Physica A 569 (2021) 125772

Contents lists available at ScienceDirect

Physica A

journal homepage: www.elsevier.com/locate/physa

Information exchange promotes and jeopardizes cooperation on interdependent networks

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ARTICLE INFO

Article history:
Received 10 October 2020
Received in revised form 13 December 2020
Available online 23 January 2021

MSC:
00-01
99-00

Keywords:
Information exchange
Cooperation
Prisoner's dilemma game
Interdependent networks

ABSTRACT

Information exchange has a significant influence on human behaviour decision-making. To explore the impact of the information exchange mechanism on the evolution of cooperative behaviour on the complex networks, we establish two-layer interdependent networks. Individuals have a certain probability of having information exchange with individuals on another network. In detail, when individuals residing on different networks are connected by links, the update of strategies not only depends on their own payoffs, but also depends on the strategy selections of the corresponding nodes and neighbours on the other network. Numerous simulations reveal that high cooperation level can be achieved for a large coupling probability and intermediate heterogeneity. Counter-intuitively, cooperation is not always promoted by the expansion of information sources. Our study thus enhances the understanding of the evolution of cooperation on interdependent networks.

1. Introduction

As we all know, cooperative behaviour is widely observed in human society and biological systems. However, due to the theory of biological evolution, the emergence and maintenance of cooperation seem to be a still challenging problem. The proposal of evolutionary game theory is to explain such a phenomenon [1–4]. The development of evolutionary game theory on complex networks made the research of cooperative behaviour theoretical, formulaic and systematic, which facilitated the scholars' understanding and further discussion of the problem. In the research process of evolutionary game theory, scientists put forward some mechanisms that can promote cooperation. Under the framework of evolutionary game theory, Nowak summarized five mechanisms that can promote the evolution of cooperation [5]: kin selection [6,7], direct reciprocity [8], indirect reciprocity [9,10], network reciprocity [11–13] and group selection [7]. Among which Nowak and May proposed network reciprocity in 1992 [11] and received much attention. Along this line, many potential mechanisms have been proposed, such as introducing asymmetric information [14,15], reward [16–18], punishment [19–24], aspiration [25–27], reputation [28–31] and other interplay mechanisms [32–34]. For a comprehensive understanding, we recommend the readers refer to [12,35].

Information exchange plays a significant role in the human decision process. During the outbreak of COVID-19 pandemic, affected by the information on the Internet, people rushed to buy toilet paper, food, medicine, etc. All of these behaviours put tremendous pressure on the production supply chain. Therefore, it is necessary to understand the

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https://doi.org/10.1016/j.physa.2021.125772
0378-4371/

influence of information sources' diversity, uncertainty, and transmission efficiency on human behaviours. Based on what has mentioned above, many scholars study this problem from the perspective of interdependent networks [36–39]. Unlike with single-layer networks, the properties of the interdependent and interactive networks are more consistent with the real social systems due to the interdependencies between different networks [40–43]. At present, the research on the interdependent networks can be divided into three categories according to the coupling mode: Most commonly, the interdependent networks are connected with the utilities of players [37,39,44–47], by which players' payoffs are not only based on themselves, but also the payoffs of external players. The interdependent networks can also be connected with information flow and the popularity of different strategies [48]. Szolnoki et al. found that the information exchange of players' strategy selections on different networks can enhance cooperation, when the information exchange is embodied in the individual updating strategy and the popularity of the potential new strategy on another network is considered [49]. Besides, the study of coevolution on interdependent networks is also worth paying attention to [50–52]. For the progress of cooperation on interdependent networks, we recommend the readers to the review [53].

People show more conformity trait in their decision-making processes, some works combined this trait with game theory and reached meaningful achievements [54–56]. Different with these works, here we combine this universal property with the information exchange process. In detail, the update intention of players on another layer is integrated into the Fermi function of players on the current layer, we further explore the influence of coupling density and the range of acquired information for cooperation on interdependent networks. We find that the effect of information exchange is a double-edged sword, it only works in an appropriate scope, the promotion effect of information exchange is only limited to prisoner's dilemma game, large coupling density ρ, intermediate heterogeneity parameter α, as well as intermediate number of neighbours.

