Autonomy promotes the evolution of cooperation in prisoner's dilemma

Liang Li

Department of Collective Behaviour, Max Planck Institute of Animal Behavior, Konstanz 78547, Germany;
Centre for the Advanced Study of Collective Behaviour, University of Konstanz, Konstanz 78547, Germany;
and Department of Biology, University of Konstanz, Konstanz 78547, Germany

Chen Chen

Department of Human Resource and Organizational Behavior, School of Business, University of International Business and Economics, Beijing 100029, People's Republic of China

Aming Li*

Department of Zoology, University of Oxford, Oxford OX1 3PS, United Kingdom
and Department of Biochemistry, University of Oxford, Oxford OX1 3QU, United Kingdom

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Population structure has been widely reported to foster cooperation in spatially structured populations, where individuals interact with all of their network neighbors defined by the spatial structure in each generation. However, most results rely on the assumption that individuals strictly interact with all of their neighbors during evolution. In reality, human beings, with sophisticated psychology, are willing to interact with *some of their neighbors* from time to time. Thus, individuals may not play games with all neighbors due to their psychological factors. Here we investigate how the autonomy, one of the basic psychological needs, affects the fate of cooperators in various social networks. By constructing a dynamical effective network, we find that the introduction of autonomy favors cooperative behavior. Further systematical studies by eliminating heterogeneity and the dynamic characteristics of the network reveal that autonomy plays a pivotal role in the evolution of cooperation. Moreover, we find that a moderate effective network degree, defined by the product of the original network degree and the level of autonomy, maximizes the cooperation on networks connecting individuals with fixed neighbors. Our results offer a possible way for organizations to improve individuals' cooperation and shed light on the importance of individuals' psychology on the evolution of cooperation.

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I. INTRODUCTION

Cooperation between individuals underpins the emergence of organizations and the success of diverse systems ranging from multicellular organisms to human society [1–3]. To understand the evolution of cooperation among selfish individuals in the context of Darwinian evolution, researchers have long been resorting to the powerful framework of evolutionary game theory [1,4–8]. Apart from the prominent metaphor illustrating the behavior of cooperators and defectors, it is important to capture who interacts with whom in a given population. In large populations, individuals normally do not interact evenly with everybody else. In recent years, the underlying spatial structures or social networks capturing heterogeneous interactions in structured populations have attracted more and more attention [9–14]. Indeed, with the discovery of the characteristic fingerprint of many realistic interactions, several results are reported pertaining to various structures of complex networks [15,16], where nodes represent individuals and links indicate who interacts with whom [9,14]. In an underlying typical evolutionary process on structured populations, individuals interact with all of their neighbors over the spatial structure [9,10,14,15,17]. By doing so, clusters of cooperators over networks could emerge, and thus network reciprocity is regarded as an important rule to facilitate the evolution of cooperation [13,18].

In our general social interactions, the individual psychology greatly affects who and when to interact. Autonomy, one of the fundamental psychological needs in human beings, is widely studied in the field of organization management and social psychology [19,20]. Autonomy describes one feels volitional and reflectively self-endorsed in actions [21]. Specifically, in social networks, a low level of autonomy corresponds to fewer interactions, which indicates an individual interacts with fewer neighbors among her connections. Commonly, as long as an individual has neighbors in the social network, she has to interact with every neighbor in each round of interactions [22], even if the individual prefers just interacting with some of her neighbors or keeping silent in some rounds. This setting, although important, cannot reflect the scenario where individuals are capable of making an informed and uncoerced decision in interactions. In this study, we introduce the autonomy to the traditional setting where individuals have the self-determination to select neighbors to play.

We systematically investigate how autonomy affects the evolution of cooperation in structured populations. Specifically, in each generation, every individual is able to interact

*Corresponding author: aming.li@zoo.ox.ac.uk

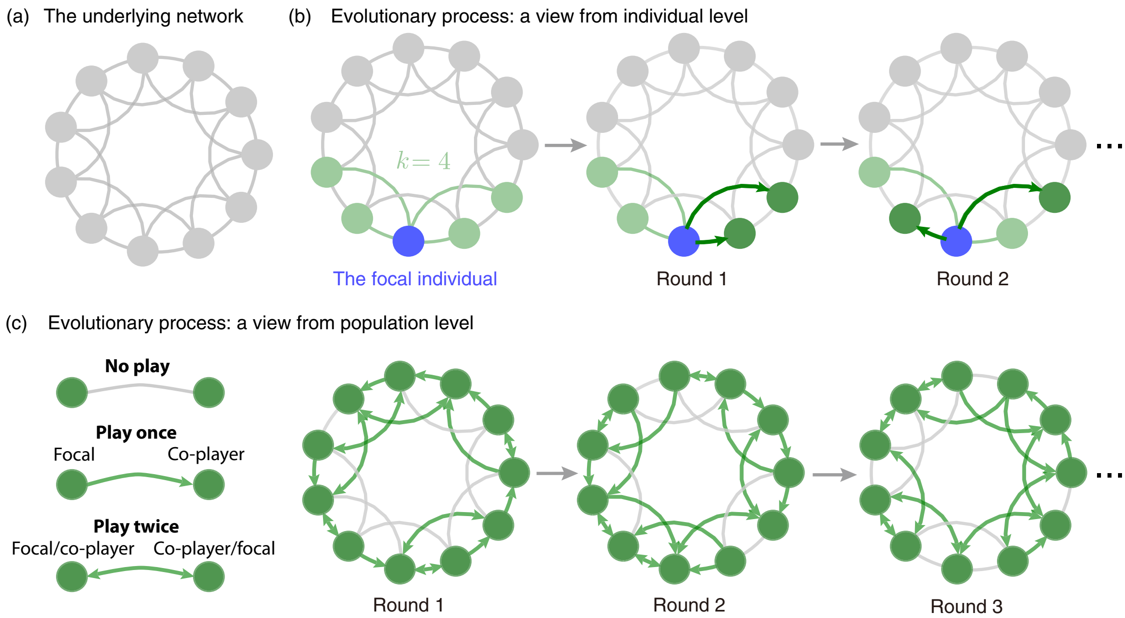

FIG. 1. Illustration on the evolutionary process with autonomy. (a) The underlying regular ring graph where each node has four neighbors (network degree $k = 4$) (b) Evolutionary process from the view of individual i (blue). All neighbors of i are marked and connected with light green. Based on the level of autonomy (α), individual i randomly chooses $\lfloor k_i\alpha \rceil$ neighbors in each round to interact, where $\lfloor \cdot \rceil$ indicates the round operation. For example, two neighbors (dark green) are selected by i when $\alpha = 0.5$, named effective neighbors. Since the effective neighbors are chosen randomly, they could be different over different rounds, which induces the dynamical effective network where the corresponding effective links are marked in dark green as well. All nodes in the underlying network follow the same protocol as we have shown for node i. (c) Evolutionary process from the view of network. Over the evolutionary process, three different connections emerge. The gray ones represent the connected two neighbors that do not play any game in this round. The one-way arrow points to the coplayer selected by the focal. The two-way arrows represent two individuals playing the game twice, once as the focal and once as the coplay.

