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Impact of peer pressure on cooperation evolution in the networked prisoner's dilemma game with migration mechanisms

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In social and ecological systems, individual migration behavior and peer pressure are crucial factors influencing decision-making and cooperative behavior. However, how migration regulates the evolution of cooperation and the specific role of peer pressure in this process remain to be further investigated. To address this, this study develops a model that incorporates migration mechanisms and peer pressure within the framework of the networked prisoner's dilemma game. Specifically, we modify the population structure and introduce a migration strategy based on payoff maximization, enabling individuals to dynamically adjust their positions according to the local environment. The model also considers the impact of peer pressure on individual decision-making and introduces heterogeneity in individuals' sensitivity to pressure, thereby systematically examining the role of both factors in the evolution of cooperative behavior. Based on this framework, we further compare our model with a scenario in which no migration mechanism is present to evaluate its impact on cooperative dynamics. The results reveal that the migration mechanism significantly promotes the evolution of cooperative behavior. Under this mechanism, higher individual sensitivity leads to an increased level of cooperation, and stronger peer pressure intensity more effectively enhances the promotion of cooperation. Additionally, the influence of population structure on cooperation frequency cannot be overlooked. An increase in vacant nodes provides cooperators with greater buffering space and more migration opportunities, making cooperative behavior more stable and facilitating its propagation within the system. These findings suggest that appropriately regulating individual mobility and reinforcing peer pressure constraints can enhance the stability and propagation of cooperative behavior, providing significant theoretical support for social governance, organizational management, and group collaboration.

Keywords: prisoner's dilemma, peer pressure, migration mechanism, cooperation, two-dimensional grid network

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1. Introduction

Cooperation is a phenomenon that is both complex and fascinating.[1–3] Darwin emphasized in his theory of evolution that "natural selection leads to the survival of the fittest," meaning that individuals with higher fitness are more likely to survive and reproduce.[4,5] In this context, rational individuals often face difficulty in cooperating at the expense of their own interests, particularly when confronted with a trade-off between individual and collective benefits.[6] Despite competition being the dominant force in nature, however, cooperative behavior remains widespread, observed in phenomena ranging from microscopic cells and microorganisms[7] to macroscopic social groups.[8] Cooperation not only enables individuals to accomplish tasks they cannot complete independently, but also yields greater overall benefits to the collective.[9] Given this, understanding the mechanisms underlying cooperation and how to effectively promote it within social contexts has become an urgent issue that requires further investigation. In this regard, evolutionary game theory, as a key theoretical framework, plays a crucial role in analyzing how cooperation can be sustained in competitive environments.[10–12]

As research progresses, complex networks have become an important area of study. Scholars have investigated how different types of network structures influence the spread and maintenance of cooperative behavior in various games. In particular, network topologies such as regular networks,[13,14] small-world networks,[15–17] and scale-free networks[18–20] have been widely utilized in the study of cooperation evolution. Building on this foundation, researchers have conducted in-depth analyses of classical game models under different complex topologies, examining a wide range of models, including the prisoner's dilemma game (PDG),[21–23] the snowdrift game (SDG),[24–26] the stag hunt game (SHG),[27] and the public goods game (PGG),[28,29] among others. Alongside these studies, Nowak summarized five well-known mechanisms that promote the frequency of group cooperation based on varying network structures:[30] kin selection, direct reciprocity, indirect reciprocity, group selection, and network reciprocity. Furthermore, a growing body of research

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has explored the role of individual characteristics, such as reputation,[31–33] desire,[34] memory mechanisms,[35,36] attribute persistence,[37] and punishment,[38] as well as the coevolution of these traits with strategies, highlighting their collective impact on cooperative behavior.

Additionally, mobility, as a widespread characteristic of individuals in the natural world, has garnered significant attention. In simple terms, mobility can promote population mixing, thereby weakening network reciprocity. This has prompted the proposal and extensive study of various migration mechanisms. For instance, Jiang *et al.*[39] explored the role of adaptive migration in fostering cooperation within spatial games, proposing a migration strategy based solely on local information. Their findings indicate that adaptive migration can enhance cooperation by fine-tuning vacancy density and migration speed, triggering cooperation surges in environments dominated by defectors and improving the stability of cooperation. Similarly, Cheng *et al.*[40] introduced a novel migration model within the framework of the evolutionary prisoner's dilemma, where individuals migrate according to the payoffs they receive in the game. Their results suggest that cooperation is significantly enhanced when an individual's migration probability correlates positively with their payoff, particularly in environments with higher player density. Furthermore, Xiao *et al.*[41] proposed a directional migration model for public goods games, investigating how individual migration behavior influences the evolution of cooperation. Their study revealed that individuals are more successful in enhancing cooperation by avoiding defectors rather than actively seeking out cooperators.

