideas inspire you with further ideas, you will get to add those to your list. However, copying/plagiarizing others' ideas is prohibited, and such ideas will be rejected by the researchers. Please read the ideas of your peers carefully, because at the end of the study there will be a short test on how well you recall those ideas.

Third, you will be shown the ideas of all 6 members in the group, which you will need to rate on novelty. Then, you will need to update the list of the 2 peers you are following: you can either keep your existing peers, or you can unfollow either/both of them and follow new people in their place. In the round that follows, a new object will be given for you to generate ideas on, and you will get to see the ideas of these new peers in that round.

You can win a $5 bonus if you are one of the top 5 people with the most number of unique (non-redundant) and, of course, acceptable ideas.

Begin Study →

Figure S15: Instruction page for the egos of the dynamic condition.

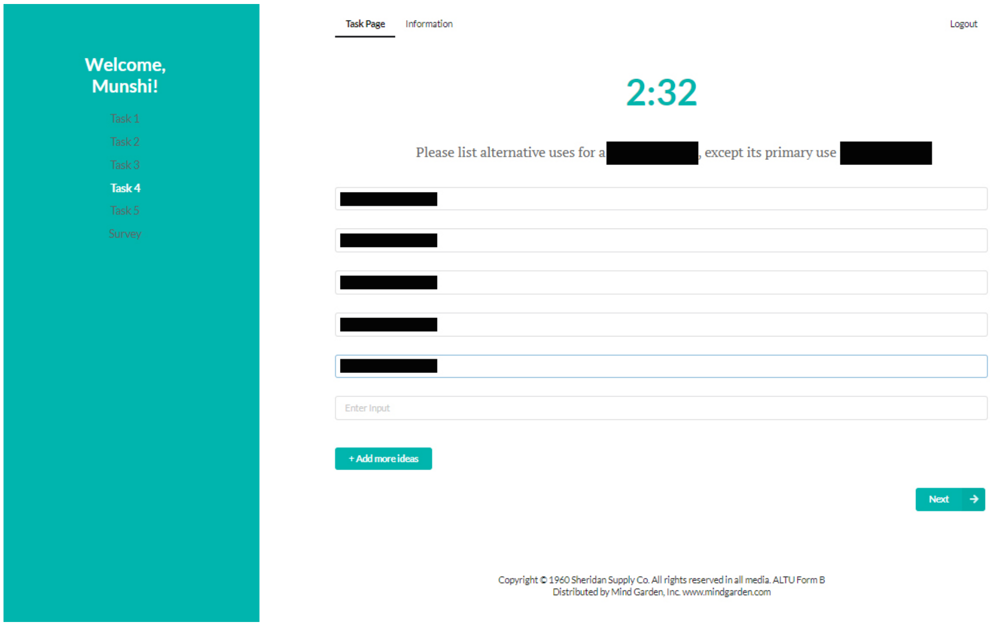


Figure S16: Initial idea submission interface. This was used in turn-1 for the egos of static and dynamic conditions, as well as for the alters and solo participants.

