Limitation of time promotes cooperation in temporal network games

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Abstract

Temporal networks are obtained from time-dependent interactions among individuals, whereas the interactions can be emails, phone calls, face-to-face meetings, or work collaboration. In this article, a temporal game framework is established, in which interactions among rational individuals are embedded into two-player games in a time-dependent manner. This allows studying the time-dependent complexity and variability of interactions, and the way they affect prosocial behaviors. Based on this simple mathematical model, it is found that the level of cooperation is promoted when the time of collaboration is equally limited for every individual. This observation is confirmed with a series of systematic human experiments that forms a foundation for comprehensively describing human temporal interactions in collaboration. The research results reveal an important incentive for human cooperation, leading to a better understanding of a fascinating aspect of human nature in society.

Keywords: cooperation, non-cooperative game, temporal network, time limitation

1 Introduction

Many complex collaborative systems in nature, society, and engineering can be modeled through networks based on graph theory. In a network, nodes represent collaborating individuals, and links represent their friendships [1]. In simple or simplified network modeling, links are weightless, undirected, and static. In order to improve the ability to depict real systems, weighted [2], directed [3], and dynamic [4] network models are established. The application of these network models in social science proved that the closer the framework is to reality, the stronger its ability to explain behaviors. As one of such social behavior in human interactive systems, cooperation is of particular importance which has attracted broad attention for more than half a century [5–8]. Although humans are not exempted from selfishness, and they obey the fundamental principles of Darwinian competition-based evolution, cooperation is ubiquitous in and across societies [9]. While the impetus for the human 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 [10], and also to the formation of alliances in times of conflicts [11], it is still puzzling as why they have achieved such high levels of cooperation in general. Human altruistic behavior distinguishes them remarkably from other mammals, forming the bedrock for their astonishing evolutionary success in history.

The studies of human cooperation in n-person games begin with population games, also known as mean-field games [12–14]. In a well-mixed population, cooperation can hardly prevail with imitative update rules when individuals play non-cooperative games such as the Prisoner's Dilemma (PD) game [15]. If the population exhibits a relatively stable social structure, the consequence may be different [16–26] – a finding rooted in the seminal paper by Nowak and May [27], observing clusters of cooperators on a square lattice that protected them from invading defectors. Nevertheless, social networks are seldom static. People disconnect and then reconnect to form connections with new partners from time to time. This reality has revealed new mechanisms for cooperation that may sustain even under extremely adverse conditions, when the temptation to defect is high and where on static network cooperation is perishing [28]. Moreover, an individual usually does not interact with all his friends all the time but likely does so only occasionally.

To account for the above-observed phenomena, some researchers considered dynamic networks. Implications of dynamic interactions on human cooperation are profound. Recent human experiments as well as theoretical analysis both have confirmed this to the fullest [2, 29–33]. It is argued, for example, that these observations demonstrate the effects of reputation [4]. Individuals may connect with unfamiliar individuals after browsing their gaming records but cut some existing connections with unsatisfactory partners. Some may take breaking ties, instead of performing defection, as a way to penalize defectors [29]. Interestingly, the implication of dynamic reconnection fades out as individuals are taking more specific moves to play games with their partners [4]. In light of this, an interesting question is whether 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 [34], the dynamic reconnection in such a system is a reallocation of collaboration time in a time-limited collaborative condition. Will too much emphasis put on the structure of our social networks result in neglecting the temporal aspects of our interactions? In this article, this critical question will be addressed.

Due to the complexity of temporal systems, using evolutionary game theory to model collaboration behavior is quite challenging. First, the evolution mechanism of a temporal system itself is complicated and hard to describe by a simple mathematical model. Secondly, in a temporal game, the individual strategy involves not only the moves but also the allocation of time in each round of the game. Furthermore, this openness allows individual strategy and network topology to co-evolve in a more flexible way than the existing dynamical gaming networks [35, 36], which brings up the difficulty in modeling coupled systems.