In recent years, the relationship between peer pressure and cooperation has been extensively explored, with numerous studies demonstrating that peer pressure can profoundly influence the evolution of cooperation.[42–47] Building on this, many researchers have employed simulation studies, particularly focusing on punishment as a mechanism to explore its effects. For instance, in the context of the PDG, Yang[48] showed that cooperation could be enhanced by applying the same punishment to individuals adopting different strategies. He further emphasized that in evolutionary games, appropriate punishment can play a crucial role in promoting cooperative behavior. Moreover, research has indicated that the density of initial cooperators and the intensity of punishment both significantly impact the evolution of cooperation, highlighting the essential role of peer pressure in social interactions. In line with this, Gao *et al.*,[49] building on Yang's work, investigated how varying sensitivities to pressure influence cooperation. Their findings revealed that when the pressure sensitivities of cooperators and defectors are identical, the system's evolutionary dynamics exhibit distinct phase transition characteristics. Under weak pressure, the system remains in a state of full defection; under moderate pressure, it transitions from full defection to coexistence and ultimately to full cooperation. In contrast, under strong pressure, abrupt changes may occur. Notably, when individuals possess different sensitivities to pressure, the promotion of cooperation is more pronounced.

Although significant progress has been made in recent years regarding the relationship between peer pressure and cooperation, a relatively underexplored perspective remains: the incorporation of social mobility into the study of peer pressure. Inspired by these studies, we propose a profit-maximizing migration model on a grid network with periodic boundary conditions to investigate how peer pressure influences the evolution of cooperation in the PDG. In this model, when an individual's utility at their current position (i.e., total payoff minus peer pressure) reaches its maximum, they typically choose to remain. Otherwise, individuals are likely to migrate in search of more profitable locations. However, migration is not without cost, and individuals must account for the associated migration costs. In making migration decisions, individuals weigh the utility and assess whether the benefits of migration outweigh the costs. Through extensive simulation experiments, we investigate the effects of various factors on cooperative behavior, including the migration mechanism, the proportion of empty sites, individual sensitivity, peer pressure intensity, temptation to defect, and migration cost. The results indicate that the migration mechanism significantly promotes the evolution of cooperation. Under this mechanism, higher individual sensitivity leads to an increased frequency of cooperation. Furthermore, stronger peer pressure intensity further enhances the emergence of cooperative behavior. In addition, a higher proportion of empty sites also contributes to elevated levels of cooperation.

To more clearly highlight the unique aspects of this study in terms of model design and research findings, a comparative analysis with several representative related studies is provided below. In contrast to the adaptive migration model proposed in Ref. [39], this study adopts a migration model based on payoff maximization. Notably, both studies demonstrate that optimizing the proportion of empty sites can effectively promote cooperation. Building on the work of Ref. [40], this study not only considers payoff as a determinant of migration probability but also introduces peer pressure as an additional influential factor. In contrast to the findings of Ref. [40], which suggest that a lower proportion of empty sites is more favorable for cooperation, our results indicate that a higher proportion of empty sites more effectively promotes cooperative behavior. Moreover, building upon Ref. [49], which investigates the impact of peer pressure on cooperation, this study further incorporates a migration mechanism. The results indicate that, in the presence of migration, stronger peer pressure more effectively promotes cooperation, which contrasts with the findings

reported in Ref. [49].

The structure of the rest of the paper is as follows. In Section 2, we describe our model, including the rules for quantifying peer pressure, the migration mechanism, and the impact of peer pressure on individual strategies. In Section 3, we present the simulation results and provide a detailed analysis. Finally, in Section 4, we summarize the conclusions and put forward the direction for future work.

