Limitation of time promotes cooperation in temporal games

Jiasheng Wang[1,2], Yichao Zhang[1,2*], Guanghui Wen[3,4*], Jihong Guan[1,2*], Shuigeng Zhou[5,6], Guanrong Chen[7], Krishnendu Chatterjee[8], Matjaž Perc[9,10,11]

[1*]Department of Computer Science and Technology, Tongji University, 4800 Cao'an Road, Shanghai 201804, China.
[2]Key Laboratory of Embedded System and Service Computing (Tongji University), Ministry of Education, Shanghai 200092, China.
[3]Department of Systems Science, School of Mathematics, Southeast University, Nanjing 210016, China.
[4]School of Engineering, RMIT University, Melbourne VIC 3000, Australia.
[5]Shanghai Key Laboratory of Intelligent Information Processing, Shanghai 200433, China.
[6]School of Computer Science, Fudan University, 220 Handan Road, Shanghai 200433, China.
[7]Department of Electrical Engineering, City University of Hong Kong, 83 Tat Chee Avenue, Kowloon Hong Kong SAR, China.
[8]Institute for Science and Technology, A-3400 Klosterneuburg, Austria.
[9]Faculty of Natural Sciences and Mathematics, University of Maribor, Koroška cesta 160, 2000 Maribor, Slovenia.
[10]Department of Medical Research, China Medical University Hospital, China Medical University, Taichung, Taiwan.
[11]Complexity Science Hub Vienna, Josefstädterstraße 39, 1080 Vienna, Austria.

Abstract

Temporal networks are obtained from time-dependent interactions between individuals. The interaction can be an email, a phone call, a face-to-face meeting, or a collaboration. We propose a temporal game framework where interactions between rational individuals are embedded into two-player games with a time-dependent aspect of interaction. This allows studying the time-dependent complexity and variability of interactions and how they affect prosocial behavior. Based on a simple mathematical model, we find that the level of cooperation is promoted when the time of collaboration is limited and identical for every individual. We confirm and validate this with a series of systematic human experiments that forms a foundation for comprehensively describing human temporal interactions in collaborative environments. Our research reveals an important incentive for human cooperation, and it lays the foundations for better understanding this fascinating aspect of our nature in realistic social settings.

Keywords: temporal networks, non-cooperative game, human subjects, cooperation

1 Introduction

Many complex collaborative systems in nature, society, and engineering can be modeled through networks. In a network, nodes represent collaborating individuals, and links represent their friendships [1]. In the early stage of network modeling, links are simplified to be weightless, undirected, and static. In order to improve the ability to depict real systems, weighted [44], directed [34], and dynamic [29] network models have been put forward successively. The application of these network models in various fields has fully proved that the closer the framework is to reality, the stronger its ability to explain behaviors. As an intriguing behavior in human collaborative systems, the emergence of cooperation has attracted researchers from social and natural sciences for half a century [7, 18, 36, 37]. Although we are certainly not exempt from selfishness and the fundamental principles of Darwinian evolution, cooperation is nevertheless ubiquitous across human societies [31]. While the impetus for our strong cooperative drive has been linked to the difficulties of the genus *Homo* in rearing offspring that survived and to the emergence of alloparental care [24], and to the formation of alliances in times of conflicts [6], it is still puzzling as to why we have, as a species, achieved such high levels of cooperation. Our altruistic behavior distinguishes us markedly from other mammals, and they indeed form the bedrock for our astonishing evolutionary success.

The studies of human cooperation in n-person games begin with population games, also known as mean-field games [9, 22, 28]. In such a well-mixed population, cooperation can hardly prevail with imitative update rules when individuals play non-cooperative games such as the prisoner's dilemma [47]. If the population exhibits a relatively stable social structure, the consequence may be different [2, 14, 15, 17, 25, 33, 39–42, 49] – a finding with roots in the seminal paper by Nowak and May [32], who observed clusters of cooperators on a square lattice that protected them from invading defectors. Nevertheless, social networks are seldom static. We disconnect, reconnect, and then form connections with new people over time. This realization has revealed new mechanisms for cooperation that may sustain cooperative behavior under extremely adverse conditions, when the temptation to defect is high and where on static networks cooperation would long perish [35]. An individual also does not interact with all his friends all the time but likely does so only occasionally.