In this paper, a temporal gaming framework is proposed based on the structure of temporal networks [37, 38]. The main objective 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 usually takes a team to accomplish a project when applying for funding. The project leader would typically collaborate with a member to accomplish a specific part of it. Meanwhile, the member or the leader may also be involved in more than one project. Simultaneously, the total number of working time, such as months, for each participant is limited, which is identical for everyone. In such a scenario, a temporal gaming network is naturally laid out. Here, the collaboration between two team members is closer to the stag hunt game than the PD game. Since cooperation normally dominates the collaboration system playing the stag hunt game, it is not easy to differentiate the impacts from various mechanisms. For this reason, the PD game is adopted in this paper.

One of the main contributions of this paper is a detailed online experiment for demonstrating the proposed theoretical framework. First, a gaming platform is established to implement a temporal game. Then, the level of cooperation is tested on the platform in a divide and conquer (D&C) mode [4, 39, 40], where the difference from the present setting with those of the existing works [23, 29, 30, 41] is in the targeted decisions. Finally, the level of cooperation is tested on the platform in a time-dependent mode, where both the time limitation for individuals and the targeted decisions are considered. The reasons for adopting these mechanisms are explained in Section *Experimental design*. The objective is to find whether the limitation on time resources governs human cooperation in the games, which is the focus of this study.

To understand the impact of the limited time, we invited 183 human subjects and carried out a set of comparative online experiments. In a match of the game, the participants are allocated to the nodes of some pre-generated networks. Two classes of networks are tested, namely the Barabási-Albert scale-free network [42] and the Watts-Strogatz small-world network, for they are the most popular social network models. It will be shown that the limitation to the individuals' time resources indeed promotes the participants' level of cooperation, which aligns with the theoretical prediction, as further discussed 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 and each round of the play. 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 [43] 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 this PD model, a player gains $\mathcal{T}$ (the 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 a collective decision.

The temporal game model proposed in the present paper is based on the game model used in [39, 40], taking into account the time of interactions. As the model is time-dependent, each interaction is assigned a specific duration. The total game time for each individual in one round is set to be a constant, which is the same for all individuals to be realistic in real-life scenarios. An individual's interactions with different partners are assumed to be 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 temporal games, the payoff of each interaction is proportional to the time it spends. In one round of the game, the accumulated payoff of the 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 and $\tau_{i,j}$ is the duration of the interaction between individuals i and j. This is shown in Fig. 1A, where individual i and j are colored red and blue, $N_i = 4$ and $\tau_{i,j} = 8$. Note that $\tau_{i,j}$ 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 an individual has in each round, which is a constant for every individual in the proposed model. In Fig. 1A, $\mathfrak{T} = 24$. If individual i does not want to collaborate with j, then i will not play the game with j any longer. Simultaneously, i will reject j's gaming request. In this case, $\tau_{i,j}$ will be 0 as indicated by the relation between the red and the green in Fig. 1A.

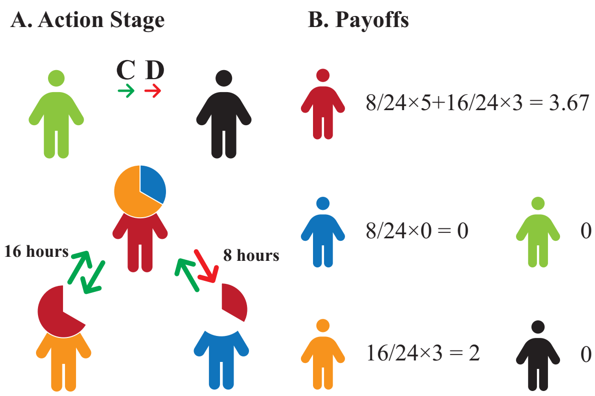

Fig. 1 Illustration of the temporal game. Panel A shows one round of the temporal game among five individuals. The individual colored red has four friends, in which the individuals colored orange and blue are his gaming partners. If the game between two individuals lasts for 24 hours, the payoff of a 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 are interacting with i in this round. Then, 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 ones are his partners in this round. Based on Eq. 2, the payoffs of the five individuals are listed in Fig. 1B.