2. Theoretical model

Assume that individuals in a population of size N are uniformly distributed on a two-dimensional square lattice of size $L \times L$ with periodic boundary conditions, considering the proportion of free space to be f_0. In this paper, the grid points are represented by the set $W = \{w_{11}, w_{12}, \ldots, w_{1L}, w_{21}, w_{22}, \ldots, w_{2L}, \ldots, w_{L1}, w_{L2}, \ldots, w_{LL}\}$ in a two-dimensional coordinate system, and the population is denoted by the set $V = \{1, 2, \ldots, i, \ldots, N\}$. It is assumed that the distance between any two adjacent grid points is d. Consequently, the number of free grid points is $N_f = L \times L \times f_0$, and the number of occupied grid points is $N = L \times L - N_f$, which corresponds to the individuals in a population of size N. Specifically, the set of grid points occupied by individuals in the population is termed the physical set, mathematically represented as $\Psi = \{\psi_1, \psi_2, \ldots, \psi_N\}$, where ψ_i signifies the grid point occupied by individual i. Complementarily, the set of grid points not occupied by individuals in the population is referred to as the non-physical set, mathematically denoted as $\Psi = \{\bar{\psi}_1, \bar{\psi}_2, \ldots, \bar{\psi}_{N_f}\}$. Initially, the physical set is indicated as $\Psi^0 = \{\psi_1^0, \psi_2^0, \ldots, \psi_N^0\}$, and the non-physical set is indicated as $\Psi^0 = \{\bar{\psi}_1^0, \bar{\psi}_2^0, \ldots, \bar{\psi}_{N_f}^0\}$.

In the network population, an individual i is randomly selected, and then an individual j is chosen from the neighbors (von Neumann neighbors) of individual i. The two individuals engage in a weak PDG. Each individual has two strategies: cooperation and defection, denoted as C and D, respectively. If both individuals choose cooperation, they each receive a reward, denoted by R. In contrast, if both individuals choose defection, they each receive a punishment, denoted by P. If one individual chooses cooperation while the other chooses defection, the individual who cooperates receives the sucker's payoff, denoted by S, while the defector receives the temptation payoff, denoted by T. When the conditions for the four parameters, such as $T > R > P > S$ and $2R > T + S$, are satisfied, the model conforms to the framework of the PDG. To maintain simplicity and generality, we set $R = 1$, $T = b$ $(1 \le b \le 2)$, $S = P = 0$, which results in a weak PDG scenario. Thus, the payoff matrix for two individuals playing a weak PDG scenario is represented as

$$M = \begin{pmatrix} 1 & 0 \\ b & 0 \end{pmatrix}. \tag{1}$$

2.1. Individual payoff and peer pressure

Initially, an individual i $(i \in V)$ is randomly selected from the network population. We assume that individual i is located at grid point $w_{g^0 h^0}$ $\left(w_{g^0 h^0} \in W\right)$ in the two-dimensional network, corresponding to element ψ_i^0 in the physical set Ψ^0. The set of neighbors (von Neumann neighbors) of individual i is denoted as Ω_i^0. Furthermore, with individual i at the center, a circle with radius r is drawn, and the set of grid points within the coverage area, excluding the individual itself, is denoted as M_i^0. In this network, the state of the population during the evolutionary process can be described by $S = \{s_{w_{11}}, s_{w_{12}}, \ldots, s_{w_{1L}}, \ldots, s_{w_{L1}}, s_{w_{L2}} \ldots, s_{w_{LL}}\}$, where $s_{w_{mn}}$ represents the number of individuals adopting the cooperation strategy (C) among the first-order neighbors of grid point w_{mn}. Initially, the state of the population is denoted as $S^0 = \left\{s_{w_{11}}^0, s_{w_{12}}^0, \ldots, s_{w_{1L}}^0, \ldots, \ s_{w_{L1}}^0, s_{w_{L2}}^0, \ldots, s_{w_{LL}}^0\right\}$

Assume at time step t, the state of the population is $S^t = \left\{s_{w_{11}}^t, s_{w_{12}}^t, \ldots, s_{w_{1L}}^t, \ldots, s_{w_{L1}}^t, s_{w_{L2}}^t, \ldots, s_{w_{LL}}^t\right\}$. Within this state, an individual i $(i \in V)$ is initially randomly selected from the network population. The grid point of individual i in the two-dimensional network is denoted as $w_{g^t h^t}$ $\left(w_{g^t h^t} \in W\right)$, and this grid point $w_{g^t h^t}$ corresponds to element ψ_i^t in the physical set Ψ^t. Subsequently, an individual j $(j \in V)$ is selected from the neighbor set Ω_i^t of individual i to engage in a game. The grid point of individual j in the two-dimensional network is denoted as ψ_j^t, and this grid point $w_{p^t q^t}$ corresponds to element ψ_j^t in the physical set Ψ^t. The payoff of individual i is the cumulative payoff from interactions with all its neighbors, denoted as π_i^t. Therefore, we have

$$\pi_i^t = \sum_{j \in \Omega_i^t} a_i^t M \left(a_j^t\right)^{\mathrm{T}}. \tag{2}$$