To account for the above aspects, dynamic networks are studied. The implications of dynamic interaction patterns on human cooperation are indeed profound, and recent human experiments, as well as theoretical research, confirm this to the fullest [12, 38, 44, 48, 50, 52]. It was argued, for example, that such observations demonstrate the effect of reputation [29]. Individuals may connect with unfamiliar individuals after browsing their gaming records while cutting the existing connections with unsatisfactory partners. Some may take breaking ties, instead of performing defection, as a way to penalize defectors [38]. Interestingly, the implication of dynamic reconnection fades out when individuals choose specific moves to play games with their partners [29]. In this light, an interesting question is whether the dynamic reconnection is relevant to the level of cooperation in a human collaborative system if there is a time limit on the duration of a game? From the perspective of biological markets [5], the dynamic reconnection in such a system is a reallocation of collaboration time in a time-limited collaborative environment. Is too much emphasis put on the structure of our social networks, resulting in neglecting the temporal aspects of our interactions? In what follows, we will address these critical questions in detail.

Due to the complexity of temporal systems, using evolutionary game theory to model individuals' collaborations is reasonably challenging. First of all, the evolution mechanism of a temporal system itself is complicated, difficult to describe by a simple mathematical model. Secondly, in the temporal games, an individual strategy involves not only the moves in games but also the allocation of time in a round. This openness allows individual strategies and network topologies to co-evolve in more flexible ways than the existing dynamical gaming networks [30, 57], which further raises the difficulty of modeling the coupled systems.

In this paper, we present a temporal gaming framework upon the structure of temporal networks [23, 26]. The goal is to test the impact of limited time on the level of cooperation in two-player collaborative systems. Such systems are common in reality. For instance, it typically takes a team to accomplish a project when applying for funding. The project leader typically would collaborate with a member to accomplish a specific part of it. Correspondingly, the member or the leader can also be involved in more than one project. Simultaneously, the total number of working months for each participant is limited and identical. In such a scenario, a temporal gaming network is naturally composed. Admittedly, the collaboration between two team members is closer to the stag hunt game than the Prisoner's Dilemma (PD) game. Consider cooperation normally dominates the collaboration system playing the stag hunt game, one can hardly differentiate the impacts from other mechanisms. We adopt the PD game in this paper.

One of our key contributions is a detailed online experiment for the theoretical framework. We first establish a gaming platform to implement a temporal game scenario. Next, we test the level of cooperation on the platform in a divide and conque (D&C) mode [29, 51, 56], where the difference from the settings of the existing works [12, 20, 38, 39] is the targeted decisions. Finally, we test the level of cooperation on the platform in a time-involved mode, where the time limitation for individuals and targeted decisions are considered. The reasons for adopting these mechanisms will be provided in Section *Experimental design*. What we are looking for is whether the limitation on time resources governs human cooperation in the games. In what follows, we will focus on this factor.

To clarify the impact of the limited time, we invited 183 human subjects and designed a set of comparative online experiments. In a match, the participants are allocated to the nodes of pre-generated networks. We test two classes of networks, the Barabási and Albert's scale-free network [3] and Watts and Strogatz's small-world networks, since they are the most well-known social network models. We show that the limitation to the individuals' time resources statistically promotes the participants' level of cooperation, which aligns with the theoretical prediction presented below.

2 Theoretical framework of temporal games

2.1 Temporal game model

In a two-strategy (i.e., only two moves are allowed) game, define i's strategy as $\Omega_i = \begin{pmatrix} X_i \\ 1 - X_i \end{pmatrix}$, where X_i can only take 1 or 0 in each game. If $X_i = 1$, i is a cooperator denoted by C. If $X_i = 0$, i is a defector denoted by D. Take the PD game [27] for example, in the PD game, the payoff table is a 2×2 matrix. Given i's strategy, i's payoff in the game playing with all his neighbors (denoted by N_i) can be written as $G_i = \Omega_i^T \begin{pmatrix} \mathcal{R} & \mathcal{S} \\ \mathcal{T} & \mathcal{P} \end{pmatrix} \sum_{j \in N_i} \Omega_j$. In the PD model, it gains $\mathcal{T}$ (temptation to defect) for defecting a cooperator, $\mathcal{R}$ (reward for mutual cooperation) for cooperating with a cooperator, $\mathcal{P}$ (punishment for mutual defection) for defecting a defector, and $\mathcal{S}$ (sucker's payoff) for cooperating with a defector. Normally, the four payoff values satisfy the following inequalities: $\mathcal{T} > \mathcal{R} > \mathcal{P} > \mathcal{S}$ and $2\mathcal{R} > \mathcal{T} + \mathcal{S}$. Here, $2\mathcal{R} > \mathcal{T} + \mathcal{S}$ makes mutual cooperation the best outcome from the perspective of the collective.