From 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, depending on the topology of the collaborative network. For a heterogeneous network as the Barabási-Albert (BA) networks [44], $P(k_i, k_j) \sim \frac{k_j P(k_j)}{\langle k \rangle}$. For homogeneous networks such as the Watts-Strogatz (WS) networks [45], $P(k_i, k_j) \sim P(k_j)$.

An illustration of such a collaborative network is shown in Fig. 2A. To clarify the generating procedure of the network, the communication log among the individuals in this round is shown in Fig. 2B. In the log, Alice tries to collaborate with Tom for $\mathfrak{T}$, while Tom had agreed to work with Jerry and Frank when he received Alice's request. Thus, Alice turns to Frank and Jerry, but it is a bit late to make appointments with them as they are partially engaged. As a result, Alice takes $0.8\mathfrak{T}$ to play with Frank and Jerry but wastes $0.2\mathfrak{T}$ in this round.

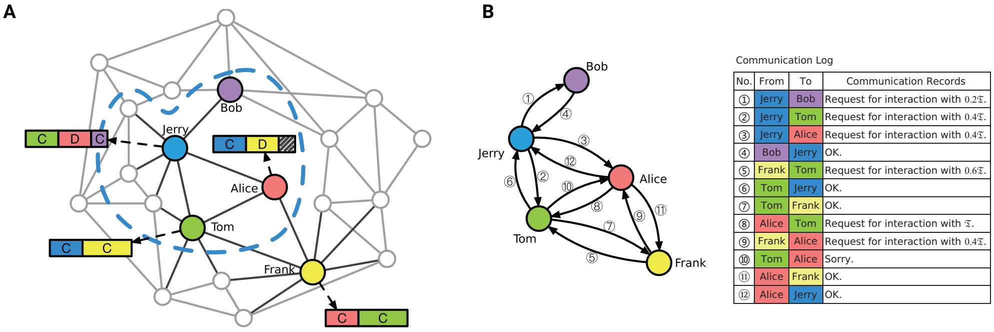

Fig. 2 Illustration of temporal games in a two-player collaborative system. (A) One round of the temporal game on a social network. The blue circle is Jerry's neighborhood. Alice, Bob, and Tom are Jerry's partners in this round. The color of a time slot represents a partner; for instance, yellow represents 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 is 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 two players is performed for a duration of time. Thus, the level of cooperation is measured by the duration and their moves. 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 game.

Note that current studies on decision time [46, 47] in experimental psychology and response time in experimental economics [48, 49] focus on the time instant for making a decision rather than the duration of time spent by moves. As such, the object of those studies is different from that of temporal games.

2.3 Mathematical modeling the available time of individuals

As is well known, in a game between two players, each player has to practice one of the four possible actions, namely, cooperating with a cooperator (CC), cooperating with a defector (CD), defecting a cooperator (DC), and defecting a defector (DD). Here, define a state vector $\mathbf{\Phi}$ by $(\Phi_{CC}, \Phi_{CD}, \Phi_{DC}, \Phi_{DD})$, in which each entry corresponds to the probability of the indicated action. 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 action outcomes. Since players update their moves with the memory-one strategies in each time step, the update can be considered a Markov process. A Markov transition matrix M_i can be used to realize the update. For two players, i and j, one has

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

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 players i and j's probabilities of cooperation in the next round after experiencing CC,