This paper is organized as follows: first, we introduce the evolution model of prisoner's dilemma game with information sharing in the interdependent networks in Section 2. Then we get a series of results aiming at this problem in Section 3. Lastly, we make a summary and discuss its potential implications.

2. Model

To explore the influence of information exchange on human behaviours, we establish interdependent networks with the same lattice structure and periodic boundary conditions, on which individuals play the prisoner's dilemma game (*PDG*). As shown in Fig. 1, whether there are links between corresponding nodes on the interdependent networks is controlled by connection density ρ (the probability of the connection between node i and node i' is ρ). To a certain extent, ρ represents the efficiency of information exchange. $\rho = 0$ means that there is no connection between those layers, and the information exchange is totally impossible. When $\rho = 1$, nodes on the networks are fully connected, and the efficiency of information exchange is highest. The upper and lower networks are randomly distributed with half of the strategy C (cooperation) and the other half of the strategy D (defect). The dynamic updating of individuals follows the Monte Carlo simulation rules. In each step, a focal agent i is randomly selected to play with his neighbours. The two cooperators will each get a reward R when they meet. When a cooperator encounters a defector, the defector gains the temptation of defection T, while the cooperator gains only the sucker's payoff S. When two defectors meet, they will each receive the punishment P. These payoffs satisfy the relationships $T > R > P > S$ and $2R > P + S$. Here we use the weak prisoner's dilemma game and the parameters are set as $T = b$, $R = 1$, $P = S = 0$. The value range of parameter b is $1 < b < 2$. Player i acquires total payoff P_i by playing games with all its neighbours, while j acquires total payoff P_j by playing games with all its neighbours.

Strategy updating is only possible between the players on the same layer. When there is no interconnection between the players residing on different layers, the strategy updating mode of the individual follows the traditional Fermi function, by which the individual i will randomly choose a neighbour j and study the strategy of j with probability:

$$P_{i\to j} = \frac{1}{1 + \exp[(p_i - p_j)/K]}, \tag{1}$$

where K is the amplitude of noise or its inverse ratio is the so-called selection intensity, generally $K = 0.1$ [57,58].

When there is an interconnection between players residing on different layers, the update of the focal individual is not only affected by its update intention of the current layer, but also affected by the update intention of the corresponding player and its neighbours on another layer. This reflects the mechanism of information exchange. Thus the update follows the following function:

$$P_{i\to j} = \frac{(q_i)^{\alpha}}{1 + \exp[(p_i - p_j)/K]},\ q_i = n/n_s (n \neq 0, n_s \neq 0) \tag{2}$$

Here q_i is the parameter which is influenced by information sharing, where n_s is the sum of the corresponding player on another layer and its neighbours which have the same strategy as individual i, and n is the number of individuals in n_s that desire to change their strategies. The traditional Fermi function is used to define n by whether there is a desire to update its strategy. To avoid the frozen state and some extreme values, here, the minimum and maximum value of q_i is fixed as 0.01 and 1, respectively. α is a heterogeneity parameter, positive α includes the heterogeneity in our model, while $\alpha = 0$ returns to the traditional situation [59].

In a complete Monte Carlo step, each agent on the interdependent networks has an average opportunity to update his strategies. The network size is $L = 100$, and the last 5000 steps determine the density of cooperation and defect in a total of 3×10^4 or 1×10^4 Monte Carlo steps simulation. To make the results more accurate, the final result of each parameter setting is the average value of 20 simulation results.

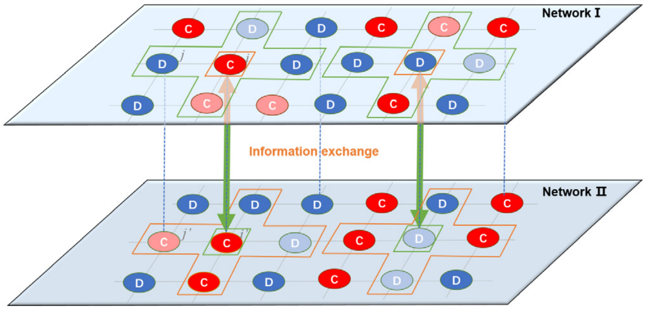

Fig. 1. The diagrammatic sketch of interdependent networks. Red nodes represent cooperators and blue represent defectors, and the lighter colours mean that they do not have the desire to update. Several dotted lines connect the upper and lower network, which means there is information exchange between the two nodes. For example, there is a link between agent i and i', two cooperators in the cross area on network II desires to change their strategy while there are three cooperators in that cross area, therefore $q_i = 2/3$.

