Efficient team structures in an open-ended cooperative creativity experiment

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Creativity is progressively acknowledged as the main driver for progress in all sectors of humankind's activities: arts, science, technology, business, and social policies. Nowadays, many creative processes rely on many actors collectively contributing to an outcome. The same is true when groups of people collaborate in the solution of a complex problem. Despite the critical importance of collective actions in human endeavors, few works have tackled this topic extensively and quantitatively. Here we report about an experimental setting to single out some of the key determinants of efficient teams committed to an open-ended creative task. In this experiment, dynamically forming teams were challenged to create several artworks using LEGO bricks. The growth rate of the artworks, the dynamical network of social interactions, and the interaction patterns between the participants and the artworks were monitored in parallel. The experiment revealed that larger working teams are building at faster rates and that higher commitment leads to higher growth rates. Even more importantly, there exists an optimal number of weak ties in the social network of creators that maximizes the growth rate. Finally, the presence of influencers within the working team dramatically enhances the building efficiency. The generality of the approach makes it suitable for application in very different settings, both physical and online, whenever a creative collective outcome is required.

collective creativity | open-ended experiments | weak ties | exploit/explore

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Creativity is one of the most distinctive features of human beings. The ability to conceive new ideas, objects, technologies, and business is one of the founding factors of our societies in their quest for progress and better living conditions. As such, creativity is a powerful engine behind innovation, be it artistic, scientific, technological, or social.

The investigation of the very nature of creativity has a very long history, from the philosophy of creativity to aesthetics to experimental approaches to crack its very nature (1–3). For centuries scholars have raised questions about the emergence of creativity, its determinants, and the differences of creativity in very different domains. More recently, heralded by pioneering works of Shaw, Simon, and Newell (4) and due to the terrific progress made in complexity science (5–7) and artificial intelligence, the new field of computational creativity (for instance, ref. 8) emerged with the scope of defining and understanding creativity through the concrete implementation of artificial creative systems. This way, the set of questions about creativity expanded to include what makes a system creative, whether technology can enhance human creativity, and what the best environments are to foster and nurture creativity.

One of the most intriguing aspects of creativity concerns the interplay between individual exploits and collective achievements. Unlike earlier times, modern creative industries (music, games, cinema, publishing, computer programs, etc.) rely on complex creation processes, where many actors (from dozens to thousands) contribute little chunks of content in a complex process eventually converging to a final product. Final products can be songs, interactive scripts, video games, screenplays, computer codes (9), or texts (10, 11).

Recent studies have investigated collective creative processes leading to innovation from very different perspectives, e.g., the creation of knowledge on a Q&A website (12); the impact of mobility of scientists on scientific research (13); the design of frameworks to speed up research discoveries (14); and the role of serendipity in creative processes (6). Finally, some of us recently proposed a modeling framework for the emergence of novelties (5, 7, 15, 16), based on the notion of "adjacent possible expansion" theorized by Stuart Kauffman (17) and capable of reproducing many statistical patterns linked to the emergence of novelties in a very general way.

One of the open critical questions concerning collective creative processes concerns the efficient team structure. Many efforts have been devoted to identifying the conditions favorable for creativity to emerge (18–20). In real social systems, agents have strong ties defined as frequently repeated connections and weak ties indicating sporadic interactions. Following Granovetter (21), the presence of "weak ties" in a social network might be one of the most critical drivers of collective creativity, allowing for the flow of new information and eventually leading to the development of new creative ideas. However, although few weak ties within a social group indicate the absence of new information circulating between the members of the groups, too many weak ties might prevent an efficient communication between the individuals. In refs. 18 and 19 it is

Significance

Understanding how to best form teams to perform creative tasks is a fascinating although elusive problem. Here we propose an experimental setting for studying the performances of a population of individuals committed to an open-ended cooperative creativity task, namely the construction of LEGO artworks. The real-time parallel monitoring of the growth of the artworks and the structure and composition of the dynamically working teams allow identifying the key ingredients of successful teams. Large teams composed of committed and influential people are more effectively building. Also, there exists an optimal fraction of weak ties in the working teams, i.e., an optimal ratio exploit/explore that maximizes the building efficiency.

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reported that a more significant number of weak ties should correspond with higher creativity at work, up to a point; beyond this point, there is less benefit realized from more substantial amounts of weak ties, and they may constrain creativity at work. Several models have been designed for studying the interplay between social relations and the emerging dynamics of information and cooperation (22–24). In ref. 25, it has been reported that in heterogeneous groups a vast number of weak ties can negatively affect the spreading velocity of information in a social network.