CD, DC, and DD, respectively. Thus, 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 total available time of individuals in the temporal games, 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 spend in round r is denoted by $S_i(r) = \mathfrak{T} - \sum_{j \in P_i} \tau_{u_{ij}(r-1)}$, where $\mu_{ij}(r-1)$ is the random portion of time within the request from i in round $r-1$. If i applies for playing with j from $S_i(r)\mu_{ij}(r)$, 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 that j wishes to play. Therefore, the expectation of difference during individual i's available time from round r to $r+1$ is

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

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

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

Since $S_i(r) \geq 0$ for all r, the iterative formula of $S_i(r)$ can 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 process of $S_i(r)$ in the system cannot be modeled in a mean-field manner, one can hardly find and present its analytical solution. Therefore, the following presents only simulation results and empirical results from human online experiments. In the simulations, all agents uniformly adopt the same strategy; therefore, the results are reproducible. Let the number of agents be N_A. It will be shown 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 stabilized thereafter, indicating that finding new partners is problematic from the beginning of a match.

3 Results

To show the impact of time redistribution, first, the evolution of moves is simulated when agents play a traditional PD game with their neighbors in the BA and WS networks. In any network, a player starts a game with a gaming request to a neighbor. In 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 a 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 [50]. The strategy will wipe the cooperators out in 100 rounds. If one agent defects in a round, the gaming pair will be taken apart with a certain probability. The separation means that the time assigned to the pair will be redistributed in the next round. More details on the simulations will be provided later in Section *Simulation on the social networks*.

In Fig. 3(a) and 3(b), the results show that the level of cooperation decays as the rounds increase for agents playing the 'divide-and-conquer' (D&C) games [4, 39, 40] in both BA and WS networks. After being affected by the temporal mechanisms, the rates of decay slow down, as shown in Fig. 3(c) and 3(d). The differences in the level of cooperation between the temporal games and the D&C games [4, 39, 40] are shown in Fig. 3(e) and 3(f), which will be amplified when human subjects play the games. The amplification may originate from the $S(r)$ shown in Fig. 3(g) and 3(h), which will be much lower when humans play the temporal games.

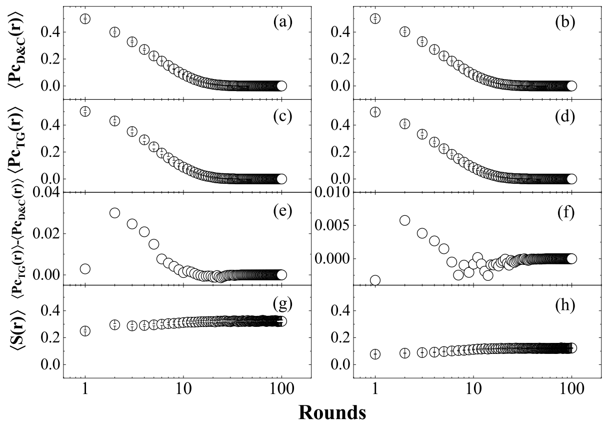

Fig. 3 Evolution of the average proportion of cooperation $\langle P_c(r)\rangle$ in the 'divide-and-conquer' (D&C) and temporal gaming networks. (a) and (c) show $\langle P_c(r)\rangle$ of the D&C games and temporal games in the BA networks, respectively. (b) and (d) show $\langle P_c(r)\rangle$ of the two types of games in the WS networks, respectively. (e) and (f) show the differences 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, the results are shown in semi-log coordinates.

To verify the above theoretical results, we invited 183 volunteers to attend eight online experiments. For clarity, the basic information of each match is summarized in Table 1.

By 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 the theoretical prediction, indicating that the limitation on time promotes the level of cooperation in gaming over a real social network.

To explain the observed behavior, the average available time $S(r)$ is measured for four time-involved matches. The evolution of $S(r)$ for the two BA networks and

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)

two WS networks are shown in Fig. 4(e)-Fig. 4(h), respectively. For clarity, 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 the theoretical prediction. The difference in $P_c(r)$ between the theoretical prediction and the 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 that should be noted is that the level of cooperation generally decays with the increasing rounds in Fig. 4. This 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 volunteers to play online for more than one hour simultaneously. Even reasonable participation fees and attractive rewards were paid to the winners of each match. Some of the winners' strategies will be shown in Section **Top Voted Strategies** of the **Supplementary Information** (**SI**), where one can see that the level of cooperation decays when the participants guess that the match is ended.