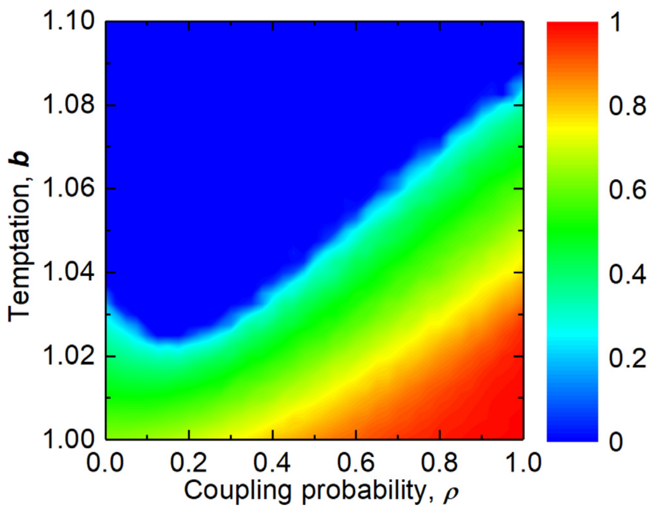

Fig. 2. The phase diagram of the average cooperation frequency on upper and lower networks for different parameter sets of coupling probability ρ and defect temptation b. A smaller b and a larger ρ can promote cooperative behaviour in the system.

3. Results

We report our numerical results by plotting the final proportion of cooperation in the population as the system evolves into a stable state. First, numerous simulations are conducted to determine the average cooperation frequency, and the phase diagram under different parameter combinations of ρ and b is shown in Fig. 2. From Fig. 2, we can observe the influence of information exchange efficiency and network reciprocity on the cooperation level in the system from a macro perspective. For smaller b, cooperators are in an advantageous position. If we start to increase the value of b, which means weakening network reciprocity, defectors begin to expand rapidly. When b is large enough, there are only defectors left. A larger b shows a greater temptation to defect, and the cooperators cannot form reciprocal relationships on the networks. Therefore, as mentioned above, the corresponding cooperation frequency decreases with an increase of b provided for a fixed information exchange efficiency. Nevertheless, for a fixed b, if a larger ρ is adopted while the value of ρ is more than 0.15, the frequency of cooperators will increase. It is also worth noting that the above observation is only limited to prisoner's dilemma game, the results are totally opposite in stag hunt game and chicken game (see Fig. A.1). For its potential reason, we guess it is the mixed strategy Nash equilibrium that kills the efficiency of location synchronization effect, which is the main reason that sustains cooperation on interdependent networks. We also tested the above phenomenon on regular small-world network(RSW) and regular random graph (RRG) and got the same results (see Fig. A.2). In the following, we only restrict our model in spatial prisoner's dilemma game and square lattice to analyse these impressive results.

Fig. 3 shows the proportion of different links and cooperation between upper and lower networks in the evolution process. When ρ equals to 0.2, which means the efficiency of information exchange between the two networks is low, the fraction of CC and CD links quickly decrease and reach to 0 after a hundred steps in this case of defect temptation is a bit large. But after the strengthening of information exchange efficiency, the situation changes. CC and CD links both