The temporal game model proposed in this paper is based on the game model [51, 56] taking into account the time of interactions. As the model is time-involved, each interaction is assigned a specific duration. The total game time for each individual in a round is set to be constant and the same for all individuals to be realistic to real-life scenarios. An individual's interactions with different partners are assumed, independent. The payoff of the game between individuals i and j can be written as $s_{i,j} = \Omega_{i,j}^T \begin{pmatrix} \mathcal{R} & \mathcal{S} \\ \mathcal{T} & \mathcal{P} \end{pmatrix} \Omega_{j,i}$. In the temporal games, the payoff of each interaction is proportional to the time it spans. In one round of the game, the accumulated payoff of individual i is defined as

$$\Lambda_i = \sum_{j \in N_i} \frac{\tau_{i,j}}{\mathfrak{T}} \times s_{i,j}, \tag{1}$$

where N_i is the set of i's neighbors; $\tau_{i,j}$ is the duration of the interaction between individuals i and j. As shown in Fig. 1A, let i and j be the individuals colored red and blue. Then $N_i = 4$ and $\tau_{i,j} = 8$. Notably, $\tau_{i,j}$ should satisfy the constraints of $\tau_{i,j} \in [0, \mathfrak{T}]$ and $\sum\limits_{j \in N_i} \tau_{i,j} \leqslant \mathfrak{T}$. Here, $\mathfrak{T}$ is the total time resource of an individual in each round, which is a constant for all individuals in our model. In Fig. 1A, $\mathfrak{T} = 24$. If individual i does not want to collaborate with j, then i will not apply for a game with j any longer. Simultaneously, i will reject j's gaming request. In this case, $\tau_{i,j}$ will be 0 as the relation between the red and the green in Fig. 1A.

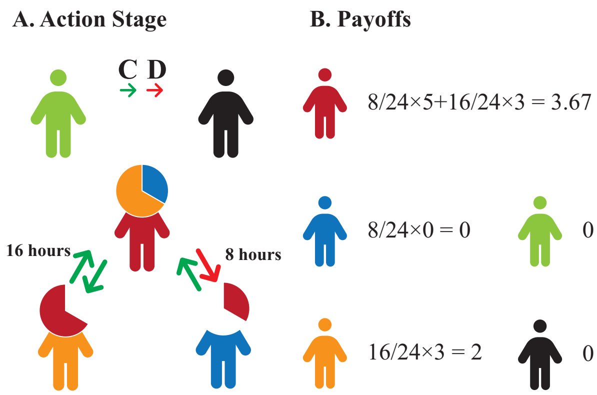

Fig. 1 Illustration of the temporal game. Panel A shows a round of the temporal game among 5 individuals. The individual colored red has 4 friends, in which the individuals colored orange and blue are his gaming partners. If the game beween two individuals lasts for 24 hours, the payoff of a cooperator is 3 and 0, gaining from a cooperator and a defector, respectively. The payoff of a defector is 5 and 1, gaining from a cooperator and a defector, respectively.

Let P_i be the set of partners who interacted with i in the round, Eq. 1 can be written as

$$\Lambda_i = \sum_{j \in P_i} \frac{\tau_{i,j}}{\mathfrak{T}} \times s_{i,j}, \tag{2}$$

where $\tau_{i,j}$ is greater than 0. For the red individual in Fig. 1A, the orange and the blue are his partners in this round. Based on Eq. 2, the payoffs of the 5 individuals are listed in Fig. 1B. In a mean-field view, Eq. 2 can be written as

$$\Lambda_{k_i} = \sum_{k_j} \frac{\tau_{k_i,k_j}}{\mathfrak{T}} P\left(k_i, k_j\right) s_{k_i,k_j}, \tag{3}$$