with some of their neighbors arbitrarily that are selected according to the individual's autonomy. We find that autonomy generally favors cooperators in sparse homogeneous and heterogeneous networks, while this effect shrinks as the network becomes dense. As autonomy brings the heterogeneity in interactions even on homogeneous networks, we further fix the actual interaction network and find that the associated middle level of network degree maximizes the stable frequency of cooperation. Our results open an avenue to explore the effect of individual autonomy on the evolution of cooperation.

II. MODELING FRAMEWORK

We consider the canonical prisoner's dilemma in various structured populations, represented by regular ring graphs, random networks [23], and scale-free networks [24]. For an individual i (network node) with k_i neighbors (network degree) on the underlying network [Fig. 1(a)], she interacts with a certain number of her neighbors according to the level of autonomy. Generally, α is the i's level of autonomy, and specifically i randomly selects $\lfloor \alpha k_i \rceil$ effective neighbors over all the k_i neighbors to play games in each round, where $\lfloor \cdot \rceil$ denotes the round operation [Fig. 1(b)]. When $\alpha = 1$, every individual interacts with all of their neighbors in each round; thus our framework degenerates to the classical evolutionary dynamics in structured populations [9,10,15]. Note that, when $0 < \alpha < 1$, in different rounds the individual i may select a different, yet fixed amount of ($\lfloor \alpha k_i \rceil$), effective neighbors [see Fig. 1(b) for the evolutionary process]. This is different from the probability-based effective neighbor selection [25] and constant partner selection regime [26], where the number of effective neighbors is either variant under binomial distribution or irrelevant to the number of i's neighbors.

For a typical prisoner's dilemma, each player has two strategies: cooperation and defection. In each round of the interaction, both players first choose their strategies independently and simultaneously. Each player receives R if both select cooperation and P if both select defection. When a player with the strategy defection meets a neighbor with the strategy cooperation, the player receives T while the neighbor receives S. These can be succinctly encoded in a payoff matrix

$$\begin{array}{c c} & \begin{array}{cc} \mathrm{C} & \mathrm{D} \end{array} \\ \begin{array}{c} \mathrm{C} \\ \mathrm{D} \end{array} & \begin{pmatrix} R & S \\ T & P \end{pmatrix}. \end{array} \tag{1}$$

After accumulating payoffs from all effective interactions with effective neighbors in each round, all individuals get the chance to update their strategies. Following the classical rule of imitation dynamics [15], an individual i updates its strategy by comparing its payoff P_i with the payoff P_j of a randomly selected effective neighbor j. When $P_j > P_i$, i imitates the strategy of j with the probability $(P_j - P_i)/(Dk_{>}\alpha)$, where $k_{>}$ denotes the larger number between k_i and k_j, $D = T - S$, and $Dk_{>}\alpha$ is used to normalize the imitation probability [9,15,27]. Otherwise (i.e., $P_j \leqslant P_i$), i keeps her strategy.

Following the general practice in numerical simulations, we simplify the prisoner's dilemma with a single parameter $T = b \in (1, 2]$, and set other parameters as $R = 1$ and

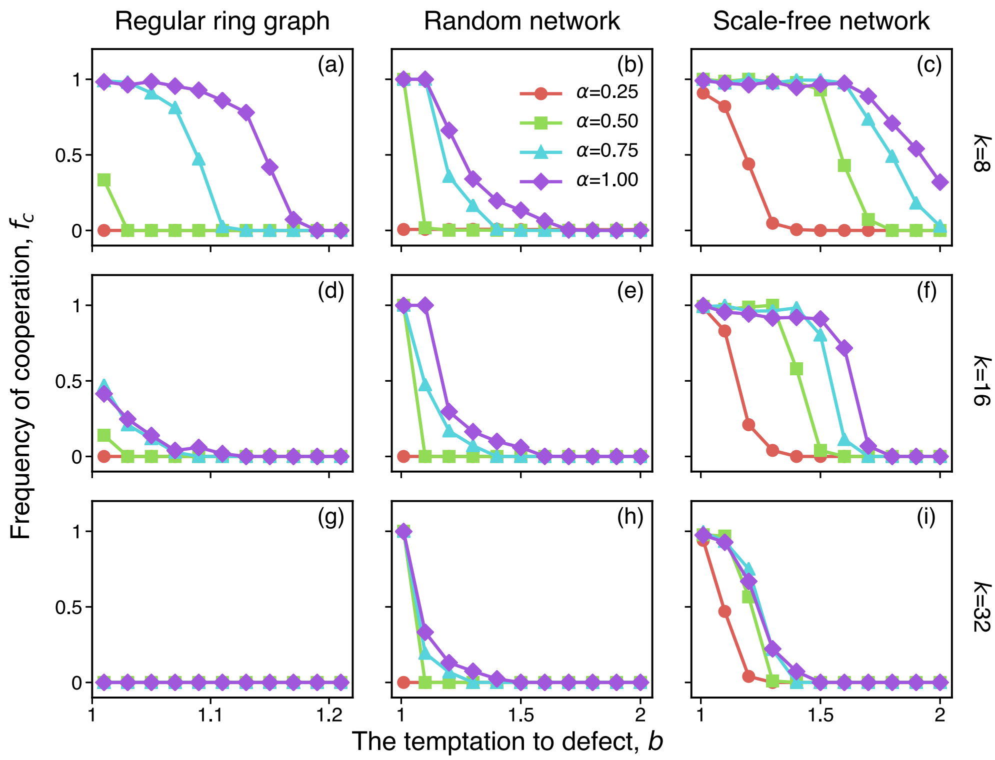

FIG. 2. Frequency of cooperation, f_c, as a function of the temptation to defect, b, on different networks with different levels of autonomy, α, and network degrees, k. The effective networks are dynamic and the payoffs are accumulated.