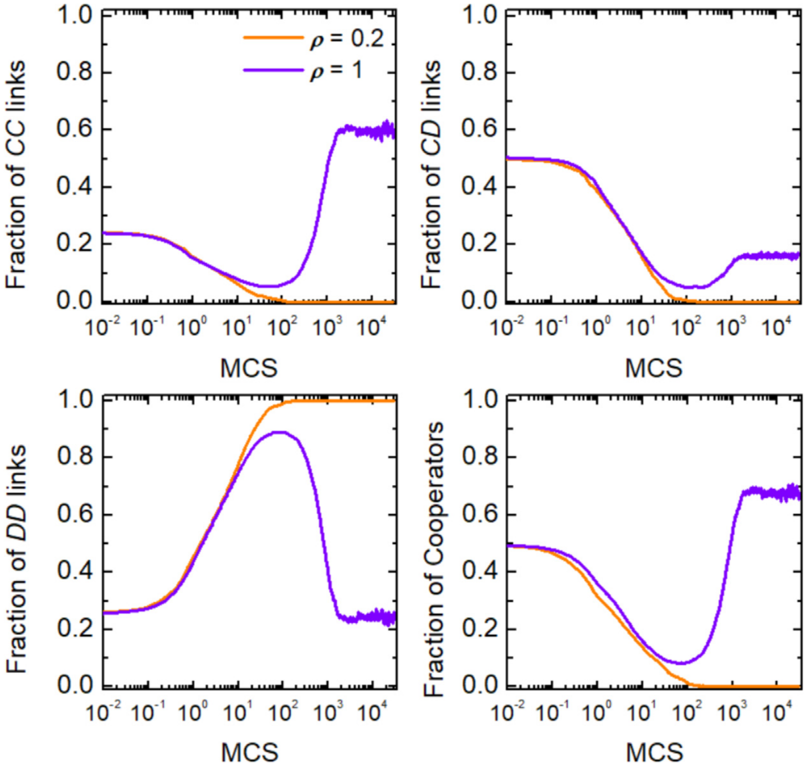

Fig. 3. Time courses of the evolution of cooperation for the fraction of strategy links of corresponding nodes and cooperation level under different efficiency of information exchange ρ. The graphs reveal the fraction of *CC* links, *CD* links, *DD* links and cooperation rate. The orange line shows $\rho = 0.2$ and violet line shows $\rho = 1$. The results are obtained with $b = 1.05$ and MCS $= 30\,000$.

show a trend of decreasing and then increasing, while *DD* links initially increase, then falls to stability. High-frequency information exchange makes the strategy update more dependent on whether other individuals' strategies are updated, and reduces the dependence of update on pure payoff comparison, which brings a better environment for cooperators to survive and expand.

We present the cumulative probability of strategy changes in Fig. 4. We use the orange line to represent $\rho = 0.2$, which means that information exchange efficiency is low. Violet represents that ρ is equal to 1, which means that information exchange is of really high frequency. Cumulative probability means the summary of probability that the fraction of C to D or D to C during the whole evolution. When ρ is equal to 0.2, compared with the fraction of D to C, the process of C to D is much slower. When there is a small amount of information exchange, cooperators are quickly eroded by defectors, leading to less transformation from defectors to cooperators, and it is easier to achieve a stable state of saturation. If we make the information exchange cover all nodes, just as the violet lines show, we can find that fraction from D to C is a bit higher than the situation in $\rho = 0.2$. High efficiency of information exchange makes more agents who take part in the game cautious and conformity, and the defectors are more likely to change their strategies because of the information they exchange.

To better reflect the relationship between information exchange and strategy evolution from a microscopic perspective, we set up a unique distribution from a prepared initial state: As the graphs of the first column shown in Fig. 5, here is a circular area where cooperators are set up on the upper and lower networks is corresponding, and the position of another circular area is not corresponding. Through this initial distribution, we want to see how strategies change in different information environments. This method of using different specific initial states to observe results is derived from [60]. As shown in the top two lines of graphs, when ρ is equal to 0.2, everything is just similar to the traditional situation. The cooperators are quickly occupied by defectors, and then the whole system is filled with defectors. However, the bottom two lines of the graphs show a totally different situation. The areas where there are no corresponding cooperators between the upper and lower networks are gradually shrinking or even disappearing, while the corresponding positions of the upper and lower networks are the areas of cooperators gradually expanding, which ultimately gives the cooperators in the system enough advantages. What is more, the edge of the light red areas is always surrounded by red and blue, which means that the existence of individuals with a low value of q has a strong protective effect on cooperators. It is difficult for cooperators to keep their strategy unchanged, especially when the temptation to defect is greater and information exchange is inefficient. But when the reason for updating strategy is not only based on payoffs for all players, the strategy of cooperating can be better protected.