where $P(k_i, k_j)$ is the probability that a link exists between i and j, dependent on the topology of the collaborative network. We show an illustration of such a collaborative network in Fig. 2A. To clarify the generating procedure of the network, we provide the communication log among the individuals in this round in Fig. 2B. In the log, Alice tried collaborating with Tom for $\mathfrak{T}$, while Tom had agreed to work with Jerry and Frank when he received Alice's request. Thus, Alice turned to Frank and Jerry, but it was a bit late to make appointments with them as they were partially engaged. As a result, Alice took $0.8\mathfrak{T}$ to play with Frank and Jerry and wasted $0.2\mathfrak{T}$ in this round. For a heterogeneous network as the Barabási-Albert (BA) networks [4], $P(k_i, k_j) \sim \frac{k_j P(k_j)}{\langle k \rangle}$. For a homogeneous networks as the Watts and Strogatz (WS) networks [54], $P(k_i, k_j) \sim P(k_j)$.

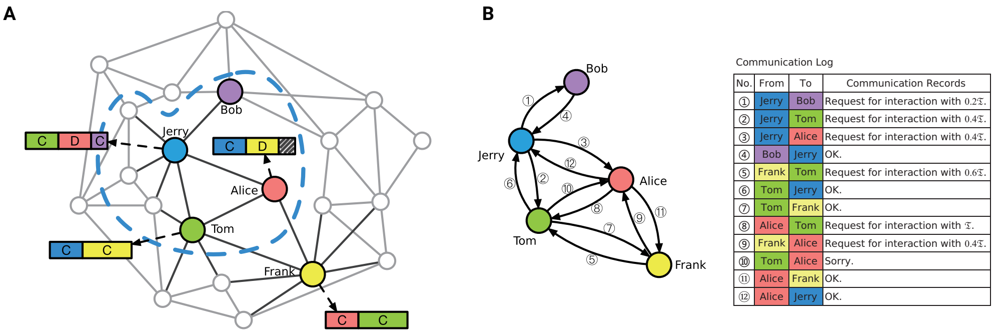

Fig. 2 Illustration of the temporal games in a two-player collaborative system. (A) One round of the temporal game on a social network. The blue circle is Jerry's neighborhood. Alice, Bob, and Tom are Jerry's partners in this round. The color of a time slot represents a partner; for instance, yellow represents Frank. C or D in the time slot denotes the move from the individual at the tail of a directed dashed line to the indicated specific partner. (B) The generating procedure of the circumstance presented in (A). In the communication log, the records are sorted by their sequence numbers in ascending order. Only if both players agree to collaborate (the response to a request is OK) will their colors appear in each other's collaboration schedule, i.e., a time slot in (A).

2.2 Proportion of cooperation in the temporal game

In the temporal game, each game between partners is coupled with a duration. Therefore, the level of cooperation should be measured by the duration and their moves. We define the proportion of cooperation as $P_c = \frac{T_C}{T_G}$, where T_G is the total duration of the moves and T_C is the total duration of cooperation in the games.

Note that current studies on decision time [10, 11] in experimental psychology and response time in experimental economics [45, 55] focus on the time of making a decision rather than the duration of moves. Therefore, the object of such studies is different from that of temporal games.

2.3 Mathematical modeling the available time of individuals

As is known, for each game between two players, each player has to experience one of the four possible cases, namely, cooperating with a cooperator (CC), cooperating with a defector (CD), defecting a cooperator (DC), and defecting a defector (DD). We define a state vector $\mathbf{\Phi}$ by $(\Phi_{CC}, \Phi_{CD}, \Phi_{DC}, \Phi_{DD})$, in which each entry corresponds to the probability of experiencing the respective outcome. Generally, a memory-one strategy can be written as $\mathbf{p} = (p_{CC}, p_{CD}, p_{DC}, p_{DD})$, corresponding to the probabilities of cooperating under each of the previous outcomes. Since players update their moves with the memory-one strategies in each time step, the update can be considered a Markov process. One can find a Markov transition matrix M_i to realize the update. For two players, i and j, we have

$$M_i = \begin{pmatrix} p_{CC}s_{CC} & p_{CC}(1-s_{CC}) & (1-p_{CC})s_{CC} & (1-p_{CC})(1-s_{CC}) \\ p_{CD}s_{DC} & p_{CD}(1-s_{DC}) & (1-p_{CD})s_{DC} & (1-p_{CD})(1-s_{DC}) \\ p_{DC}s_{CD} & p_{DC}(1-s_{CD}) & (1-p_{DC})s_{CD} & (1-p_{DC})(1-s_{CD}) \\ p_{DD}s_{DD} & p_{DD}(1-s_{DD}) & (1-p_{DD})s_{DD} & (1-p_{DD})(1-s_{DD}) \end{pmatrix}, \quad (4)$$