Here, a_i^t denotes the strategy adopted by individual i at time step t, and a_j^t denotes the strategy adopted by individual j at time step t, where $a_i^t, a_j^t \in \{C, D\}$. Specifically, if individual i chooses the cooperation strategy (i.e., $a_i^t = C$), then we set $a_i^t = (1, 0)$; conversely, if individual i chooses the defection strategy (i.e., $a_i^t = D$), then we set $a_i^t = (0, 1)$.

The decisions of individuals in real life are often influenced by their surrounding environment and social relationships, particularly by pressure from peers. Even if a strategy theoretically provides the highest payoff, individuals may still opt for other strategies due to the fear of peer ostracism or the desire for social approval. Therefore, when analyzing the outcomes of the game, it is essential to account for the influence of peer pressure. In this study, an individual's sensitivity to pressure and the external pressure experienced by both the individual and their neighbors are collectively defined as peer pressure. Specifically, sensitivity to pressure refers to the individual's responsiveness to external pressure, reflecting the extent to which they are influenced by it. External pressure

refers to the pressure an individual perceives from their neighbors when their strategy differs from that of their first-order neighbors. This pressure may prompt the individual to adjust their strategy in order to seek group approval or avoid social exclusion. Hence, at time step t, the peer pressure experienced by individual i is given by

$$A_i^t = \begin{cases} \alpha \times \beta \times \left(|\Omega_i^t| - s_{\psi_i^t}^t \right), & a_i^t = C, \\ \alpha \times \beta \times s_{\psi_i^t}^t, & a_i^t = D. \end{cases} \tag{3}$$

Here, α $(0 \le \alpha \le 1)$ denotes the pressure sensitivity; β $(0 \le \beta \le 1)$ denotes the intensity of peer pressure; $|\Omega_i^t|$ denotes the number of neighbors of individual i at time step t.

2.2. Migration mechanism and utility function

The migratory behavior of individuals is a significant phenomenon widely observed in both human society and the natural world. This behavior allows individuals to break free from the constraints of existing relationships, interact with new individuals, and thereby establish new interactive relationships. It is assumed that each randomly selected individual in the population has the opportunity to migrate to a circular area with radius r centered on itself. The set of grid points within this area, excluding the individual itself, is available for migration, provided that these grid points are vacant, i.e., not occupied by any other individual. If an individual migrates, it incurs a certain migration cost O. Moreover, the migration decisions of individuals are typically driven by the principle of utility maximization. Specifically, by evaluating the changes in utility associated with different options, individuals tend to choose the location that can maximize their own utility.

Therefore, a utility function is introduced as a tool for analyzing individual migration decisions, integrating and quantifying key factors such as game payoffs, peer pressure, and migration costs. This utility function not only helps us to more comprehensively understand the motivations behind individual behavior but also provides a solid theoretical foundation for constructing effective migration models. Specifically, if an individual remains at the original grid point, the utility function for that individual is defined as the difference between the payoff and the peer pressure. Conversely, if an individual migrates, the utility function of the individual is defined as the difference between the payoff and the peer pressure, minus the migration cost. At time step t, if there are no vacant grid points within the migration range of radius r around individual i, individual i will not migrate, and its neighbors will remain unchanged. If there are vacant grid points within this migration range, denoted as $w_{\bullet *}$, then individual i may migrate to this empty grid point $w_{\bullet *}$, and the neighbors of individual i may be updated. Furthermore, if there exists multiple vacant grid points, denoted as $w_{x_1y_1}$ and $w_{x_2y_2}$, and the utility functions of individual i at grid points $w_{g^t h^t}$ and $w_{x_2y_2}$ are both lower than the utility function at a vacant grid point $w_{x_1y_1}$, individual i will migrate to the vacant grid point $w_{x_1y_1}$ that maximizes its utility (if multiple vacant grid points yield the same maximum utility, one will be chosen randomly); otherwise, individual i will not migrate. After the migration decision is made, the first-order neighbors of individual i are denoted as $N_1(i)$, as mathematically expressed below:

$$\Omega_i^t = \begin{cases} \Omega_{i\to w_{x_1y_1}}^t, & \text{if } \exists w_{x_1y_1},\, w_{x_2y_2} \in M_i^t \setminus \Psi^t,\ st \max\left\{u_{i\to w_{x_1y_1}}^t, u_{i\to w_{x_2y_2}}^t, u_i^t\right\} = u_{i\to w_{x_1y_1}}^t, \\ \Omega_i^t, & \text{else.} \end{cases} \tag{4}$$

Here, $\Omega_{i\to w_{x_1y_1}}^t$ denotes the neighbors of individual i after migrating from the original grid point to the empty grid point $w_{x_1y_1}$. Ω_i^t denotes the neighbors of individual i remaining at the original grid point $w_{g^t h^t}$. u_i^t denotes the utility function of individual i remaining at the original grid point $w_{g^t h^t}$. $u_{i\to w_{x_1y_1}}^t$ denotes the utility function of individual i migrating from the original grid point $w_{g^t h^t}$ to the empty grid point $w_{x_1y_1}$. $u_{i\to w_{x_2y_2}}^t$ denotes the utility function of individual i migrating from the original grid point $w_{g^t h^t}$ to the empty grid point $w_{x_2y_2}$. Specifically, $u_i^t = \pi_i^t - A_i^t$, $u_{i\to w_{x_1y_1}}^t = \pi_{i\to w_{x_1y_1}}^t - A_{i\to w_{x_1y_1}}^t - O$, $u_{i\to w_{x_2y_2}}^t = \pi_{i\to w_{x_2y_2}}^t - A_{i\to w_{x_2y_2}}^t - O$. Under this condition, if $u_{i\to w_{x_1y_1}}^t$, then an individual randomly selects an empty grid point from the set of available empty grid points for migration.

$$\mathring{u}_i^t = \begin{cases} u_{i\to w_{x_1y_1}}^t, & \text{if } \Omega_i^t = \Omega_{i\to w_{x_1y_1}}^t, \\ u_i^t, & \text{if } \Omega_i^t = \Omega_i^t. \end{cases} \tag{5}$$

2.3. Strategy updating rule

After the migration decision, the state of the population is updated to $\mathring{S}^t = \left\{\mathring{s}_{w_{11}}^t, \mathring{s}_{w_{12}}^t, \ldots \mathring{s}_{w_{1L}}^t, \ldots, \mathring{s}_{w_{L1}}^t, \mathring{s}_{w_{L2}}^t, \ldots, \mathring{s}_{w_{LL}}^t\right\}$ the physical set is updated to $\Psi^t = \left\{\mathring{\psi}_1^t, \mathring{\psi}_2^t, \ldots, \mathring{\psi}_N^t\right\}$, and the non-physical set is updated to $\Psi^t = \left\{\mathring{\tilde{\psi}}_1^t, \mathring{\tilde{\psi}}_2^t, \ldots, \mathring{\tilde{\psi}}_{N_f}^t\right\}$. Next, under the state $\mathring{S}^t$, individual i in the population update its strategies. The specific strategy updates are described as follows. If individual i has no neighbors, then no strategy update is performed. If individual i has neighbors, then an individual k $(k \in V)$ is randomly selected from its neighbors Ω_i^t, with strategy a_k^t, and the probability of individual k being se-

lected is $1/|\Omega_i^t|$. Individual i attempts to find a better strategy through the following imitation dynamics (Fermi dynamics). Therefore, the probability that an individual i at time step $t+1$ adopts the strategy a_k^t of individual k at time step t is given by

$$P\left(a_i^{t+1} \leftarrow a_k^t\right) = \frac{1}{|\Omega_i^t|} \frac{1}{1+\exp\left[\frac{\left(\mathring{u}_i^t - \mathring{u}_k^t\right)}{K}\right]}. \tag{6}$$

Here, $K \in [0,\infty)$ quantifies the uncertainty in the strategy updating process of individuals. If $K \to \infty$, random drift occurs. If $K \to 0$, deterministic imitation occurs. Without loss of generality, it is typically assumed that $K = 1$.[50,51]