$P = S = 0$ [9,15,27]. Here b denotes the temptation to defect. Simulations are conducted for a population of $N = 900$ individuals. Initially, individuals are randomly distributed over the network and each has the same probability to act as cooperator or defector. For every single simulation, the equilibrium frequency of cooperation, f_c, is evaluated by averaging the last 2000 rounds after the full evolution of 20 000 rounds. For each set of parameters, we average frequencies over 100 independent simulations to obtain the corresponding f_c.

III. RESULTS

A. Autonomy promotes the evolution of cooperation on dynamic effective networks

We first explore how autonomy affects the evolution of cooperation on three different networks (i.e., regular ring graphs, random networks, and scale-free networks). Despite that the underlying network is invariant, our modeling framework further generates a dynamical interaction network, consisting of all individuals as well as their effective neighbors. By investing these dynamic effective networks with various degrees and accumulated payoffs, we find the cooperation is inhibited by the degree of the network ($\alpha = 1$ in each column in Fig. 2), and strongly related to the network structures. Indeed, the increase of the number of neighbors drives these systems towards the canonical mean-field behavior where cooperators become extinct (different rows in Fig. 2) [6]. Over the respective parameters (the b values), cooperation dominates more in a scale-free network than the rest of the networks (each row in Fig. 2) where the weakly connected cliques and specific network structures play an important role (Appendix A) [22,28]. All these are consistent with previous results [15]. Surprisingly, we find the level of autonomy (α) generally promotes the cooperation regardless of the network degree and the type of networks (Fig. 2). This might be related to the fact that the cliques in the networks shrink in both size and numbers under low level of autonomy (Appendix A), or because the lower the level of autonomy, the more the network reciprocity is broken. Therefore, the higher the level of autonomy, the more cooperation is promoted.

Several tests are further conducted to verify our simulations and findings. We first check the absorbing state in the evolutionary process by running 5×10^6 iterations with 100 individuals on all three networks (Appendix B). Results show the benefit of a high level of autonomy and verify the effectiveness of our simulation set (Appendix B). We further test the evolution under the strict prisoner's dilemma by considering $R = b - c$, $S = -c$, $T = b$, and $P = 0$. Again, simulations on three networks show consistent results (Appendix B). Finally, we capture the strategy imitation dynamics by Fermi function controlled by intensity of selection, β. Evolution on three networks with $\beta = 0.1$, 1, and 10 also show the consistent results (Appendix B).

Since a lower α leads to a smaller number of effective neighbors, the accumulated payoffs vary dramatically at different autonomy levels [29]. To further explore the effect of such heterogeneity in payoff, we further normalize the payoff by the number of effective neighbors. Specifically, for a focal individual i playing game with N effective neighbors and acquiring payoff P_{ij} after playing the game with neighbor j, we now consider the updating of the strategy based on the normalized payoff $\sum_{j=0}^{N} P_{ij}/N$. Although here the impact of network structures has been reduced and the advantage of low

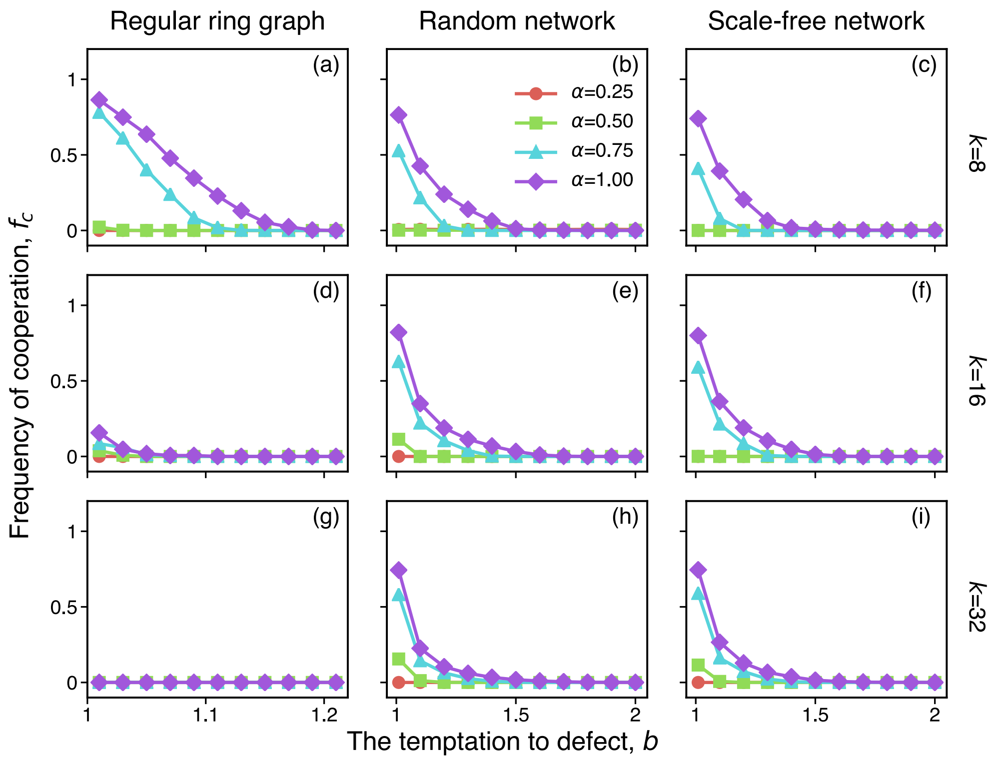

FIG. 3. Frequency of cooperation as a function of the temptation to defect, b, with different levels of autonomy. The effective networks are dynamic and the payoffs are normalized.

degrees are weaker (especially in random networks and scale-free networks), we confirm the promotion of cooperation by autonomy level is still primary (Fig. 3). This is also related to the network reciprocity mediated by the level of autonomy. Overall, all show that the single factor of autonomy robustly enhances cooperation over the dynamic effective networks.