where the vectors $\mathbf{p} = (p_{CC}, p_{CD}, p_{DC}, p_{DD})$ and $\mathbf{s} = (s_{CC}, s_{CD}, s_{DC}, s_{DD})$ denote i and j's probabilities of cooperation in the next round after experiencing CC, CD, DC, and DD cases, respectively. Then the evolution of i's state vector $\mathbf{\Phi}_i(t)$ is given by

$$\mathbf{\Phi}_i(r) = \mathbf{\Phi}_i(r-1)M_i. \tag{5}$$

To model the the available time of individuals in the temporal games, we first assume that no players at round $r-1$ reject the requests from an individual i if they are available. The time left for him to make use of in round r can be denoted by $S_i(r) = \mathfrak{T} - \sum_{j\in P_i} \tau_{u_{ij}(r-1)}$, where $\mu_{ij}(r-1)$ denotes the random portion of time in the request from i in round $r-1$. If i applies for playing with j for $S_i(r)\mu_{ij}(r)$, the successful probability of the request is

$$\omega_{i,j}(r,\mu_{ij}(r)) = \begin{cases} 1, & S_j(r) \geq S_i(r)\mu_{ij}(r), \\ 0, & S_j(r) < S_i(r)\mu_{ij}(r), \end{cases} \tag{6}$$

assuming j wish to play. Therefore, the expectation of difference in individual i's available time from round r to $r+1$ is

$$\begin{aligned} \varrho_i(r) = &-\textstyle\sum_{j\in N_i - P_i(r-1)} \omega_{i,j}(r,\mu_{ij}(r))\,(S_i(r) \\ &+\textstyle\sum_{l\in P_i(r-1)} \alpha_{il}(r-1)\left(\mathbf{\Phi}_{il}(r)\cdot\begin{bmatrix}\chi_{i,CC}\\ \chi_{i,CD}\\ \chi_{i,DC}\\ \chi_{i,DD}\end{bmatrix}\right)\Bigg)\,\mu_{ij}(r), \end{aligned} \tag{7}$$

where $\chi_\mathbf{i}$ denotes i's probabilities of reassigning time after experiencing the four outcomes. $\alpha_{il}(r)$ denotes the time share which i assigns to l at round r. Note that

$$\sum_{l\in P_i} \alpha_{il}(r) + S_i(r) = 1. \tag{8}$$

Considering $S_i(r) \geq 0$ for all r, the iterative formula of $S_i(r)$ should be written as

$$S_i(r+1) = Relu(\varrho_i(r) + S_i(r)), \tag{9}$$

where $Relu(x) = \begin{cases} x, & x \geq 0, \\ 0, & x < 0. \end{cases}$ As the evolution procedure of $S_i(r)$ in the system can not be modeled in a mean-field way, one can hardly present an analytical solution to it. Therefore, we will present the simulation results and empirical results from human online experiments in the following. In the simulations, we uniformly set the agents to adopt the same strategy to have the results reproducible. Let the number of agents be N_A. We will show that the average available time $S(r) = \frac{\sum_i S_i(r)}{N_A}$ falls to a low level at the first round. It is stablized after then, indicating that finding new partners is problematic from the beginning of a match.

3 Results

To show the impact of time redistribution, we first simulate the evolution of moves when agents play a traditional Prisoner's dilemma (PD) game with their neighbors in the BA and WS networks. In a network, a player starts a game with a gaming request to a neighbor. In our simulations, all the agents in the network are selected one by one, following a random sequence. For a selected agent, it evenly allocates the time left to its requests to the uncoordinated neighbors. If the requested neighbor has enough time to accept the gaming request, he will accept it. After one round of the game, agents will uniformly update their moves with the Zero-Determinant Extortionate strategy proposed in reference [46]. The strategy will wipe the cooperators out in 100 rounds. If an agent defects in a round, the pair will be taken apart with a certain probability. The separation means the time assigned to the pair will be redistributed next round. More details on the simulations will be provided in Section *Simulation on the social networks*.