Despite the abundant literature on the subject, the problem of how to best assemble a group of people with a specific creative task is wide open. Here we address this problem by proposing an experimental setting where a population of participants is called to develop 3D artworks in open-ended environments using LEGO bricks collectively. Here open-endedness refers both to the dynamical composition of the working teams (participants were free to join and leave teams at any time) and to the loose constraints on the outcome. Participants were challenged to contribute to the emerging artworks by either building new parts or removing even substantial parts of them.

Through our experimental setup, we were able to record social interactions among the participants using Radio Frequency Identification (RFID) sensors developed within the SocioPatterns project (26–28). The same sensors were adopted to monitor which artwork a specific participant contributed to and for how long, among the several evolving in parallel. The networks of interactions of users and users–artworks are intrinsically dynamical (29, 30). The RFIDs allowed us to monitor the dynamics of the social bonds which are continuously formed and broken and to follow the constant restructuring of the working teams (31–34).

In parallel with the social interactions, we monitored the growth of each artwork through infrared depth sensors that provide in real time an accurate 3D reconstruction of the artworks. This way, we could relate the dynamical composition of teams, as mirrored through several observables, to the efficiency of the building activity, measured through the growth rate.

The analysis of the ensemble of the data allowed us to draw several important conclusions. First, faster growth of the artworks is more likely to occur when the working teams have specific topological features, namely an optimal balance between weak and strong ties in a preferably large group. Also, the presence of influencers within the working teams greatly enhances the building efficiency. Finally, a high level of commitment, i.e., focusing on only one artwork, improves building efficiency. The combination of all these circumstances emerges as a sufficient condition to enhance the effectiveness of the collective creative task.

Results

The experiments took place in the framework of an open event dubbed KREYON Days that took place in Rome, Italy, from 2015 to 2017. On each day, for 3 d, from 9 AM until 7 PM, participants were allowed to join and leave the experimental hall at any time freely. Upon entrances, participants were registered and provided with RFID sensors (shown in Fig. 1*A*) to be returned upon leaving the hall. Entrances and exits were recorded. The RFID sensors allowed us to map face-to-face interactions between individuals with a temporal resolution of 20 s. In other words, 2 participants are considered as interacting if they stand in front of each other within a radius of 1 m for at least 20 s. Through the RFID sensors, we were able to record the total activity time of each user as well as of his/her social interactions (see *SI Appendix*, section S1 for more information). In the experimental hall, we installed three 1-m square large LEGO building platforms, and a large stash of LEGO bricks was available. We chose LEGO bricks due to their popularity and the immediacy of interaction they allow, independently of age, gender, manipulation, and artistic skills. Fig. 1*B* shows a picture of one of these platforms. Each building platform had, at any given time, an assigned topic (e.g., "spring," "Halloween") and each participant was free to decide to which building platforms to contribute, not necessarily following the topic. The presence of various artworks was necessary to study whether participants focused their efforts on a single artwork or multiple ones and how this