4 Discussion

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

It should be noted that the limitation of time is ubiquitous in human collaboration systems, which is essentially different from the incentives, such as global reputation [51, 52] and anonymity [53], associated with human psychology. In a sense, the behavior observed in the performed experiments is more deterministic than random. Introducing some other mechanisms like rewarding [54] and costly punishment [55, 56] to the temporal systems will be a natural extension of study in this direction. Apart from

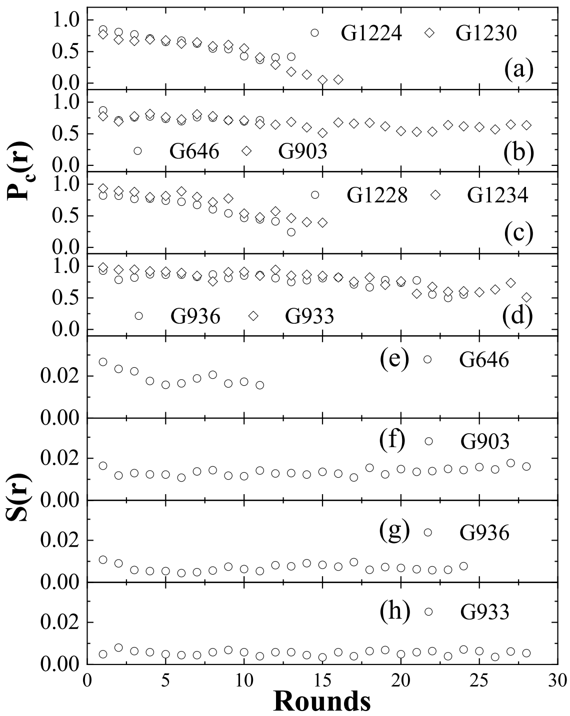

Fig. 4 Evolution of the proportion of cooperation $P_c\,(r)$ and the average available time $S\,(r)$ in the temporal games played by human subjects. (a) and (c) show the results of the D&C games on the BA networks and WS networks, respectively. (b) and (d) show the results of the temporal games on the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

the mechanisms, the impact from different types of games, for instance, the snow-drift game [57] and the public goods game [19], is also of interest and significance.

This work considers the temporal game framework and presents some rather surprising new results. There are several interesting future directions for investigation in terms of both theoretical and experimental studies. However, the basic theoretical model and the key experimental results presented in this paper 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 for the emergence of cooperation from network models, profoundly impacting disciplines on 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 realistic temporal two-player collaborative systems, two issues are considered in the performed empirical study. First, the interactive time is determined by negotiation. The setting resembles the temporal properties of a real game in society. A dynamic reconnection is implemented in the network by rejecting a friend's request and then proposing a game with another friend [29, 31]. Second, a *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 or to defect in each round of the game [4, 39, 40]. Most existing research on gaming networks is performed under a framework where individuals choose the same move to interact with all their neighbors [29–31]. On the contrary, in real-world scenarios, people do not normally defect their long-term partners after being defected by some other partners. In a realistic social network, they would choose a specific move to play with another partner, referred to as the D&C game in the literature [39, 40]. When the diffusive decision scheme is replaced by the D&C or a targeted decision scheme, the impact of dynamic reconnection on promoting cooperation will become negligible [4].

The coupling between temporal interaction and rational decision-making can be seen everywhere in real life. Nevertheless, the existing theoretical frameworks seem insufficient to explain the widespread cooperation in temporal social games. Under the framework of temporal games, a series of online game experiments were performed. The experimental data reveal 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 demonstrates the potential of the temporal game framework to explain various collective behaviors in real two-player collaborative systems.