In Fig. 3(a) and 3(b), the results show the level of cooperation decays with rounds for agents playing the 'divide-and-conquer' (D&C) games [29, 51, 56] in both networks. After being affected by the temporal mechanisms, the rates of decay slow down in Fig. 3(c) and 3(d). We show the difference in the level of cooperation between the temporal games and the D&C games [29, 51, 56] in Fig. 3(e) and 3(f), which will be amplified when human subjects play. The amplification may originate from $S(r)$ shown in Fig. 3(g) and 3(h), which will be much lower when humans play the temporal games.

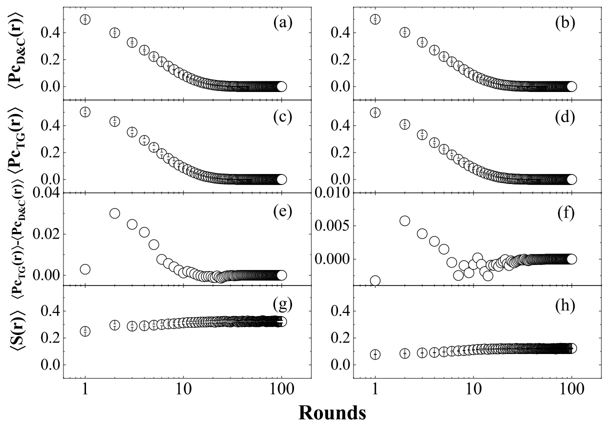

Fig. 3 Evolution of the average proportion of cooperation $\langle P_c(r) \rangle$ in the 'divide-and-conquer' (D&C) and temporal gaming networks. (a) and (c) show $\langle P_c(r) \rangle$ of the D&C games and temporal games in the BA networks, respectively. (b) and (d) show $\langle P_c(r) \rangle$ of the two classes of games in the WS networks, respectively. (e) and (f) show the difference of $\langle P_c(r) \rangle$ between the D&C games and the temporal games in the BA and WS networks, respectively. Each plot denotes the average of 10 simulation runs. As the system evolves dramatically at the beginning of the experiments, we show the results in semi-log coordinates.

To test the validity of our theoretical results, we invite 183 volunteers to attend 8 online experiments. For conciseness, we show the basic information of each match in Table 1. After comparing Fig. 4(a) with Fig. 4(b) and Fig. 4(c) with Fig. 4(d), one can see that the decay of $P_c(r)$ in the temporal games is slower than that in the D&C games. The result confirms our theoretical prediction, indicating the limitation on time promotes the level of cooperation in gaming social networks.

Table 1 The basic information of matches.

Game Number	Game Type	Type of Network	Number of Participants	Number of Rounds	Corresponding Panel in Fig. 4
G1224	D&C	BA	39	13	Fig. 4(a)
G1230	D&C	BA	17	16	Fig. 4(a)
G646	Temporal Games	BA	50	11	Fig. 4(b) and Fig. 4(e)
G903	Temporal Games	BA	44	28	Fig. 4(b) and Fig. 4(f)
G1228	D&C	WS	34	13	Fig. 4(c)
G1234	D&C	WS	21	15	Fig. 4(c)
G936	Temporal Games	WS	22	24	Fig. 4(d) and Fig. 4(g)
G933	Temporal Games	WS	22	28	Fig. 4(d) and Fig. 4(h)

To explain the behavior, we measure the average available time $S(r)$ in the four time-involved matches. The evolution of $S(r)$ for the two BA networks and two WS networks are shown in Fig. 4(e)-Fig. 4(h), respectively. For conciseness, the basic information of matches is listed in Table 1. One can see that $S(r)$ fluctuates around a small positive value in the four panels, revealing the difficulty of finding new partners when humans play the temporal games is more significant than our theoretical prediction. The difference in $P_c(r)$ between the theoretical prediction and human behavior suggests that the rising of the difficulty of finding new partners may lead to the promotion of $P_c(r)$, which to some extent explains why the limited time promotes the level of cooperation in a real social network.

The other behavior which should be noted is that the level of cooperation generally decays with rounds in Fig. 4. The behavior is caused by the number of rounds for each match being limited, although it is random. This limitation mainly comes from the time of the subjects, since it is complicated to ask about 100 students to play online for more than an hour simultaneously, even though we pay them acceptable participation fees and provide attractive rewards for the winners of each match. We show some of the winners' strategies in Section **Top Voted Strategies** of **Supplementary Information** (**SI**). One can see that the level of cooperation decays when the participants guess that the match is ending.