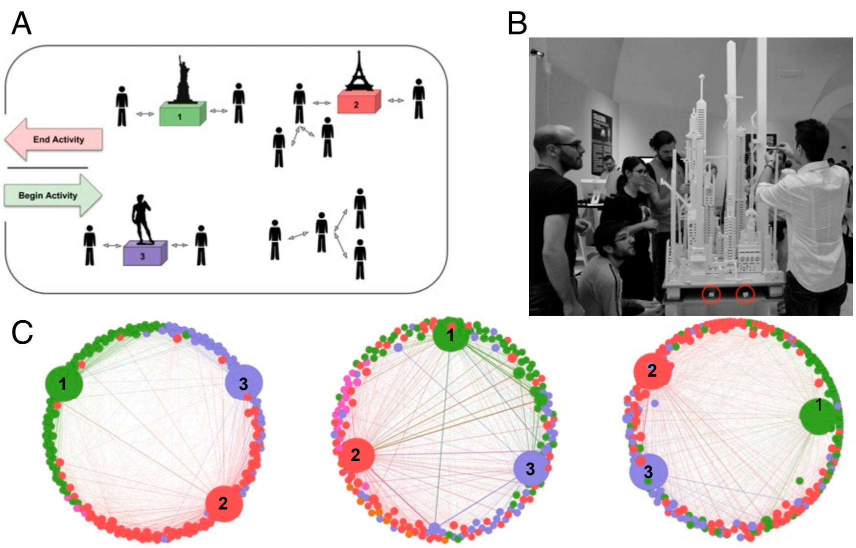

Fig. 1. (*A*) Scheme of the experiment. Participants were asked to wear RFID sensors allowing for the recording of their face-to-face interactions with time steps of 20 s. We deployed 3 building areas into the experimental hall, equipped with RFIDs to map the amount of time spent in the surroundings of each one. Each participant could freely join and leave the activity at any time. (*B*) Picture of one of the building areas. RFIDs can be seen right below the base. Participants were asked to wear RFIDs at the waist level to allow the RFIDs of the building areas to detect them when they were close. (*C*) The aggregated network obtained from the RFID data in 3 different days of the experiment. Larger nodes represent the building areas, while different colors represent communities detected through the Louvain method for community detection, which assigns each node in the network to a unique community of highly interconnected nodes (35).

affected the growth of the artworks. RFID sensors were also positioned all around the building platforms to monitor who contributed at which side of the artworks, when, and for how long. Through the RFID sensors, we reconstructed the dynamical networks of the participants as well as those of participants and building platforms, with a 20-s time resolution. Fig. 1*C* shows the aggregated networks obtained by the 3 dynamical networks in the 3 distinct days of activity. These networks were constructed by considering all of the links that were active at least once, weighting each link with the total activation time. The application of a community detection algorithm (35) to these networks reveals a clear community structure organized around the artworks (larger nodes in Fig. 1*C*), so that each artwork belongs to a different community. All of the interactions recorded by the RFIDs during the experiment and the times series of the artwork volumes are provided in Datasets S1–S9 and described in *SI Appendix*, section S9.

To understand how the evolution of the team composition (revealed by the dynamical networks of interactions) affects the efficiency of the collective creative task, it is essential to monitor the development of the artworks in time. Thus, we placed infrared depth sensors on top of each building platform, with their axes orthogonal to the plane of the platforms. These sensors allowed us to monitor the growth, in time, of the volume of each artwork. The depth sensors adopted have a sample rate, which is higher than that of the RFID sensors. Hence, we aggregated the volume measurements in time steps of 20 s starting from the beginning of the experiment. Measuring time t in steps of 20 s, we denote with $V(t)$ the volume, measured in the number of standard bricks, of an artwork as a function of time t. To compare the growth of different artworks, each reaching a different maximum volume, we normalized the volumes so that their maximum value is 1. The normalized volume is denoted by $\hat{V}(t)$.

SI Appendix, Fig. S7 shows examples of the time evolution of $\hat{V}(t)$ for the 3 artworks in each day. It is evident how the growth of each artwork does not proceed with a regular pace. It is characterized instead by bursts and collapses alternated with moments of relative stasis. A natural way to quantify the building efficiency is by looking at the absolute value of the average growth speed in a time interval of Δt, defined as

$$v(t;\Delta t) = \left| \frac{\hat{V}(t+\Delta t) - \hat{V}(t)}{\Delta t} \right|. \quad \textbf{[1]}$$

Although other choices are indeed possible, the definition of $v(t)$ is quite straightforward and useful in identifying moments of stasis and fast change of the artworks. Fig. 2*A* reports the time evolution of $v(t;\Delta t)$ with $\Delta t = 1{,}200$ s for the artworks of a generic day (see *SI Appendix*, section S3 for more complete information). Note that in Eq. **1** we are considering the average value of the variation of the volume; i.e., the growth speed is definite positive. Please refer to *SI Appendix*, section S8 for a discussion about the cases in which the absolute value is removed. The artworks play an important role in the organization of the dynamic interaction network of the participants. In *SI Appendix*, Fig. S3 we show that participants have longer interaction times with the artwork than with one another, while the latter interactions are more frequent but shorter. Thus, we investigated the effect of its structure on the overall growth of the artworks by singling out the subgraph of all of the contributors to a specific artwork at each time step. Given all of the participants active at one particular time step t and all of the recorded interactions between them and with the artworks, we denote the overall network as $\mathcal{G}_t$. At each time step, we can identify a working team of an artwork s as the subset $g_s(t;\Delta t) \subset \mathcal{G}_t$ of all of the participants that in the time interval $I_t = [t, t+\Delta t]$ have at least 1 recorded contact with any of the RFID sensors under the artwork s. The identification of the working teams for each artwork s allowed us to isolate which part of the interaction networks was relevant for the building activity performed in the time interval I_t.