B. Autonomy affects the evolution of cooperation on the static effective network

Having shown that the dynamic effective networks promote cooperation, to eliminate the effect of network dynamics, we next seek to carry out simulations on static effective networks. Here, a static effective network is implemented by initializing the effective neighbors according to the level of autonomy and keeping the specific effective neighbors throughout the evolution. Namely, the networks in all rounds in Fig. 1(b) are the same as the one induced by the first round. We find, as the degree of the network (k) increases, a high level of autonomy plays a role of the first facilitator, then inhibitor for the evolution of cooperation (Fig. 4). Generally, when the degree of the network is small ($k \leqslant 8$), the autonomy promotes cooperation. However, when k is over a threshold, autonomy impedes cooperation. The threshold depends on the type of network—a threshold around 8 for regular ring graphs and random networks and a threshold around 16 for scale-free networks. Near the threshold of the network degree, the frequency of cooperation is similar at all levels of the autonomy [a phenomenon similar to Fig. 4(f)]. This could be understood from the network fragmentation caused by the level of autonomy. For networks with low degrees, the effective network is fragmented into small pieces, thus breaking networking reciprocity and inhibiting cooperations for building stable clusters. However, when the underlying network has larger degrees, although the network is a bit fragmented, the effective network remains reciprocal. Therefore, as the degree of the underlying network grows, the lower the level of autonomy the more cooperation is promoted.

To eliminate both network dynamics and heterogeneity of the payoffs, we conduct simulations on a static network with normalized payoffs (Appendix C). Similarly, a threshold of the network degree which makes the role of autonomy switch from facilitator to inhibitor still exists but is smaller than that in the case with accumulated payoffs. All these verify that it is the autonomy that promotes cooperation on dynamic networks, which are closest to real social networks. Moreover, a comparison of evaluations on dynamic and static networks shows that static networks promote cooperation compared with their dynamic networks. This is due to the character of network dynamics breaking the reciprocity. Namely, the probability of an individual to play with the same neighbors in different rounds is very small.

C. The synergistic effect of the network degree and the autonomy

After realizing that the network degree k and autonomy α coaffect the fate of cooperators on static networks, we further explore the importance of autonomy. Specifically, we analyze how cooperators are affected by autonomy when *the effective network degree* αk is constant. In this setting, we still find the promotion of cooperation from autonomy regardless of the way we calculate the payoffs and the characteristic of the network dynamics (Appendix D).

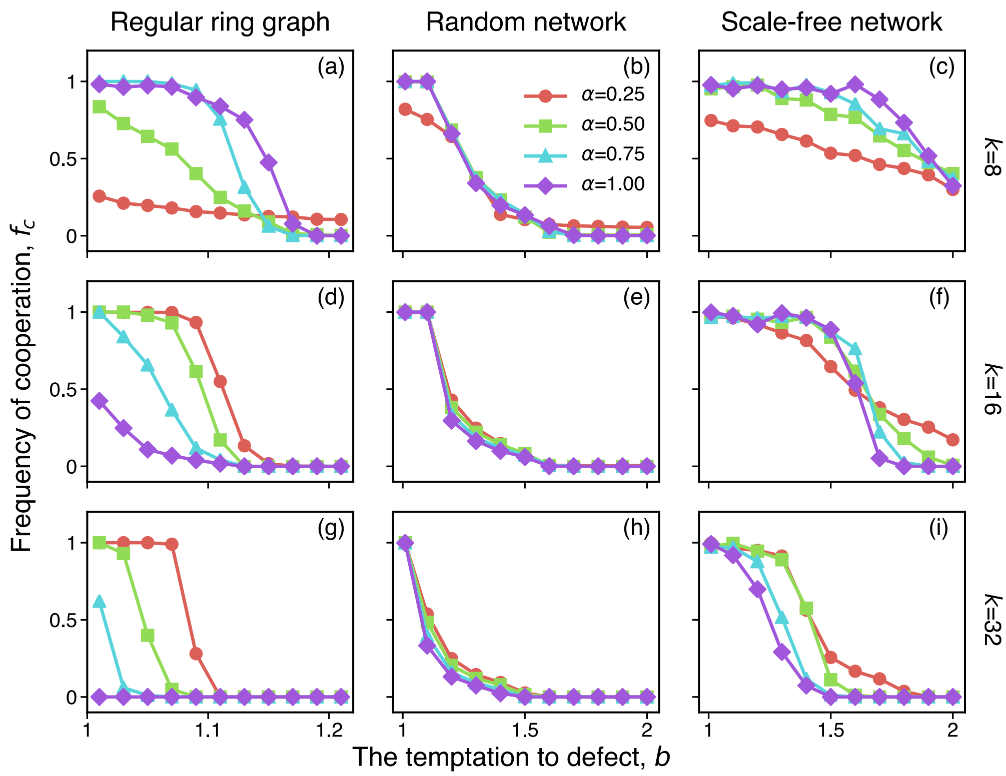

FIG. 4. Frequency of cooperation, f_c, as a function of the temptation to defect, b, on different networks with different levels of autonomy, α, and network degrees, k. The effective networks are static and the payoffs are accumulated.

To further understand the mechanism of how the effective network degree αk affects the cooperation, we show the cooperation as a function of αk at $b = 1.05$ for regular ring graphs and $b = 1.2$ for another two networks. Interestingly, we find that the moderate effective network degree, maximally, promotes cooperation (Fig. 5), which is consistent with previous studies [15,22,28]. A further analysis of the heterogeneity of the networks with different effective networks shows that this is due to the fact that an intermediate heterogeneity benefits the cooperation [30] (Fig. 6).

IV. CONCLUSION AND DISCUSSION

We have studied how autonomy, a basic need for humans, promotes cooperation on different networks with various network degrees. We find, on dynamic effective networks, the autonomy promotes cooperation regardless of the network degree. Further studies with normalized payoffs and evolution on static networks verify that it is the autonomy that promotes the cooperation instead of the heterogeneity or the other characteristics of the network dynamics. This is consistent with experimental studies in the field of management and psychology, where higher autonomy allows for more positive social relations [32], benefits in interpersonal honesty and openness [33], and promotes group cohesiveness and efficiency [34].