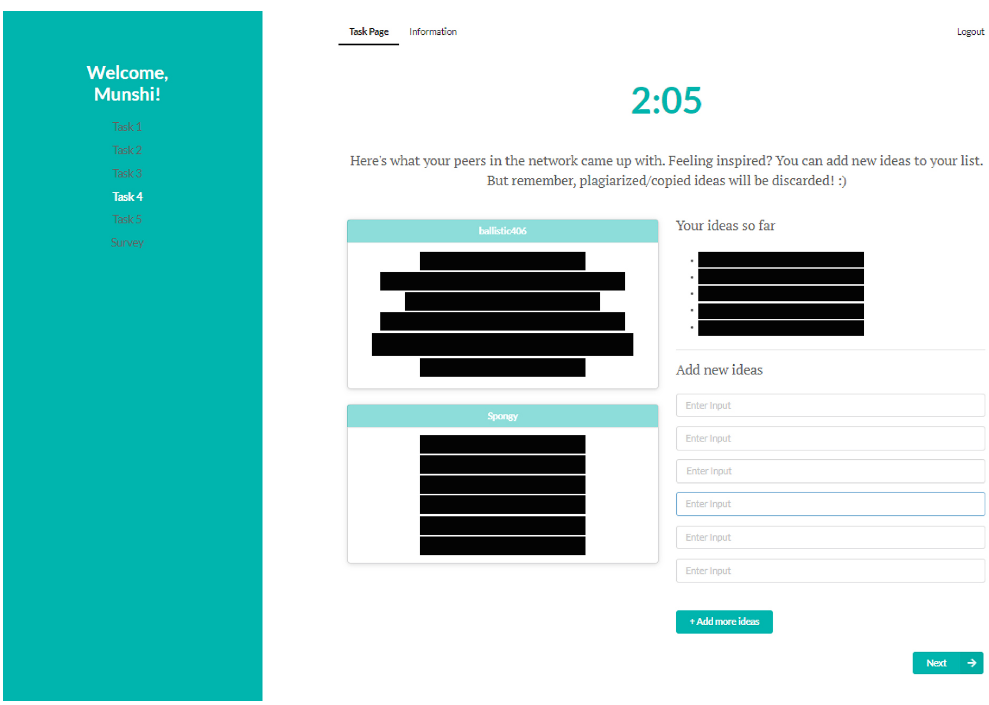


Figure S17: Turn-2 interface for the egos of static and dynamic conditions. The alters' ideas are shown on the left-side cards.

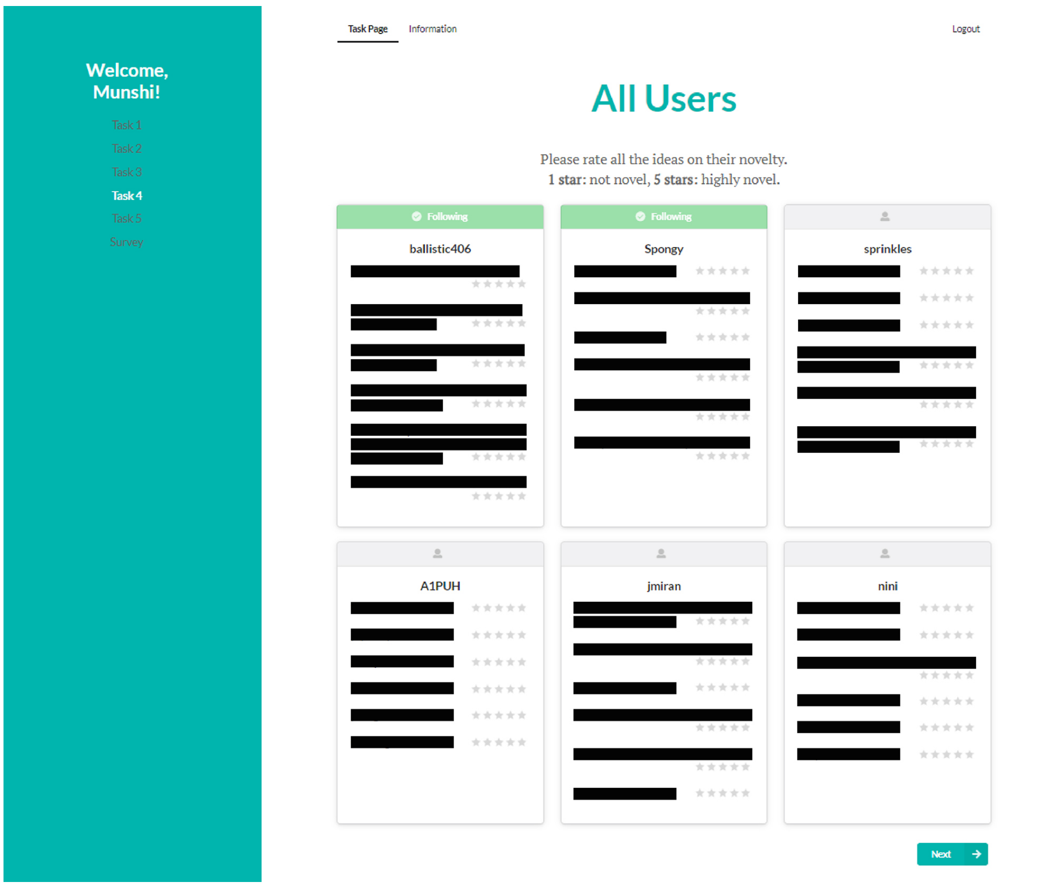


Figure S18: Rating interface for the egos in the static condition. The egos rated the ideas of all 6 alters in the respective trial.