Therefore, after the strategy update, we can derive the state of the population at time step $t+1$. The updated state of the population is denoted as $S^{t+1} = \left\{s_{w11}^{t+1}, s_{w12}^{t+1}, \ldots, s_{w1L}^{t+1}, \ldots, s_{wL1}^{t+1}, s_{wL2}^{t+1}, \ldots s_{wLL}^{t+1}\right\}$, the updated physical set as $\Psi^{t+1} = \left\{\psi_1^{t+1}, \psi_2^{t+1}, \ldots, \psi_N^{t+1}\right\}$, and the updated non-physical set as $\Psi^{t+1} = \left\{\bar{\psi}_1^{t+1}, \bar{\psi}_2^{t+1}, \ldots, \bar{\psi}_{N_f}^{t+1}\right\}$. Individual i, with itself at the center, forms two circles with radius $r = d$ and $r = \sqrt{2}d$, respectively. The vacant grid points within these areas (excluding the individual itself) constitute potential migration locations. Figure 1 illustrates the evolutionary process within a single time step, corresponding to these two migration ranges.

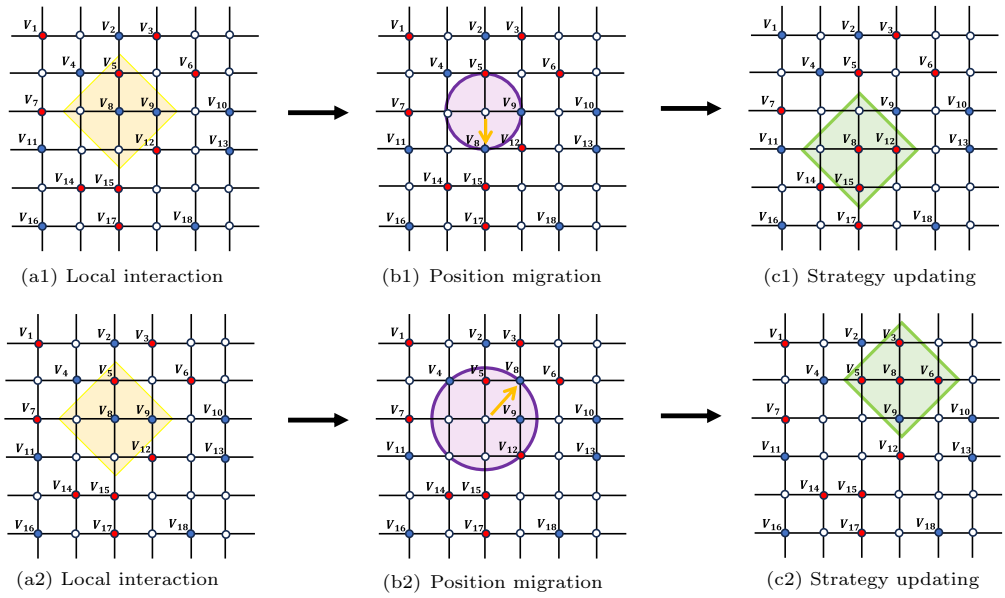


Fig. 1. Evolutionary process of individuals in a two-dimensional grid network during a single time step. Panels (a1)–(c1) show the evolutionary process of individuals within a circular migration area with radius d, while panels (a2)–(c2) show the evolutionary process within a circular migration area with radius $r = \sqrt{2}d$. Red indicates individuals choosing the cooperation strategy, blue indicates individuals choosing the defection strategy, and white indicates vacant positions (i.e., locations where individuals may migrate). In panels (a1) and (a2), the yellow square areas represent the regions where individuals engage in game interactions. In panels (b1) and (b2), the pink circular areas with vacant positions represent the migration range of individuals. In panels (c1) and (c2), the green square areas indicate the regions where individuals learn their neighbors' strategies after making migration decisions.