When autonomy is introduced, the actual interaction network is dynamical. Individuals with the same autonomy do have the authority to interact with different neighbors that are selected from the underlying network at different time steps. However, we wish to emphasize that here the dynamical network is different from other important work pertaining to coevolution where network structure and strategy evolve together in an evolutionary process [7,35–37]. In our case,

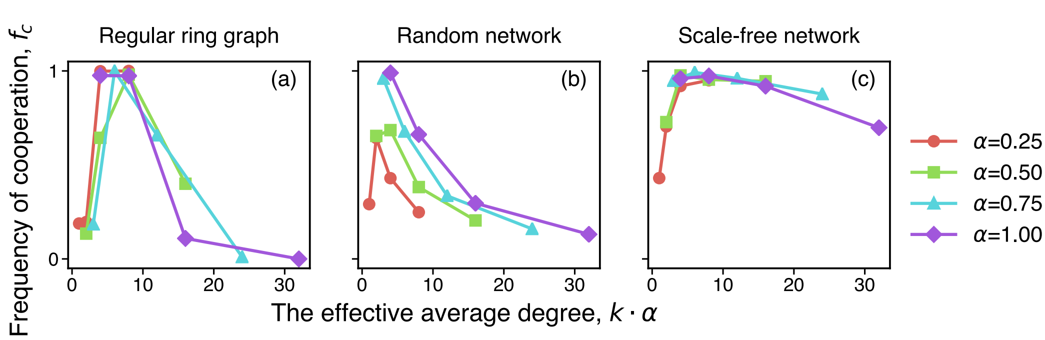

FIG. 5. Frequency of cooperation, f_c, as a function of the product of network degree, k, and the level of autonomy, α. The temptation to defect, b, is 1.05 for regular ring graph and 1.2 for scale-free network and random network. The effective networks are static and the payoffs are accumulated.

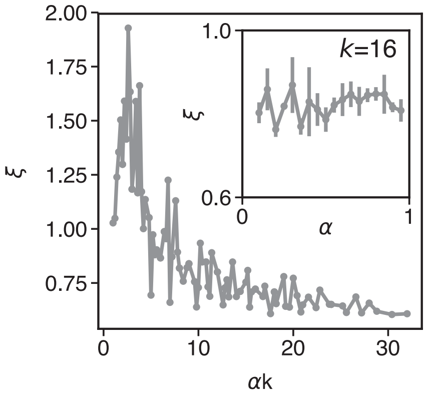

FIG. 6. Network heterogeneity (ξ) as a function of effective network degree (αk). Here ξ could be evaluated by $\frac{\langle\alpha^2 k^2\rangle-\langle\alpha k\rangle^2}{\langle\alpha k\rangle^2}$ approximately according to the definition of network heterogeneity [31], and $\langle\cdot\rangle$ denotes average operation, $\alpha \in [0.1, 1]$ with an interval of 0.05. Considering $\frac{\langle\alpha^2 k^2\rangle-\langle\alpha k\rangle^2}{\langle\alpha k\rangle^2} = \frac{\langle k^2\rangle-\langle k\rangle^2}{\langle k\rangle^2}$, we know that ξ is around $\frac{\langle k^2\rangle-\langle k\rangle^2}{\langle k\rangle^2}$ for different α as we have shown in the inner panel for $k = 16$. For the main panel, the network degree k ranges from 4 to 32 with an interval of 4.

the underlying network does not evolve intrinsically, and individuals neither build new links nor terminate existing links. Specifically, we treat the timescale of the change of links as larger than that associated with game dynamics.

We find that the level of cooperation under the dynamical network resulting from the autonomy is lower than that on static networks. On the face of it, one might conclude that the dynamical network is detrimental for cooperators. Nevertheless, further attention should be cast on the network switching frequency according to autonomy during each round. When we allow each static interaction network to last several generations, it is clear that the dynamical network could actually benefit cooperators, which is consistent with the results obtained from human behavioral experiments [38]. Indeed, by switching to another static interaction network after hundreds of rounds on the previous one, cooperation can prevail on dynamical networks. This echoes the recent finding that temporal networks generically enhance cooperation relative to their static counterparts [27]. Note that the network evolution is also exogenous to game dynamics for temporal networks.

In terms of the autonomy for each individual, here we randomly select some of their neighbors. A natural extension is to study empirical factors governing individuals to select neighbors to interact with under pairwise or multiperson games [39,40] or, in different rounds on social networks. Such factors, for example, could be the reputation of their neighbors [41], group reputation [37], or personal expectation for success [36]. For strategy updating, here players tend to imitate neighbors they have selected randomly for interaction. It is worth investigating the scenarios where players might learn from the best of all their neighbors [9] or other teaching activities [42].

Furthermore, beyond the extension on studying the evolutionary dynamics, the dynamical characteristics coming with the players' autonomy give the possibility to design the empirical interaction patterns of both nodes and links. Indeed, starting from homogeneous network settings, it is reported that by engaging with others, the universal power-law distribution of individuals' interevent intervals (the so-called bursty behavior [43]) can emerge [44]. Recently, several important models have been proposed to elucidate the origin of the bursty behavior of both nodes and links [43,45,46]. By virtue of the empirical evolutionary dynamics where the network evolution is triggered by individuals' behavior in pursuing higher payoffs, one can accordingly study the possibility of generating a given interaction pattern like burstiness from the perspective of game dynamics.

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APPENDIX A

Clique number and number of maximum cliques of different networks (Fig. 7).

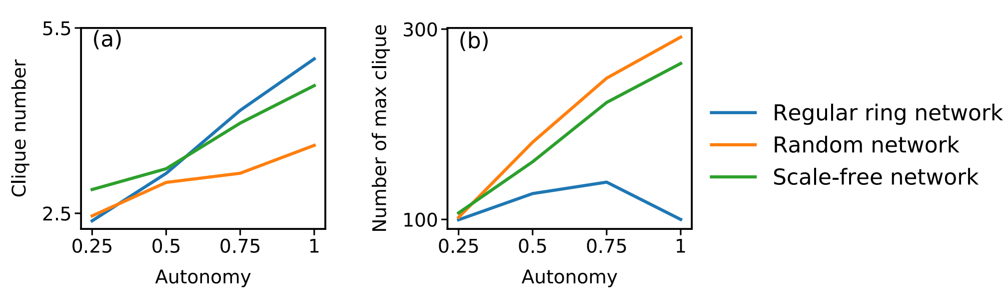

FIG. 7. Clique number and number of maximum cliques in three networks as a function of the level of autonomy. We set the average network degree as 8. Each point is averaged over simulations of 100 individuals and 30 initialized networks and 100 iterations over each network.

APPENDIX B

Robustness tests (Figs. 8–11).