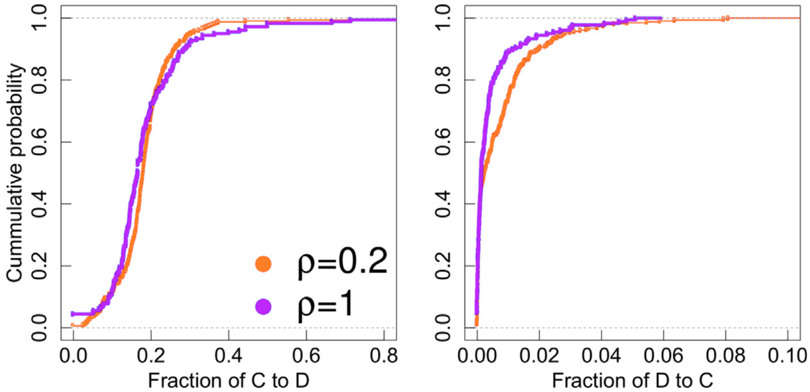

Fig. 4. From left to right, we present the cumulative probability of the fraction of C to D and the fraction of D to C. We use orange line to represent $\rho = 0.2$ and violet to represent $\rho = 1$. The results are obtained with $b = 1.05$ and MCS = 30 000.

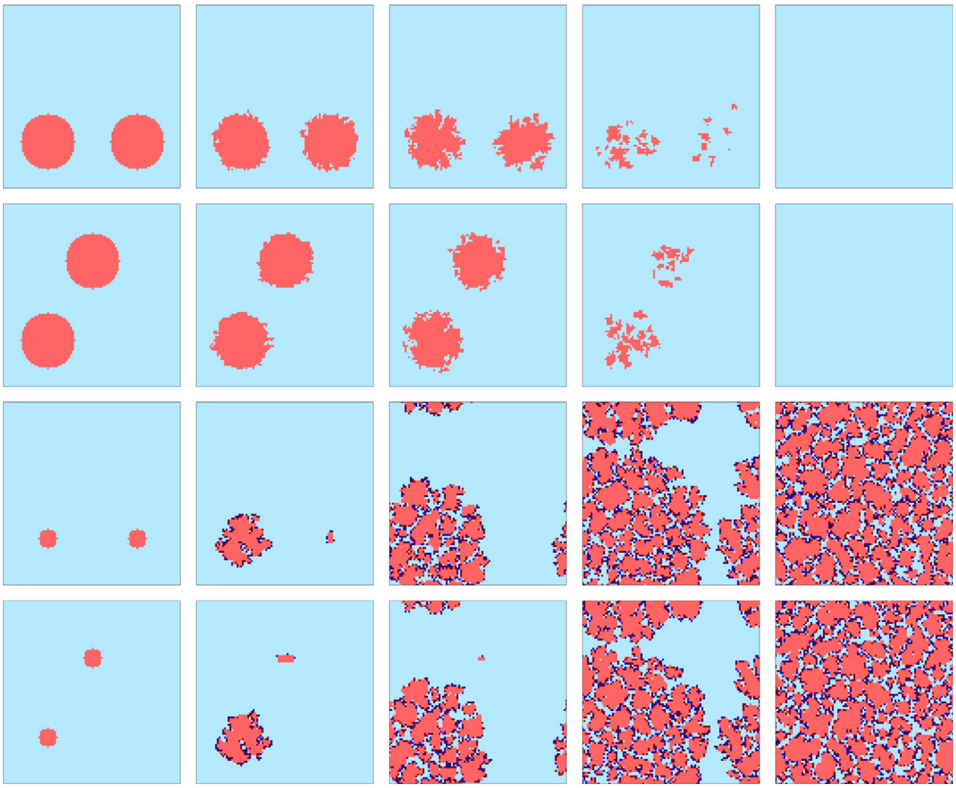

Fig. 5. Characteristic snapshots of different strategies (either cooperation or defection) on the regular lattice. The above results are obtained for the scenario of $b = 1.05$, $\rho = 1$ and $L = 100$. These graphs show the strategies and q value changing over time on the upper and lower networks. The top two lines of graphs show the situation of $\rho = 0.2$ while *MCS* is equal to 0, 7, 30, 100 and 1000 and the bottom two show $\rho = 1$ while *MCS* is equal to 0, 1000, 3000, 5000 and 10 000. The different colours represent different agents: light red: $C(q > 0.5)$, red: $C(q \leq 0.5)$, light blue: $D(q > 0.5)$, blue: $D(q \leq 0.5)$.