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 framework, 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 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 needed 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. In this setting, 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 so as to avoid the ending-game effects.

In each round of the game, individuals can make requests to interact 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, this individual has to choose a move as his response. The payoff of the game is proportional to the time 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, mimicking one day in real life. The experiment adopts $1,440$ to help the participants to understand its meaning, the value of which is irrelevant to the final 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 shown in Fig. 1.

During a 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 remaining decision time.

5.3 Simulation on the social networks

Here is the process of the simulation.

Step 1: Generate a structured population such as the BA network [42] with degree $m_0 = m = 3$ or WS 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 uniformly allocates his rest time to those 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 play the game for one round and then updates their moves, following the Zero-Determinant Extortionate strategy proposed in [50].

Step 4: If an agent defects in a 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 reaching the preset number of rounds.

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References

[1] R. Albert and A.-L. Barabási. Statistical mechanics of complex networks. *Rev. Mod. Phys.*, 74:47–97, 2002.

[2] Chen Shen, Chen Chu, Lei Shi, Matjaž Perc, and Zhen Wang. Aspiration-based coevolution of link weight promotes cooperation in the spatial prisoner's dilemma game. *Royal Society Open Science*, 5:180199, 2018.

[3] Nicolò Pagan and Florian Dörfler. Game theoretical inference of human behavior in social networks. *Nature Communications*, 10(1):5507, 2019.

[4] David Melamed, Ashley Harrell, and Brent Simpson. Cooperation, clustering, and assortative mixing in dynamic networks. *Proc. Natl. Acad. Sci. U.S.A.*, 115(5):951–956, January 2018.

[5] Robert Boyd and Peter J Richerson. Solving the puzzle of human cooperation. *Evolution and Culture*, 1:105–132, 2005.

[6] Simon Gächter and Benedikt Herrmann. Reciprocity, culture and human cooperation: previous insights and a new cross-cultural experiment. *Phil. Trans. R. Soc. B*, 364:791–806, 2009.

[7] D. G. Rand and M. A. Nowak. Human cooperation. *Trends in Cognitive Sciences*, 17:413–425, 2013.

[8] M. Perc, J. J. Jordan, D. G. Rand, Z. Wang, S. Boccaletti, and A. Szolnoki. Statistical physics of human cooperation. *Phys. Rep.*, 687:1–51, 2017.

[9] M. A. Nowak and R. Highfield. *SuperCooperators: Altruism, Evolution, and Why We Need Each Other to Succeed.* Free Press, New York, 2011.

[10] S. B. Hrdy. *Mothers and Others: The Evolutionary Origins of Mutual Understanding.* Harvard University Press, Cambridge, MA, 2011.

[11] Samuel Bowles and Herbert Gintis. *A Cooperative Species: Human Reciprocity and Its Evolution.* Princeton University Press, Princeton, NJ, 2011.

[12] J. Maynard Smith and G. R. Price. The logic of animal conflict. *Nature*, 246:15–18, 1973.

[13] Josef Hofbauer and Karl Sigmund. *Evolutionary Games and Population Dynamics.* Cambridge University Press, Cambridge, U.K., 1998.

[14] R. Cressman. *Evolutionary Dynamics and Extensive Form Games.* MIT Press, Cambridge, MA, 2003.

[15] György Szabó and Gábor Fáth. Evolutionary games on graphs. *Phys. Rep.*, 446:97–216, 2007.

[16] F. C. Santos and J. M. Pacheco. Scale-free networks provide a unifying framework for the emergence of cooperation. *Phys. Rev. Lett.*, 95:098104, 2005.

[17] Hisashi Ohtsuki, Christoph Hauert, Erez Lieberman, and Martin A. Nowak. A simple rule for the evolution of cooperation on graphs and social networks. *Nature*, 441:502–505, 2006.