4 Discussion

As a theoretical framework closer to realistic scenarios, the temporal game has demonstrated its capacity to illuminate complex behaviors in our social experiment. The human behaviors revealed from the human temporal games were rarely reported previously in the literature. When the available time resources of individuals in the gaming network are scarce, the individuals are more likely to maintain the current relationships through cooperation. The underlying mechanism is that interactions are not obligated but spontaneous. If an individual's time resource cannot afford the requested duration of the interaction, he will have no choice but to abandon it, which makes it much harder to find new partners. The accordance of empirical and simulation results confirms the significance of the mechanism. Our finding reveals a fundamental reason for lasting altruistic behaviors in real human interactions, providing a novel perspective for understanding the prevailing of human cooperative behaviors in temporal collaboration systems.

Note that the limitation on time is an objective fact in human collaboration systems, which is essentially different from the incentives, such as global reputation [16, 19] and onymity [53], associated with human psychology. In a sense, the behavior observed in our experiments is more deterministic. Introducing some other

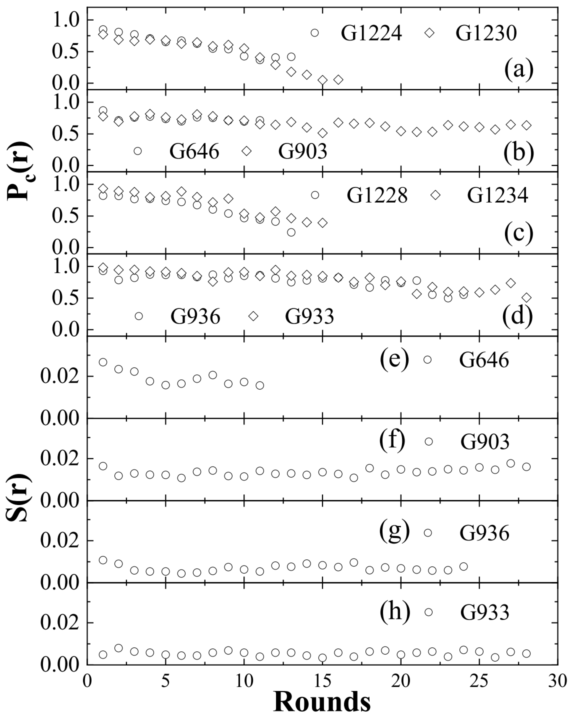

Fig. 4 Evolution of the proportion of cooperation $P_c(r)$ and the average available time $S(r)$ in the temporal games played by human subjects. (a) and (c) show the results of the D&C games in the BA networks and WS networks, respectively. (b) and (d) show the results of the temporal games in the BA networks and WS networks, respectively. Horizontal coordinates denote the number of rounds. (e) and (f) show the results of two temporal games in the BA networks. (g) and (h) show the results of two temporal games in the WS networks.

mechanisms like reward [43] and costly punishment [8, 13] to the temporal systems will be a natural extension in this direction. Apart from the mechanisms, the impact from different types of games, for instance, the snow-drift game [21] and the public goods game [42], is also of particular interest.

Our work considers the temporal game framework and presents some surprising results. There are several interesting future directions, both in terms of theoretical and experimental results. However, the basic theoretical model and the key experimental results we present in this work for temporal games are the first steps to modeling realistic networks with time-dependent interactions. Such realistic modeling will allow better analysis, prediction, and design principles for the emergence of cooperation in network models, profoundly impacting disciplines from preserving natural resources to designing institutional policies.

5 Materials and Methods

5.1 Experimental design

In order to build an experimental environment as close as possible to natural temporal two-player collaborative systems, two realistic factors are considered in our empirical study. First, the interactive time is determined by negotiation. The setting restores the temporal property of a game in reality. A dynamic reconnection is implemented in the network by rejecting a friend's request and then proposing a game with another friend [38, 50]. Second, a 'divide-and-conquer' ($D\&C$) framework, also referred to as targeted decision, is adopted, in which the individuals who propose a game or accept a gaming request have to decide whether to cooperate (C) or to defect (D) in each round of the game [29, 51, 56]. Most existing research on gaming networks is performed under a framework where individuals choose the same move to interact with all their neighbors [12, 38, 50]. On the contrary, in real-world scenarios, people do not normally defect their long-term partners after being defected by other partners. In a realistic social network, they would choose a specific move to play with a partner, referred to as the D&C game in the literature [51, 56]. When the diffuse decision scheme is replaced by the D&C or targeted decision scheme, the impact of dynamic reconnection on promoting cooperation will become negligible [29].