To show the influence of the different sizes of the neighbourhood, that is, different sizes of information source range on cooperation, we choose different information exchange efficiency to observe. As Fig. 6 shown, the scope of information sources has a certain impact on cooperation, but this effect is not positive. Whether the efficiency of information exchange is high or low, a too large or too small range of information sources is not conducive to cooperation. In the growth process of defect temptation b, the cooperation rate brought by neighbourhood size equal to 20, 12 and 8 are dominant,

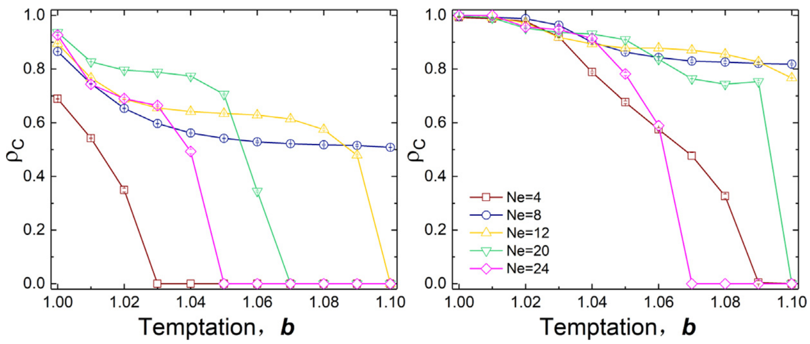

Fig. 6. The fraction of cooperators ρ_C as a function of the temptation b with error bar. The different colours show the different sizes of neighbourhoods. The left graph shows $\rho = 0.2$ and right graph shows $\rho = 1$. The results are obtained at $MCS = 30\,000$.

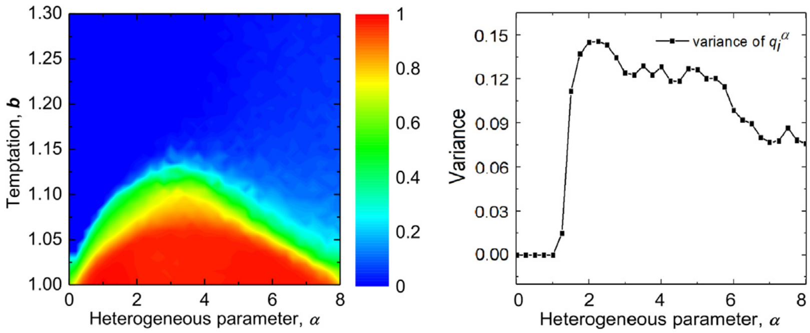

Fig. 7. The left graph shows the illustration of the average cooperation frequency for different parameter set of heterogeneous parameter α and defect temptation b. The right graph shows the variance of the α power of q_i at different value of α when $b = 1.1$. The results are obtained at $\rho = 1$ and $MCS = 30\,000$.

respectively. Too many sources of information can make the player's strategy influenced by more other players, which sometimes makes the cooperators more likely to turn into defectors because of other cooperators' desire to change their strategies. The results are similar to the research of Refs. [61,62], in which the size of the neighbourhood has no absolutely positive effect on cooperation. Thus, information exchange is not just beneficial to cooperation, but a double-edged sword.

For a given ρ, it is instructive to further investigate the relationship between heterogeneous parameter α and defect temptation b. As we can see from the left part of Fig. 7, there exist an optimal α values to promote cooperation. When α is equal to 3.2, cooperation will be maximized. However, as far as the threshold of cooperation disappearance is concerned, the larger the value of α, the greater the defect temptation b corresponding to the disappearance of cooperation. The larger value of α reduces the probability of the cooperators and defectors to change their strategies, which makes the threshold of cooperation disappearance higher and higher. However, due to the lower probability of strategy change, it will be difficult for the defector to transform into a cooperator effectively. Therefore, it is not true that the larger the α, the better the cooperation can be improved. From the right graph, we can find the relationship between the cooperation rate and the heterogeneity parameter α. When the heterogeneity parameter is large, the cooperation rate is at a high level. But when the heterogeneity parameter decreases, the cooperation rate decreases. This is similar to the findings in [63]. The existence of heterogeneity has a positive effect on cooperation.