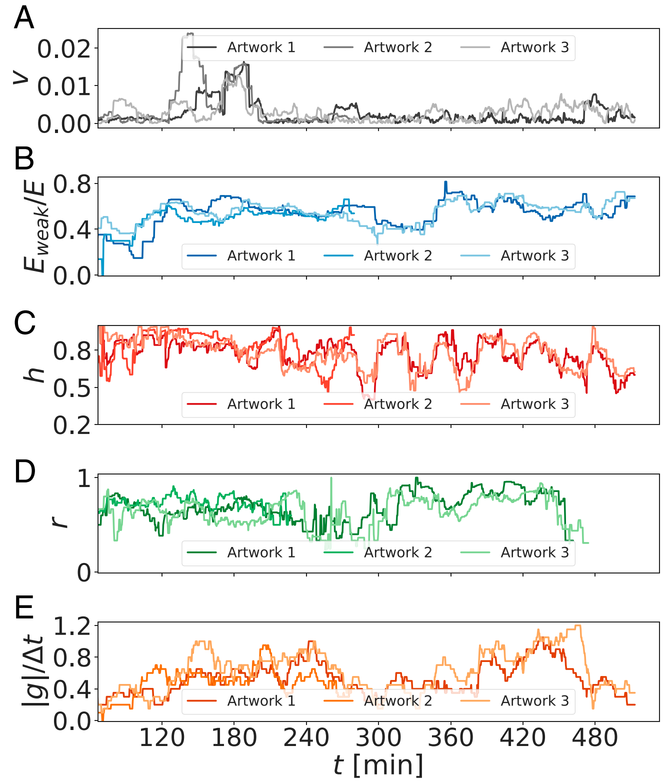

Fig. 2. (*A*–*E*) Time evolution of growth speed (*A*), weak ties (*B*), commitment (*C*), social influence (*D*), and team size (*E*) on the third day of activity of a specific artwork and for $\Delta t = 1{,}200$ s. Lines of different colors represent the time evolution of the metrics for different artworks.

Having identified the working teams, we can now proceed to investigate their properties, in terms of their dynamical composition and their topological structures. We investigate in particular 4 observables susceptible to play an essential role in the efficiency of the collective building activity.

Weak Ties. A first significant quantity to look at is the fraction of weak ties in a working team $g_s(t;\Delta t)$. A weak tie here is a link between 2 individuals whose total interaction time is relatively small compared to their total time of activity, t_{act}, until time t. We refer to the fraction of weak ties for a working team as E_{weak}/E, i.e., the fraction of links of $g_s(t;\Delta t)$ that are identified as weak ties (see *Materials and Methods* for details).

Commitment. Another important element of the collective building activity what is we define as commitment. The commitment h quantifies how evenly is distributed the total effort of an individual over the 3 artworks. h is based on the total interaction time between an individual and the artworks. h will be 1 if all such time has been spent on a single artwork and 0 if it is evenly distributed among the three (see *Materials and Methods* for details). Fig. 3*C* reports the distribution of the commitment h, which has a peak at $h = 1$ corresponding to individuals committed to only 1 artwork.

Social Influence. We now focus our attention on the role of socially influential individuals in working teams, identified as very effective information spreaders in the social network (30).

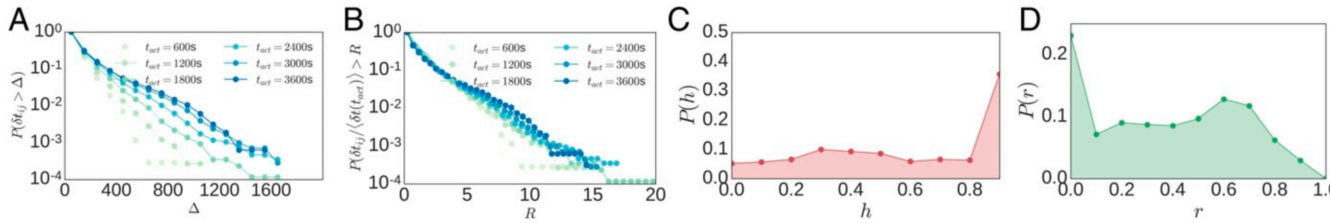

Fig. 3. (*A*) Inverse cumulative distributions of the interaction times between participants, conditioned on the total activity time of 1 of the 2 participants. (*B*) Same distributions as in *A* scaled by the average interaction time, $\langle \delta t(t_{act}) \rangle$, of individuals with a given activity time t_{act}. (*C*) Distribution of the commitment of the participants in all days of activity. (*D*) Distribution of social influence of the participants in all days of activity.