The coupling between temporal interaction and rational decision-making can be seen everywhere in real life. Still, the existing theoretical frameworks seem insufficient to explain the widespread cooperation in such temporal games. Under the framework of temporal games, we designed a series of online game experiments. With the experimental data, we present a surprising finding: limitation of time promotes cooperation in temporal games. This finding, on the one hand, urges us to reconsider how much the dynamic nature of networks can impact human cooperation. On the other hand, it implies the potential of the temporal game framework to explain various collective behaviors in real two-player collaborative systems. Our results have a profound impact on the study of pro-social behavior. By accounting for the time-dependent aspect to model a realistic network, we present an interesting finding which can improve our understanding of widespread cooperation in time-dependent collaborations.

5.2 Experimental setup and game rules

A series of online human subject experiments were designed to build a two-player collaborative system of rational individuals. A total of 183 human subjects participated in 8 matches in the experiment. The majority of subjects are students from Tongji University and Southeast University in China. To implement the designed scenario, a novel online gaming platform was developed, called the *War of Strategies* (http://strategywar.net, see (Section **Experimental Platform and Interface** of **SI** for the details of the platform).

In the online experiments, participants played a traditional Prisoner's dilemma (PD) game, where C and D were the only available actions. Each participant interacted with the individuals who had agreements with him in one round, after which the agreements need to be redrafted.

Each match on the platform comprises two stages. In the first stage, the system generates a network with a social network model. The subjects are then allocated to the nodes of the network. Therefore, the connections among the subjects are randomly predetermined. The second stage is an n-round iterated PD game, where $10 \leq n \leq 30$ is unknown to individuals to avoid the ending-game effects.

In each round of the game, individuals can make requests for interactions with their friends. In a request, the duration of the interaction is suggested by the sender and shown to the target. The request can be accepted, denied, ignored, or canceled. Once an individual accepts it, the individual has to choose a move as a response. The payoff of the game is proportional to the duration suggested in the request, which is a part or all of the sender's time resource. Once the request is sent out, this part of the resource will be occupied before receiving a response, which cannot be used again in any other interaction. If the request is accepted, the time resource will be consumed. If the request is denied, ignored, or canceled, the time resource will be returned to the sender. The total time resource assigned to each individual is $1,440$ units in each round, simulating one day in real life. We adopt $1,440$ to help the participants to understand its meaning, the value of which is irrelevant to our results. For all the individuals, each round lasts for 60 seconds. The initial aggregated payoff for each individual is 0. The payoff matrix is the same as that in Fig. 1.

During the match, the individual IDs are randomly generated. The individuals can only see their own game records, where each record includes the moves of both sides and the time durations. The topological structures beyond their immediate neighbors are invisible to them. Besides, individuals are shown their aggregated payoff, time resources, number of rounds played, and their decision time remaining.

5.3 Simulation on the social networks

Here, we will present the process of the simulation. Step 1, Generate a structured population such as the Barabási and Albert's scale-free network [3] with degree $m_0 = m = 3$ or Watts and Strogatz's small-world network with $P_{rewire} = 0.1$ and $K = 6$. Randomly assign the agents to be cooperators with a probability of 0.5. The size of the population is set to 1,024. Step 2, Shuffle the agent list and iteratively ask an agent to broadcast gaming requests to its neighbors. In each request, the agent evenly allocates its time left to its uncoordinated neighbors, i.e., $\mu_{ij}(r) = \frac{1}{|N_i - P_i(r-1)|}$, where $j \in N_i - P_i(r-1)$. If a neighbor has enough time to accept the request, he will accept it. Step 3, Each pair of the matched agents game for one round and update their moves, following the Zero-Determinant Extortionate strategy proposed in reference [46]. Step 4, If an agent defects in the round, the pair will be taken apart with a probability of 0.5, that is, $\chi = [0, 0.5, 0.5, 0.5]$. Step 5, Repeat Steps 2, 3, and 4 until the preset number of rounds.

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