4. Conclusion

To conclude, we studied the effect of information exchange for cooperation on interdependent networks. When there exist interconnections between the layers, the decision-making process is not only affected by the information of the current layer, but also influenced by the other layer. In our model, the value of ρ denotes the efficiency of information exchange, while α represents the heterogeneity parameter. Extensive numerical simulations show: (1) The faster the efficiency of information exchange, the higher the level of cooperation. (2) There is an intermediate scope of information sources for the survival of cooperation. (3) Intermediate value of α enables the most massive heterogeneity, which brings the additional reciprocity into the system.

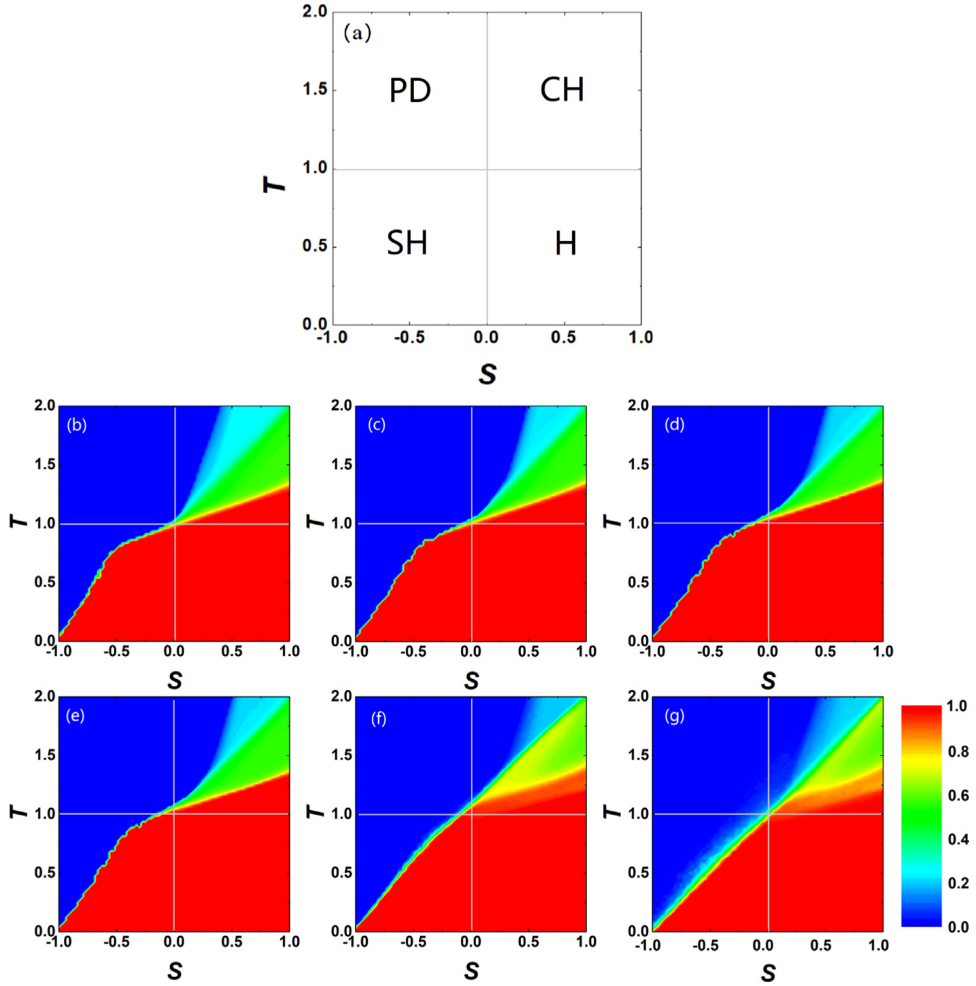

Fig. A.1. (a) Schematic representation of different games in T–S phase diagram. (b)–(d) Fraction of cooperation in T–S phase diagram for different values of coupling density ρ. (e)–(g) Fraction of cooperation in T–S phase diagram for different values of heterogeneity parameter α. For middle row, the heterogeneity parameter α was fixed as 1, from left to right, the coupling density ρ were fixed as 0, 0.5 and 1, respectively. For bottom row, the coupling density ρ was fixed as 1, from left to right, the heterogeneity parameter α were fixed as 0, 0.5 and 1, respectively.