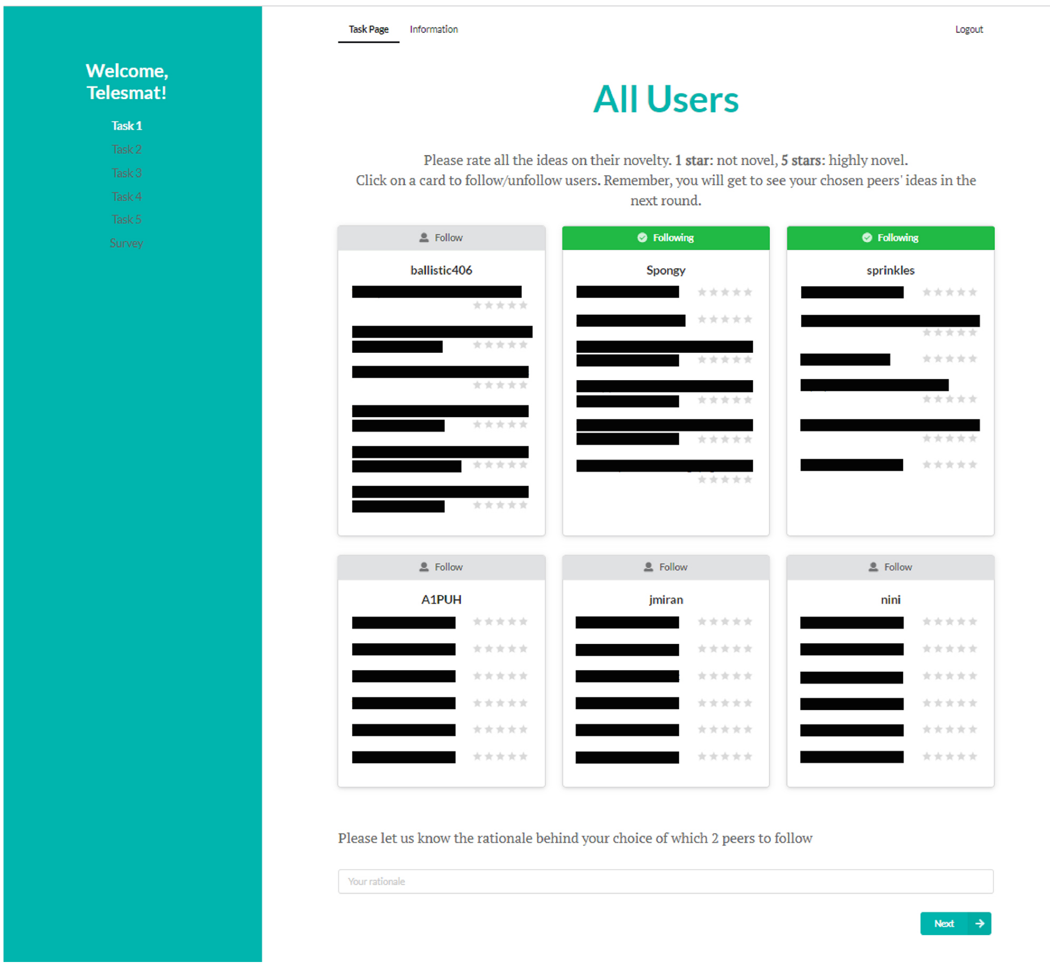


Figure S19: Rating and following/unfollowing interface for the egos in the dynamic condition.

5 Supplementary tables

Table S1: Performance comparisons between popular (p) and unpopular (u) alters. 2-tailed tests. Data aggregated over all trials, $n_p = 13$, $n_u = 23$.