To identify influential individuals in our dynamical interaction networks, we adopted the SI (susceptible-infected) model of epidemic spreading (30). In this way, every individual is associated with an observable, r_i, quantifying his/her level of influence (see *Materials and Methods* for details). Fig. 3*D* reports the distribution of the social influence r. We observe the peak of poorly influential people and a marked peak of fairly influential individuals.

Team Size. Finally, one natural measure we take into account is the size of each working team. Since the size of each working team depends on the length of the interval I_t adopted for its definition, we scale the team size ($|g_s(t;\Delta t)|$) by Δt to mitigate this effect. See *Materials and Methods* for a more precise definition of the fraction of weak ties, commitment, social influence, and team size. The 4 observables just defined are fundamental to unveil the interplay between the structure and composition of the working teams and the evolution of the artworks, i.e., the outcome of the open-ended collective building activity. Given a specific artwork and the sequence of working teams that worked on it, $g_s(t;\Delta t)$, we can look at the time series of the 4 observables defined above. Fig. 2 reports an example of these behaviors for 1 artwork and 1 choice of Δt and we refer to *SI Appendix* for a more detailed account. We can now investigate whether the overall artworks' growth is affected by the structure and composition of the working teams. To this end we correlate the growth speed and the time series reported in Fig. 2 of the fraction of weak ties (Fig. 2*B*), the level of commitment (Fig. 2*C*), the social influence (Fig. 2*D*), and the team sizes (Fig. 2*E*). Fig. 4 reports the trends of the growth speeds as a function of the 4 observables above. More in detail, for each observable and each choice of Δt, we averaged the values of the growth speeds corresponding to a binned range of values of the observable. In this way, for each bin of the observable, we obtain an average value for the growth speed. It is first interesting to observe as the scatter plots are robust with respect to the choice of Δt. An interesting pattern is observed in the relationship between the growth speed and the fraction of weak ties (Fig. 4*A*). In this case, we observe the existence of an optimal value of the fraction of weak ties to maximize the growth speed of the artworks. This result is in agreement with the framework developed by Granovetter (21): A few weak ties in a working team indicate that the working teams are not so open-ended, which results in a poor inflow of new information and reduced effectiveness in carrying out the creative task. On the other hand, too many weak ties indicate a working team whose turnover is so high that no efficient communication can be established. In other words, the fraction of weak ties is quantifying the balance between the exploit and the explore strategies of working teams (16). As the presence of weak ties fosters the diffusion of information (33), a working team with a large number of weak ties might easily explore new ideas at the cost of less communication efficiency. Due to their reduced ability to access further information, working teams with few weak ties are forced to reuse already exploited ideas. What emerges very clearly is that a right balance of weak and strong ties is leading to optimal growth for the artworks. The level of commitment (Fig. 4*B*) positively correlates with the growth speed. Working teams with more committed individuals, i.e., individuals who focused primarily on 1 single artwork, tend to be more effective in terms of the amount of volume produced during the building activity. Fig. 4*C* shows the dependence of the growth speed on social influence. In this case, we observe that a stronger presence of influential people leads to best building performance. Finally, the dependence on the team size (Fig. 4*A*) shows that larger teams tend to be more productive in terms of volume growth. This result is not surprising considering that besides having more "workforce," large teams are also able to share and test more ideas, easing the realization of new parts of the artworks. In *SI Appendix*, section S8, we isolate the cases where artworks have grown and those in which their volume decreased. While in the first case all of the results presented here are confirmed, in the second one there is no evidence that the growth speed correlates with the team size. The framework emerging can be summarized by saying that the best way to assemble a team for a creative task is to have it large, full of firmly committed, possibly influential, individuals, and with a right balance between weak and strong ties. At this point, it is still not clear whether the different features just described should all occur at the same time or not. In principle, different combinations might occur at separate times. For example, teams with the right amount of weak ties without influential individuals might still be among those very effective in the building activity. In *SI Appendix*, section S6, we applied the nonnegative matrix factorization (NNMF) dimensionality reduction algorithm (36) to identify