For how much interdependence should be between the layers for the evolution of cooperation, previously research has addressed that there is an optimal interdependence for cooperation since intermediate interconnections bring strongest heterogeneity to the system [64]. However, in our study, this is not the case, instead cooperation is favoured by large coupling density, which brings the strongest location synchronization effect to the system and thus cooperators are more willing to insist its strategy. Our results indicate that optimal interdependence between the layers for cooperation is not usually the case, it depends on the model itself. In Ref. [49], the authors show that information sharing promotes cooperation since the spontaneous emergence of the correlated behaviour between the layers deters defection and establishes the best environment for cooperation. In our study, we further considered the influence of the scope of neighbours for cooperation, we found that the promotion effect of information exchange is only limited to prisoner's dilemma game, large coupling density ρ, intermediate heterogeneity parameter α, as well as intermediate number of neighbours. Thus the effect of information exchange is a double-edged sword, it only works for the above scope. We thus provide a deeper understanding for the influence of information exchange on the evolution of cooperation.

The experimental method of behavioural economics provides economics with unprecedented replicability and controllability, which has great advantages in testing, comparing and perfecting economic theory. Our research is to construct the model from the perspective of theory. Simultaneously, recently many studies show that the results of behavioural economy experiments and theoretical research may not be consistent. Therefore, it is necessary to study how information exchange affects behavioural decision-making from an experimental perspective. We hope that our study can provide a theoretical basis for the influence of information exchange on game theory, and provide a specific reference for conducting behavioural economics experiments of information exchange.

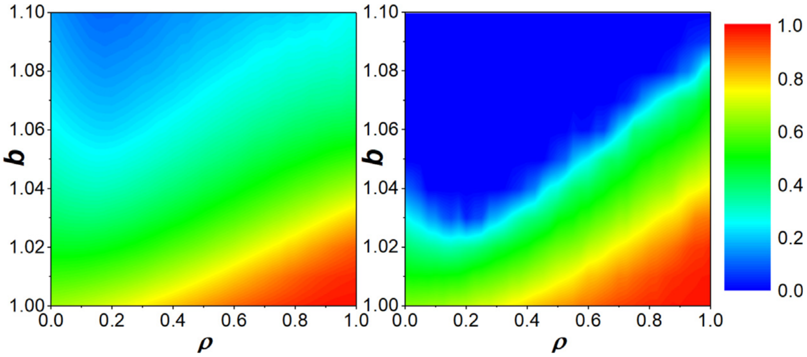

Fig. A.2. Fraction of cooperation in b-ρ phase diagram for random regular graph and regular small world network. The heterogeneity parameter α was fixed as 1.

CRediT authorship contribution statement

Zhewen Zhu: Designed research, Analysed the results, Wrote the manuscript, Reviewed the manuscript. **Yuting Dong:** Designed research, Wrote the manuscript, Reviewed the manuscript. **Yikang Lu:** Analysed the results. **Lei Shi:** Wrote the manuscript, Reviewed the manuscript.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

L.S. was supported by a key project (no. 11931015) of the National Natural Science Foundation of China (NNSFC) and NNSFC project no. 11671348. Specially, we thanks Chen Shen for discussing the research.

Appendix

Fig. A.1 plots the fraction of cooperation in T–S phase diagrams for different values of coupling density ρ (middle row) and different values of heterogeneity parameter α (bottom row). As shown in top row of Fig. A.1, the full parameter space can be divided into four regions corresponding to prisoner's dilemma game (PD), chicken game (CH), stag hunt game (SH), as well as harmony game (H). The Nash equilibrium of these games is full defection, cooperation–defection pair, cooperation–cooperation pair or defection–defection pair, and full cooperation. Obviously, large cooperation survival region can be achieved for large values of coupling density ρ and intermediate values of heterogeneity parameter α in spatial prisoner's dilemma game, which is consistent with the results that we reported before. However, the results are totally opposite in stag hunt game and chicken game, for its potential reason, we guess it is the mixed strategy Nash equilibrium that kills the efficiency of location synchronization effect, which is the main reason that sustains cooperation on interdependent networks. Despite there is a big difference for cooperation within this full parameter space, our conclusions are still robust. Information exchange does not always promote cooperation, the promotion effect is only limited to prisoner's dilemma game, large coupling density ρ, intermediate heterogeneity parameter α, as well as intermediate number of neighbours. We also clarified this phenomenon in the discussion part.

As Fig. A.2 shown, we implemented the same procedures on random regular graph (RRG) and regular small world network (RSW), and got the consistent results with lattices.

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