Metric	m_p	m_u	t**-statistic**	**df**	p	95% **C.I. for** $m_p - m_u$
Non-redundant Idea Counts	23.8	14.4	7.291	34	< 0.001	$[6.9, 12]$
Average Ratings	3.1	2.6	5.7	34	< 0.001	$[0.3, 0.6]$
Creativity Quotient	57.8	36.7	5.81	34	< 0.001	$[13.9, 28.2]$

Table S2: Omnibus test results for analyzing the overlaps between the egos' turn-1 ideas and their alters' ideas. The overlap (Jaccard index) is the response variable. The analysis of variance of aligned rank transformed data is run on a mixed effects model with two factors: the number of popular alters of the egos ('Group factor', 3 levels) and RoundID ('Round factor', 5 levels). The degrees of freedom are specified using the Kenward-Roger method. Each RoundID has $n_r = 216$ entries, one from each ego. Groups (i), (ii) and (iii), as defined in the main text, have $n_i = 273$, $n_{ii} = 476$, and $n_{iii} = 331$ entries respectively.

	Df	Df.res	F	Pr($> F$)
NumPopularAlters (Group factor)	2	669.84	66.526	$< 2.22e-16$
RoundID (Round factor)	4	866.07	57.307	$< 2.22e-16$
NumPopularAlters:RoundID	8	940.38	8.474	$3.561e-11$

Table S3: Post-hoc analysis among the three levels in the Group factor from the fitted model reported in Table S2. The degrees of freedom are specified using the Kenward-Roger method. The p-values are adjusted using Holm's sequential Bonferroni procedure.

Contrast	Estimate	SE	df	t	p
Group (iii)-Group (ii)	130	23.4	574	5.555	< 0.001
Group (iii)-Group (i)	308	26.8	597	11.481	< 0.001
Group (ii)-Group (i)	178	23.6	887	7.519	< 0.001

Table S4: Omnibus test results for analyzing the egos' turn-2 performances. Three separate models are fitted for the three creativity metrics as the response variables. The analysis of variance of aligned rank transformed data is run on a mixed effects model with two factors: the number of popular alters of the egos ('Group factor', 3 levels) and RoundID ('Round factor', 5 levels). The degrees of freedom are specified using the Kenward-Roger method. Each RoundID has $n_r = 216$ entries, one from each ego. Groups (i), (ii) and (iii), as defined in the main text, have $n_i = 273$, $n_{ii} = 476$, and $n_{iii} = 331$ entries respectively.

Metric: Non-redundant Idea Counts				
	Df	Df.res	F	Pr($> F$)
NumPopularAlters (Group factor)	2	825.86	3.701	0.025 *
RoundID (Round factor)	4	862.74	3.265	0.011 *
NumPopularAlters:RoundID	8	913.51	0.513	0.847
Metric: Average Novelty Ratings				
	Df	Df.res	F	Pr($> F$)
NumPopularAlters (Group factor)	2	535.47	11.852	$9.19e-6$ ***
RoundID (Round factor)	4	869.13	8.361	$1.28e-6$ ***
NumPopularAlters:RoundID	8	973.46	1.409	0.189
Metric: Creativity Quotient				
	Df	Df.res	F	Pr($> F$)
NumPopularAlters (Group factor)	2	1036.36	6.657	0.0013 **
RoundID (Round factor)	4	857.72	14.836	$9.98e-12$ ***
NumPopularAlters:RoundID	8	880.30	1.792	0.075

Table S5: Post-hoc analysis among the three levels in the Group factor from the three fitted models reported in Table S4. The degrees of freedom are specified using the Kenward-Roger method. The p-values are adjusted using Holm's sequential Bonferroni procedure.

Metric: Non-redundant Idea Counts					
Contrast	Estimate	SE	df	t	p
Group (iii)-Group (ii)	-70.0	26.0	727	-2.689	0.022
Group (iii)-Group (i)	-57.6	29.7	747	-1.936	0.106
Group (ii)-Group (i)	12.5	25.3	1014	0.495	0.621
Metric: Average Novelty Ratings					
Contrast	Estimate	SE	df	t	p
Group (iii)-Group (ii)	-79.4	23.4	458	-3.399	0.0015
Group (iii)-Group (i)	-127.8	26.8	483	-4.759	< 0.0001
Group (ii)-Group (i)	-48.3	24.5	721	-1.971	0.0491
Metric: Creativity Quotient					
Contrast	Estimate	SE	df	t	p
Group (iii)-Group (ii)	-85.814	24.6	1016	-3.495	0.0015
Group (iii)-Group (i)	-85.475	27.9	1022	-3.062	0.0045
Group (ii)-Group (i)	0.339	22.2	1050	0.015	0.9878