3. Simulation analysis and results

Cooperation density is a key metric that characterizes cooperative behavior in the network, defined as the proportion of cooperators within the population. The cooperator density of the population at time step t is defined as

$$F_C(t) = \frac{\sum_{m=1}^{L}\sum_{n=1}^{L} s_{w_{mn}}^t}{4N}. \tag{7}$$

To further validate the analysis, this study employs the Monte Carlo simulation method and presents the corresponding results and analysis. Specifically, we first present a schematic diagram of the migration mechanism, illustrating the process of individual strategy changes within a single time step. Subsequently, we examine the impact of three key parameters: temptation to betray b, migration cost O, and peer pressure intensity β, on cooperative strategies under different conditions. These conditions include the presence or absence of the migration mechanism, as well as varying proportions of vacant nodes. To better visualize the combined effects of these parameters, we present heatmaps that show the interactions between peer pressure and temptation to defect, as well as between peer pressure and migration cost, under the migration mechanism. Finally, we investigate the distribution of individual strategies under the migration mechanism.

During the Monte Carlo simulation, we conducted the process on a lattice of size 30×30, where the strategy of each individual is updated asynchronously.[52] To ensure the validity of the simulation results for cooperative evolution, we implemented the evolution of cooperation with a time step of 400000. To minimize the impact of random fluctuations, we performed 10 independent simulations for each set of parameter values and averaged the outcomes to improve accuracy. The cooperation ratio F_C is based on the data from the last 10^3 complete Monte Carlo steps.

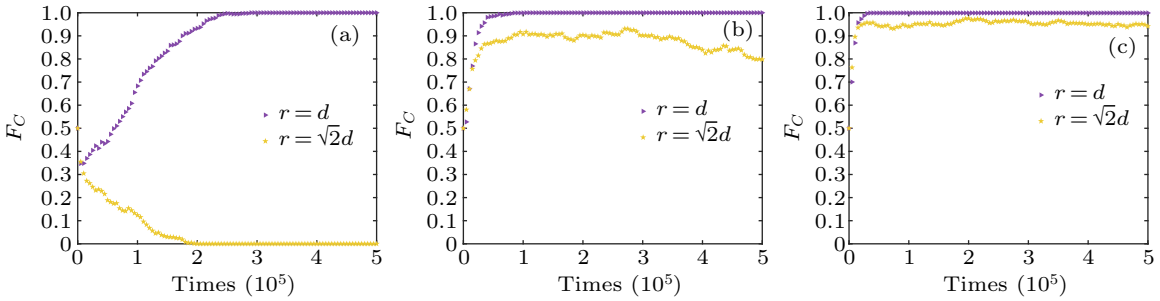


Fig. 2. Under different proportions of vacant nodes and migration ranges, the proportion of cooperators evolves over time. From left to right, the proportions of vacant nodes are 0.1, 0.2, and 0.3, with other parameters set as $b = 1.15$, $\alpha = 0.5$, $\beta = 0.5$, and $O = 0.2$.

Figure 2 illustrates the impact of migration coverage radii of d and $\sqrt{2}d$ on the evolutionary dynamics of group cooperation under the migration mechanism. It can be observed that, with a fixed proportion of empty nodes, the migration coverage area with a radius of d promotes cooperation more effectively than the area with a radius of $\sqrt{2}d$. This is because the migration coverage area with a radius of d encourages individuals to remain within nearby regions, which facilitates the formation of stable cooperative clusters around existing cooperation cores, thereby enhancing the structural protection effect. In contrast, although the migration coverage area with a radius of $\sqrt{2}d$ increases the number of available positions, it also increases the probability that cooperative individuals will 'break out' of existing clusters and enter betrayal-dominated areas, thereby disrupting the stability of the cooperative structure. Furthermore, as the proportion of empty nodes increases, the migration coverage area with a radius of d enables the system to reach a state of global cooperation more quickly, while the migration coverage area with a radius of $\sqrt{2}d$ significantly increases the cooperation frequency within the system. This phenomenon occurs because the increase in empty nodes expands the migratory space, reduces the local game density, and makes it easier for individuals to distance themselves from defectors and migrate to more favorable environments. This not only enhances the adaptability and diffusion capacity of cooperative strategies but also effectively slows the spread of defection strategies, thereby further promoting an increase in cooperation levels.