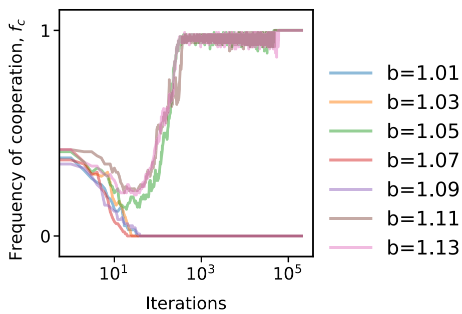

FIG. 8. An example to show the frequency of cooperation, f_c, reaches the absorbing state over long time evolution.

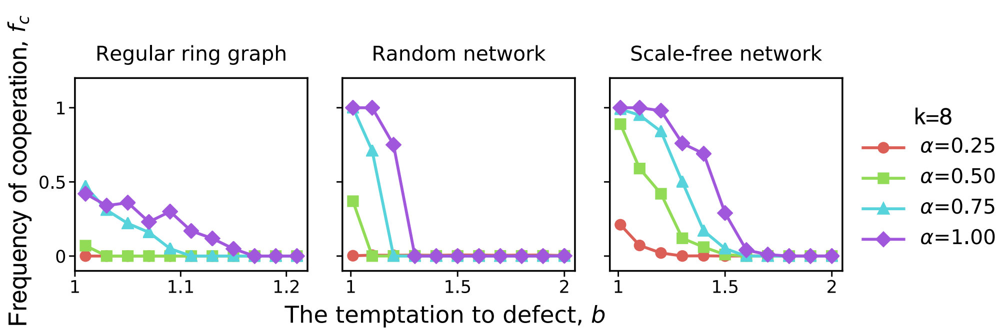

FIG. 9. Frequency of cooperation, f_c, as a function of the temptation to defect, b, on three different networks with different levels of autonomy, and α over long time evolution (5×10^6 iterations). The effective network is dynamic and payoff is accumulated. Simulations are conducted with 100 individuals. We did 100 repetitions for each α and b. Therefore the average of f_c is within [0, 1].

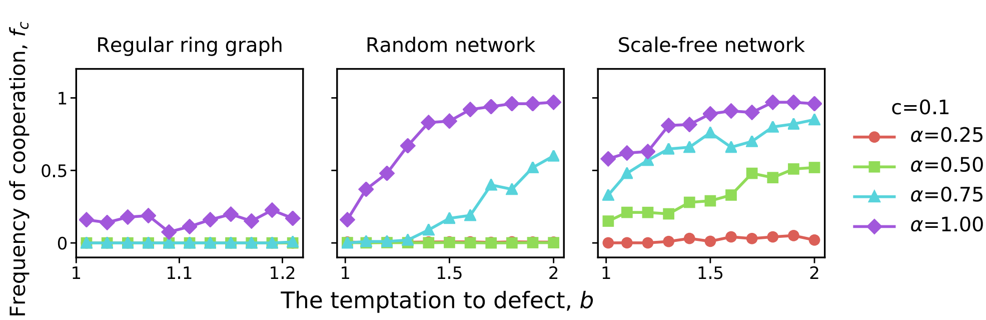

FIG. 10. Frequency of cooperation, f_c, as a function of the temptation to defect, b, on three networks with different levels of autonomy, α, and $c = 0.1$ in strict prisoner's dilemma ($[b-c, -c; b, 0]$). The effective network is dynamic and payoff is accumulated.

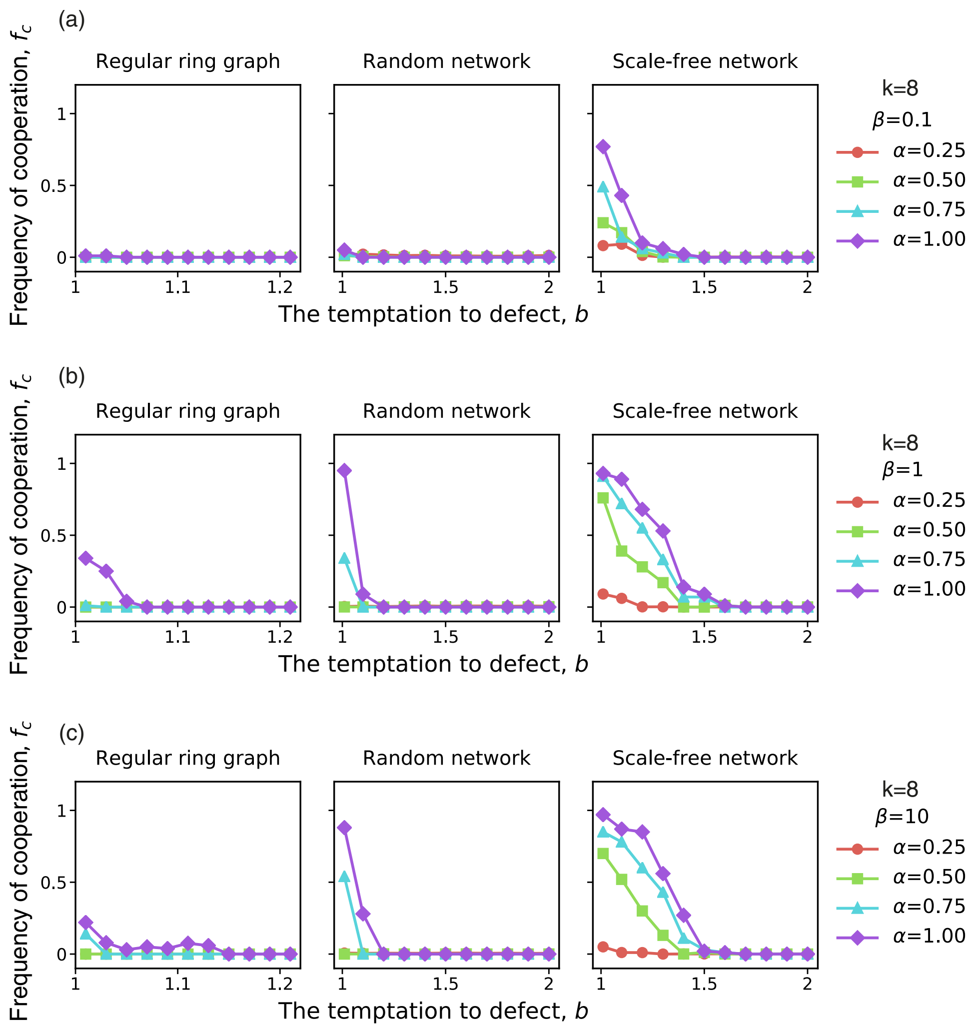

FIG. 11. Frequency of cooperation, f_c, as a function of the temptation to defect, b, on three different networks with different levels of autonomy, α, and selection strength, β. The effective network is dynamic and payoff is accumulated.