Table S6: Semantic dissimilarity comparisons among node-pairs with 0, 1 and 2 common alter(s) at the end of the 5$^{\text{th}}$ round. Node-pairs with 2 common alters were significantly less dissimilar than 0 and 1 common alter cases. 2-tailed tests, data aggregated over all trials. Number of node-pairs: $n_2 = 170$, $n_1 = 464$, $n_0 = 284$, where the subscripts denote the number of common alters of the node pairs. All p-values are Bonferroni-corrected.

	Means	t	**df**	p	95% **C.I.**
2 vs 0 common alter(s)	$m_2 = 3.01, m_0 = 3.22$	-2.962	452	< 0.01	$m_2 - m_0 = [-0.36, -0.07]$
2 vs 1 common alter(s)	$m_2 = 3.01, m_1 = 3.19$	-2.788	632	< 0.02	$m_2 - m_1 = [-0.31, -0.05]$

Table S7: Individual-level comparisons of the total non-redundant idea counts of the egos in the three study conditions. 2-tailed tests, data aggregated over all trials. Number of observations: Dynamic: $n_d = 108$, Static: $n_s = 108$, Solo: $n_c = 36$. All p-values are Bonferroni-corrected.

	Means	t	**df**	p	95% **C.I.**
Dynamic (d) vs Solo (c)	$m_d = 6.33, m_c = 4.44$	2.7	142	< 0.03	$m_d - m_c = [0.52, 3.26]$
Static (s) vs Solo (c)	$m_s = 6.77, m_c = 4.44$	2.898	142	< 0.02	$m_s - m_c = [0.75, 3.90]$

6 Power analysis for sample sizes

Link update patterns in the network evolution. In Table S8, we present the a priori power analysis of sample sizes using the t-test (difference between two independent means) given alpha, power and effect size. The effect sizes are determined from the observed data, while the allocation ratio is determined from the ratio of popular and unpopular alter counts observed in the data. To be conservative, we used 1.5 times larger standard deviations within each group than the original data, to allow for a larger noise margin.

Table S8: Power analysis: Link update patterns in the network evolution

Metric	**Alpha**	**Power**	**Std factor**	**Allocation ratio (N_p/N_u)**	**Calculated effect size**	**Calculated sample size**	**Actual sample size**
Non-redun. Idea Ct.	0.05	0.8	1.5	0.565	1.72	14	36
Avg. Novelty Ratings	0.05	0.8	1.5	0.565	1.48	18	36
Creativity Quotient	0.05	0.8	1.5	0.565	1.33	22	36

Exposure to high-performing alters is associated with better creative performances of the egos. In Table S9, we present the a priori power analysis of sample sizes using the F-test, given alpha, power and effect size. The effect sizes are determined from the observed data.

Table S9: Power analysis: Exposure to high-performing alters is associated with better creative performances of the egos

Metric	**Alpha**	**Power**	**Calculated effect size**	**Calculated sample size**	**Actual sample size**
Jaccard Index	0.05	0.8	0.32	99	1080
Non-redundant Idea Counts	0.05	0.8	0.12	714	1080
Average Novelty Ratings	0.05	0.8	0.15	408	1080
Creativity Quotient	0.05	0.8	0.19	261	1080

Following the same alters introduces semantic similarities in the egos' ideas. In Table S10, we present the a priori power analysis of sample sizes using the F-test, given alpha, power and effect size. The effect sizes are determined from the observed data.

Table S10: Power analysis: Following the same alters introduces semantic similarities in the egos' ideas

Alpha	**Power**	**Calculated effect size**	**Calculated sample size**	**Actual sample size**
0.05	0.8	0.104	882	918

Individual creative performance comparisons among various study conditions. In Table S11, we present the a priori power analysis of sample sizes using the F-test, given alpha, power and effect size. The effect sizes are determined from the observed data.

Table S11: Power analysis: Individual creative performance comparisons among various study conditions

Alpha	**Power**	**Calculated effect size**	**Calculated sample size**	**Actual sample size**
0.05	0.8	0.2	246	252