[18] F. C. Santos, J. M. Pacheco, and Tom Lenaerts. Evolutionary dynamics of social dilemmas in structured heterogeneous populations. *Proc. Natl. Acad. Sci. U.S.A.*, 103:3490–3494, 2006.

[19] F. C. Santos, M. D. Santos, and J. M. Pacheco. Social diversity promotes the emergence of cooperation in public goods games. *Nature*, 454:213–216, 2008.

[20] J. Tanimoto. Dilemma solving by coevolution of networks and strategy in a 2×2 game. *Phys. Rev. E*, 76:021126, 2007.

[21] F. Fu, T. Wu, and L. Wang. Partner switching stabilizes cooperation in coevolutionary prisoner's dilemma. *Phys. Rev. E*, 79:036101, 2009.

[22] S. Lee, P. Holme, and Z.-X. Wu. Emergent hierarchical structures in multiadaptive games. *Phys. Rev. Lett.*, 106:028702, 2011.

[23] D. G. Rand, M. A. Nowak, J. H. Fowler, and N. A. Christakis. Static network structure can stabilize human cooperation. *Proc. Natl. Acad. Sci. U.S.A.*, 111:17093–17098, 2014.

[24] Feng Fu and Xingru Chen. Leveraging statistical physics to improve understanding of cooperation in multiplex networks. *New J. Phys.*, 19:071002, 2017.

[25] Benjamin Allen, Gabor Lippner, Yu-Ting Chen, Babak Fotouhi, Martin A Nowak, and Shing-Tung Yau. Evolutionary dynamics on any population structure. *Nature*, 544:227–230, 2017.

[26] Babak Fotouhi, Naghmeh Momeni, Benjamin Allen, and Martin A. Nowak. Evolution of cooperation on large networks with community structure. *J. R. Soc. Interface*, 16:20180677, 2019.

[27] M. A. Nowak and R. M. May. Evolutionary games and spatial chaos. *Nature*, 359:826–829, 1992.

[28] M. Perc and A. Szolnoki. Coevolutionary games – a mini review. *BioSystems*, 99:109–125, 2010.

[29] D. G. Rand, Samuel Arbesman, and Nicholas A. Christakis. Dynamic social networks promote cooperation in experiments with humans. *Proc. Natl. Acad.*

Sci. U.S.A., 108:19193–19198, 2011.

[30] Katrin Fehl, Daniel J. van der Post, and Dirk Semmann. Co-evolution of behaviour and social network structure promotes human cooperation. *Ecol. Lett.*, 14:546–551, 2011.

[31] Jing Wang, S. Suri, and D.J. Watts. Cooperation and assortativity with dynamic partner updating. *Proc. Natl. Acad. Sci. U.S.A.*, 109:14363–14368, 2012.

[32] A. Szolnoki and M. Perc. Coevolutionary success-driven multigames. *EPL*, 108:28004, 2014.

[33] Z. Wang, A. Szolnoki, and M. Perc. Self-organization towards optimally interdependent networks by means of coevolution. *New J. Phys.*, 16:033041, 2014.

[34] Pat Barclay. Strategies for cooperation in biological markets, especially for humans. *Evolution and Human Behavior*, 34:164–175, 2013.

[35] Yichao Zhang, Guanghui Wen, Guanrong Chen, Jiasheng Wang, Minmin Xiong, Jihong Guan, and Shuigeng Zhou. Gaming temporal networks. *IEEE Transactions on Circuits and Systems II: Express Briefs*, 66(4):672–676, 2018.

[36] Giovanna Miritello, Rubén Lara, and Esteban Moro. Time allocation in social networks: correlation between social structure and human communication dynamics. In *Temporal Networks*, pages 175–190. Springer, 2013.

[37] Naoki Masuda and Renaud Lambiotte. *A Guide to Temporal Networks*. World Scientific Publishing, 2016.