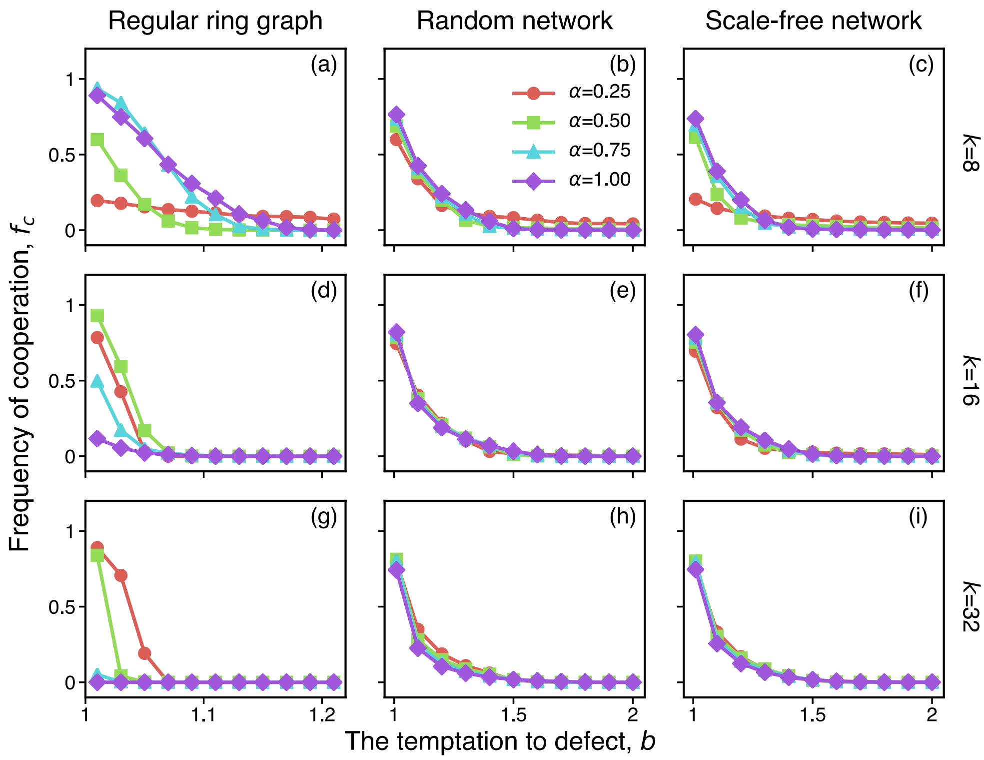

FIG. 12. Frequency of cooperation, f_c, as a function of the temptation to defect, b, on different networks with different levels of autonomy, α. The effective network is static and the payoff is normalized.

APPENDIX C

Results on static networks with normalized payoffs (Fig. 12).

APPENDIX D

Results on fixed effective network degree (Figs. 13–16).

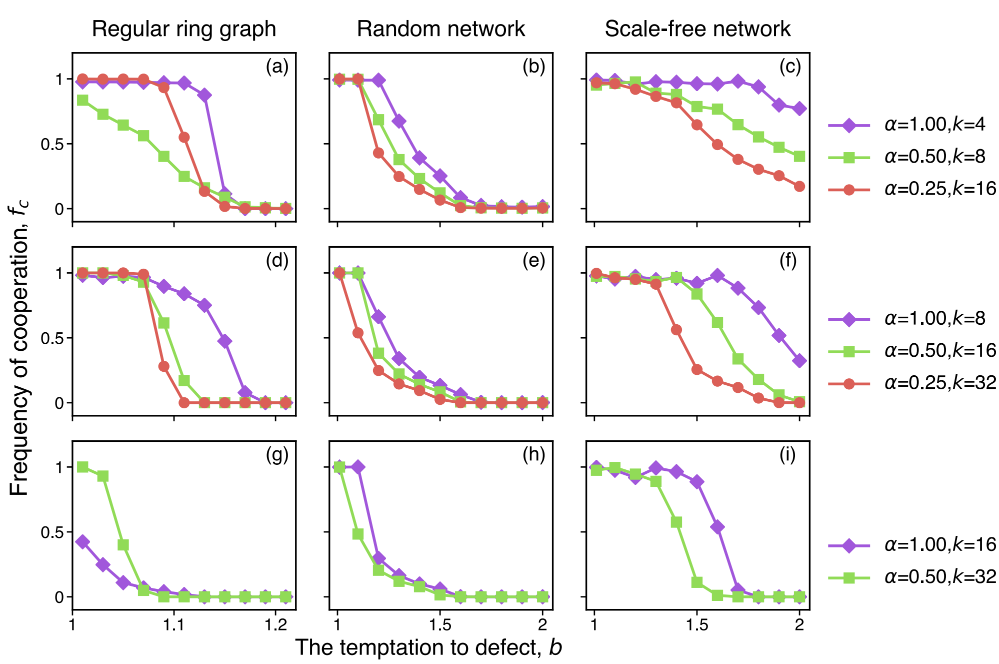

FIG. 13. Frequency of cooperation, f_c, on static effective networks as a function of b when the product of autonomy, α, and network degree, k, is fixed. The payoff is accumulated and the effective network is static.