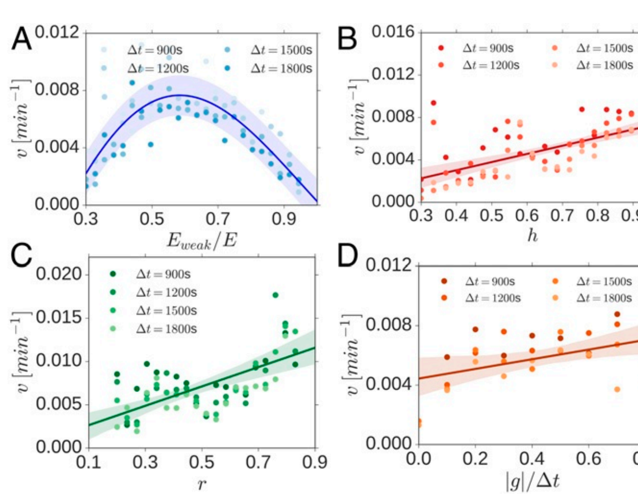

Fig. 4. (*A*–*D*) Binned scatter plots of the growth speeds of the artworks vs. the fraction of weak ties (*A*), the commitment (*B*), the social influence (*C*), and the team size (*D*). All of the observables have been computed for different time windows Δt.

mixed conditions in which high growth speed might occur. Surprisingly, we find that the only cases in which highly efficient building conditions are likely to happen are when all of the 4 conditions mentioned above are present at the same time. What emerges is then a very specific identikit of effective working teams in terms of their structure and composition. Performing the same analysis using latent Dirichlet allocation (37) leads to similar results.

Discussion

The understanding of collective creative processes has been boosted by the fast-growing relevance of creative processes, where an open-ended multitude of contributors cooperate toward an important collective outcome. The question of what is the best way to organize the interactions within the community of creators and what features a working team should have to get the best out of the collective process is wide open.

Here we provided experimental pieces of evidence of the critical ingredients underlying efficient, creative cooperation. To this end, we conceived and deployed a real-world open-ended experiment in which teams of participants were committed to the realization of artworks using LEGO bricks.

The growth of the artworks was monitored through depth sensors, while the interactions between the participants were monitored employing RFID sensors worn by each of them. In this way, we obtained a real-time parallel picture of the growth of the artworks and the evolution of social interactions. Through this comprehensive monitoring, we were able to correlate the dynamical evolution of a working team, along with its features, to the growth speed of the emerging artworks.

We have identified 4 key determinants underlying a faster growth of the artworks. In particular, we discovered the following: 1) There exists an optimal value of the fraction of weak ties within the working teams that makes their outcome particularly efficient. This result implies that the self-organized working teams greatly benefited from a balance between weak and strong ties in the network of interactions. In turn, this highlights the relevance of a subtle equilibrium between exploit and explore strategies for creative purposes. 2) Working teams with more committed individuals perform much better. 3) Influential individuals, i.e., individuals with a more significant potential to spread their ideas within the team, greatly enhance the performances of the team itself. 4) Finally, larger teams tend to perform better.

Despite the interest of these results, the experiment could be improved to allow the study of collective creativity in a more general sense. Growth speed is a simple observable measuring the level of coordination of team members, but the experimental setting allows for the monitoring of other quantities related to the popularity of the artworks. In this sense, we can monitor the ability of an artwork to attract new contributors and, at the cost of more complexity in the setup, it is possible to directly ask the participants their opinion about the originality and creativity of the artworks.

The generality and the effectiveness of the proposed experimental framework make it suitable to be extended to other kinds of joint activities both in real and in virtual worlds: for instance, the realization of collective works like texts, screenplays, music, video games, free software, or situations where work division is relevant, as in large institutions or corporations.

Materials and Methods

Experimental Protocols Approval and Participants' Consent. All methods in experiments E1 to E3 were carried out in accordance with relevant guidelines and regulations. The experimental protocols used have been approved by the General Data Protection Regulation (EU) 2016/679. Informed consent was obtained from all subjects. For participants below 18 y old, informed consent was obtained from parents or legal tutors.