[38] Petter Holme and Jari Saramäki. Temporal networks. *Phys. Rep.*, 519:97–125, 2012.

[39] Yichao Zhang, Guanrong Chen, Jihong Guan, Zhongzhi Zhang, and Shuigeng Zhou. Unfavorable individuals in social gaming networks. *Scientific Reports*, 5:17481, December 2015.

[40] Jiasheng Wang, Yichao Zhang, Jihong Guan, and Shuigeng Zhou. Divide-and-conquer tournament on social networks. *Scientific Reports*, 7(1):15484, 2017.

[41] C. Gracia-Lázaro, A. Ferrer, G. Ruiz, A. Tarancón, J.A. Cuesta, A. Sánchez, and Y. Moreno. Heterogeneous networks do not promote cooperation when humans play a prisoner's dilemma. *Proc. Natl. Acad. Sci. U.S.A.*, 109:12922–12926, 2012.

[42] A.-L. Barabási and R. Albert. Emergence of scaling in random networks. *Science*, 286:509–512, 1999.

[43] Smith. J. Maynard. *Evolution and the Theory of Games*. Cambridge University Press, Cambridge, U.K., 1982.

[44] A.-L. Barabási and R. Albert. Emergence of scaling in random networks. *Science*, 286:509–512, 1999.

[45] D. J. Watts and S. H. Strogatz. Collective dynamics of "small-world" networks. *Nature*, 393:440–442, 1998.

[46] Anthony M Evans and David G Rand. Cooperation and decision time. *Current Opinion in Psychology*, 26:67–71, 2019.

[47] Anthony M Evans, Kyle D Dillon, and David G Rand. Fast but not intuitive, slow but not reflective: Decision conflict drives reaction times in social dilemmas. *Journal of Experimental Psychology: General*, 144(5):951, 2015.

[48] Toshio Yamagishi, Yoshie Matsumoto, Toko Kiyonari, Haruto Takagishi, Yang Li, Ryota Kanai, and Masamichi Sakagami. Response time in economic games reflects different types of decision conflict for prosocial and proself individuals. *Proc. Natl. Acad. Sci. U.S.A.*, 114(24):6394–6399, 2017.

[49] Leonidas Spiliopoulos and Andreas Ortmann. The BCD of response time analysis in experimental economics. *Experimental Economics*, 21(2):383–433, 2018.

[50] Alexander J. Stewart and Joshua B. Plotkin. Extortion and cooperation in the prisoner's dilemma. *Proc. Natl. Acad. Sci. U.S.A.*, 109:10134–10135, 2012.

[51] F. Fu, C. Hauert, M. A. Nowak, and L. Wang. Reputation-based partner choice promotes cooperation in social networks. *Phys. Rev. E*, 78:026117, 2008.

[52] Edoardo Gallo and Chang Yan. The effects of reputational and social knowledge on cooperation. *Proc. Natl. Acad. Sci. U.S.A.*, 112(12):201415883, March 2015.

[53] Zhen Wang, Marko Jusup, Rui-Wu Wang, Lei Shi, Yoh Iwasa, Yamir Moreno, and Jürgen Kurths. Onymity promotes cooperation in social dilemma experiments. *Science Advances*, 3:e1601444, 2017.

[54] M. Sefton, O. Schupp, and J. M. Walker. The effect of rewards and sanctions in provision of public goods. *Econ. Inq.*, 45:671–690, 2007.

[55] Ernst Fehr and Simon Gächter. Altruistic punishment in humans. *Nature*, 415:137–140, 2002.

[56] Xiaojie Chen and Attila Szolnok. Punishment and inspection for governing the commons in a feedback-evolving game. *PLoS Comput. Biol.*, 14(7):e1006347, 2018.

[57] Christoph Hauert and Michael Doebeli. Spatial structure often inhibits the evolution of cooperation in the snowdrift game. *Nature*, 428:643–646, 2004.