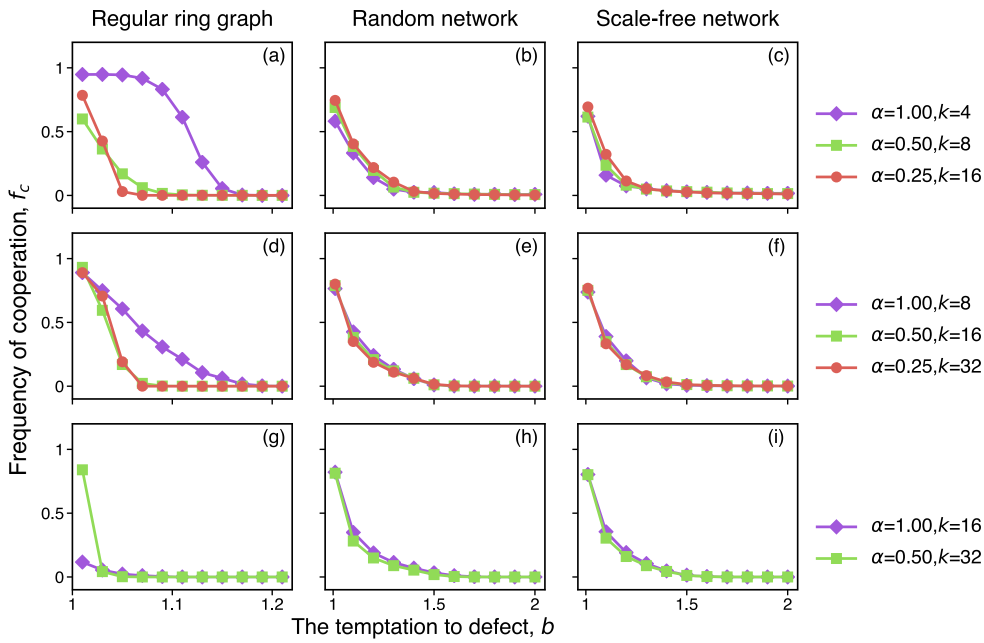

FIG. 14. Frequency of cooperation, f_c, on static effective networks as a function of b when the product of autonomy, α, and network degree, k, is fixed. The payoff is normalized and the effective network is static.

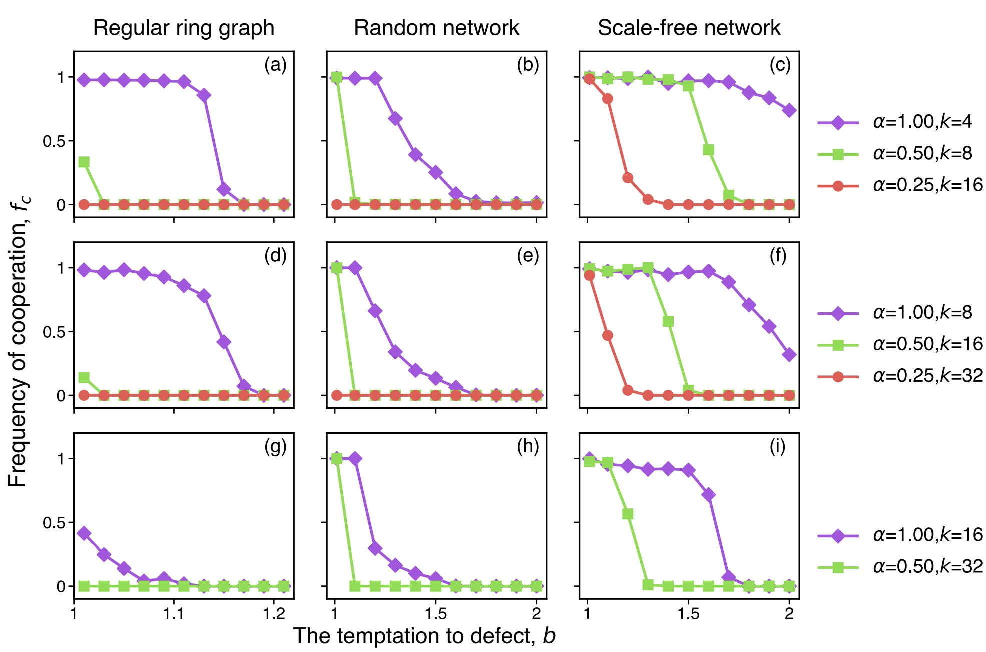

FIG. 15. Frequency of cooperation, f_c, on static effective networks as a function of b when the product of autonomy, α, and network degree, k, is fixed. The payoff is accumulated and the effective network is dynamic.

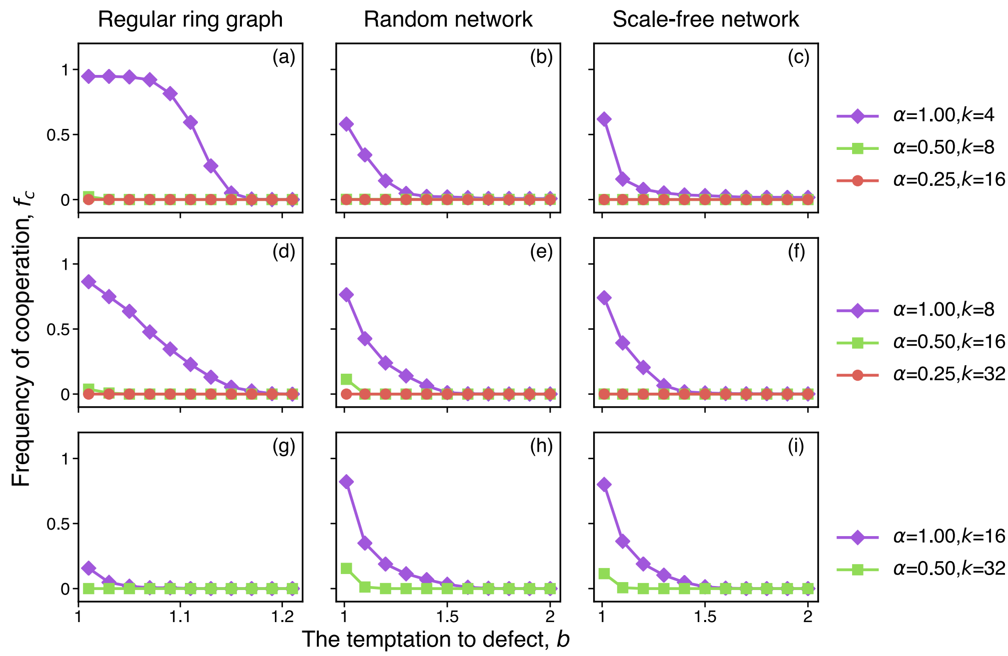

FIG. 16. Frequency of cooperation, f_c, on static effective networks as a function of b when the product of autonomy, α, and network degree, k, is fixed. The payoff is normalized and the effective network is dynamic.

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