Weak Ties. Given 2 participants i and j at time t, we indicate the weight of the link connecting them in $\mathcal{G}_t$ as $\delta t_{i,j}$. This weight represents the total interaction time of i and i, i.e., the total duration of all their contacts as recorded by their RFIDs. A participant with a larger activity time, t_{act}, will feature on average larger interaction times. This is reflected in Fig. 3*A*, where we show that the distribution of the interaction times gets broader as the total activity time t_{act} grows. Considering the average interaction time, $\langle \delta t(t_{act}) \rangle$, of an individual with an activity time t_{act}, we normalize the interaction time of i and j as $\delta t_{i,j} / \langle \delta t(t_{act}) \rangle$. Fig. 3*B* shows the distribution of these quantities, highlighting that the dependence on $\delta t(t_{act}) \rangle$ has disappeared. We can now say that the link (i, j) is a weak tie for the participant i if $\delta t_{i,j} < |\delta t|(t^i_{act})$, where $|\delta t|(t^i_{act})$ is the average of the distribution of all of the $\delta t_{i,j}$ of the participants with the same activity time of the participant i. Note that with this definition a link which is a weak tie for i might not be a weak tie for j, since they might have a different activity time. Thus, the link (i, j) is a weak tie, if and only if it is a weak tie for both i and j.

Given a working team $g_s(t; \Delta t)$, we define the fraction of weak ties in the team as E_{weak}/E, where E_{weak} is the number of links in $g_s(t; \Delta t)$ that are weak ties and E is the total number of links. A value of $E_{weak}/E = 1$ indicates that all of the links are weak ties and hence that all of the members of the working team have not interacted frequently during their activities.

Commitment. Here we give the proper definition of commitment. Similarly to the case of contacts between participants, it is possible to define the total interaction time between the individual i and 1 of the 3 artworks s (with $s \in \{1, 2, 3\}$). This interaction time δt^s_i quantifies how much of the total effort of the participant i has been devoted to the artwork s. Thus, indicating with $T_i = \sum_s t^s_i$ the total time i has spent building, we can define the commitment for the participant i as

$$h_i = 1 - \frac{1}{\log 3} \sum_s \frac{t^s_i}{T_i} \log \frac{t^s_i}{T_i}. \quad [2]$$

In this way, an individual working only on a single artwork would feature $h = 1$. On the other hand, an individual who worked evenly on the 3 artworks would feature $h = 0$. We can extend the definition of the commitment to a working team by simply averaging its values over all of the members of the team.

Social Influence. The importance of an individual within a social network is usually quantified with simple metrics such as the degree, the closeness centrality, and the betweenness centrality (38). Although initially defined for static networks, these observables naturally extend to dynamical networks (39, 40). We refer to *SI Appendix*, section S5 for a brief investigation on the correlations between centrality metrics for static networks and growth speed. A common way in which importance can be assessed is through information diffusion models, which are typically used also in epidemic spreading simulations (30). Hence, we used a simple SI model of epidemic spreading (30) running on the global dynamic interaction network of participants' interactions. In turn, every individual i, i.e., every node of the network, acts as the starting seed of a virtual infection and we measure the fraction of nodes, r_i, infected at the end of the spreading process. The social influence of an individual participant is then identified as the fraction r_i. The higher r_i is, the higher the level of influence of individual i. Note that the SI model depends on 1 parameter $\beta \in [0, 1]$, namely the transmission rate. To have an estimate of r independent of this parameter, we repeated the simulations for several values of β and averaged the different results for r_i. Fig. 3*D* shows the distribution of r for all of the participants in the experiment in all of the 3 d of activity. While the distribution is quite heterogeneous, the peak for $r_i = 0$ indicates that a considerable fraction of participants had a small influence on the others. We can extend the definition of social influence to a working team $g_s(t; \Delta t)$ by simply averaging its values over all of the members of the team. See *SI Appendix*, section S4 for more details on the simulation of the epidemic spreading process.

Team Size. The limited size of the building supports allowed only a limited number of participants to work together at the construction of each artwork at a time. Even though the RFID sensors attached to each artwork might have recorded the presence of participants just around it and not

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participating to the construction, it is reasonable to assume that a working team with a large number of members will also be one in which many different people have given their contribution to the artwork. Obviously, as $\triangle t$ increases we also expect the size of $g_s(t;\triangle t)$ to increase accordingly so that sizes at different $\triangle t$ are not comparable. To have a definition of team size easily comparable across very different situations, we consider a normalized observable as the ratio between the size of $g_s(t;\triangle t)$ and $\triangle t$, i.e., $g_s(t;\triangle t)/\triangle t$.

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