Figure 3 illustrates the impact of different levels of peer pressure sensitivity and defection temptation on the evolution of group cooperation under the migration mechanism. As shown in the figure, as the temptation to defect increases, the proportion of cooperators generally decreases. This phenomenon suggests that individuals are more likely to abandon cooperation and pursue personal gain when faced with greater temptation. At the same time, an individual's sensitivity has a significant impact on the evolution of cooperation. Specifically, when the sensitivity value is higher, the frequency of cooperation increases; conversely, when the sensitivity value is lower, the frequency of cooperation decreases. This is because a higher sensitivity value indicates a stronger response to peer pressure. When individuals have higher sensitivity, they are more likely to be influenced by the behavior of their peers, especially when faced with adverse environments or the temptation to defect. In such cases, individuals tend to adjust their positions through the migration mechanism, moving to environments with higher utility. Through this mechanism, individuals can escape the influence of low-cooperation environments and seek more favorable cooperative spaces, thereby promoting the aggregation effect of cooperators in local areas and further enhancing cooperation levels. Consequently, higher individual sensitivity encourages individuals to optimize their environment through the migration mechanism, which, in turn, enhances the stability and sustainability of cooperative behavior within the population.

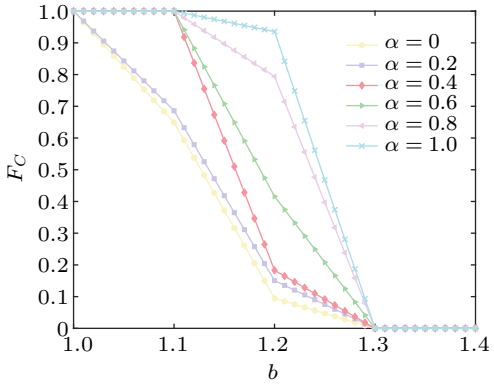


Fig. 3. When times = 400000, the relationship between the proportion of cooperators and the temptation parameter is analyzed for different individual sensitivities, while also considering the impact of the migration mechanism. All results were obtained with $f_0 = 0.2$, $O = 0.2$, $\beta = 0.5$, and $r = \sqrt{2}d$.

In Fig. 4, for a given proportion of vacant nodes, as the temptation factor increases, the frequency of cooperators decreases monotonically. This suggests that, under a high temptation factor, individuals are more likely to pursue personal gain, thereby reducing cooperative behavior. In contrast, under a low temptation factor, individuals are more inclined to choose cooperation to achieve mutual benefits. From Figs. 4(a1)–4(c1), as the proportion of vacant nodes increases, under conditions of low temptation factors, the cooperation effect significantly improves, and the time required for cooperation to reach a stable state decreases. This suggests that an

increase in vacant nodes provides individuals with more migration options, enabling them to adjust their strategies and migrate to environments with higher utility. This, in turn, facilitates the formation of cooperator clusters and enhances the likelihood of cooperation. Even under high temptation factor conditions, despite the greater challenges to cooperative behavior, an increase in vacant nodes can still mitigate the downward trend in cooperation frequency. For example, in Fig. 4(c1), despite the high temptation factor, the system continues to exhibit a relatively high cooperation frequency. Moreover, in Fig. 4(a1), when $b = 1.1$, the cooperation frequency initially decreases but then rises rapidly. This phenomenon may be attributed to individuals' initial response to the temptation factor. Some cooperators initially switch to defectors, causing a decline in cooperation frequency. However, as time progresses, the migration mechanism takes effect, with cooperators migrating to areas with higher cooperator density, thereby forming clusters. This mechanism helps counteract the erosion caused by defectors and encourages them to revert to cooperative strategies, leading to a rapid recovery and eventual stabilization of the cooperation frequency. By contrast, from Figs. 4(a2)–4(c2), in the absence of the migration mechanism, even when the proportion of vacant nodes increases and the temptation factor is relatively low, the system's cooperation frequency does not reach a high level. This is because individuals are unable to adjust their positions to optimize the strategic environment, leading to a random spatial distribution of cooperators and defectors, which prevents the formation of effective clusters. Although the increase in vacant nodes partially alleviates direct competition between individuals, it does not effectively address the spatial isolation between cooperation and defection strategies, making it difficult for cooperators to form local clusters that can resist the erosion by defectors, thus hindering the global spread of cooperation. By comparing Figs. 4(a1) with 4(a2), 4(b1) with 4(b2), and 4(c1) with 4(c2), we observe that the migration mechanism significantly promotes cooperative behavior. When the temptation factor is relatively low, the migration mechanism allows individuals to move to positions that maximize utility, with cooperators tending to cluster in areas with higher densities of cooperators, while defectors are inclined to migrate to regions with more cooperators. This dynamic adjustment enables cooperators to form clusters that surround defectors, thereby consolidating the advantage of cooperation and driving the system toward global cooperation.

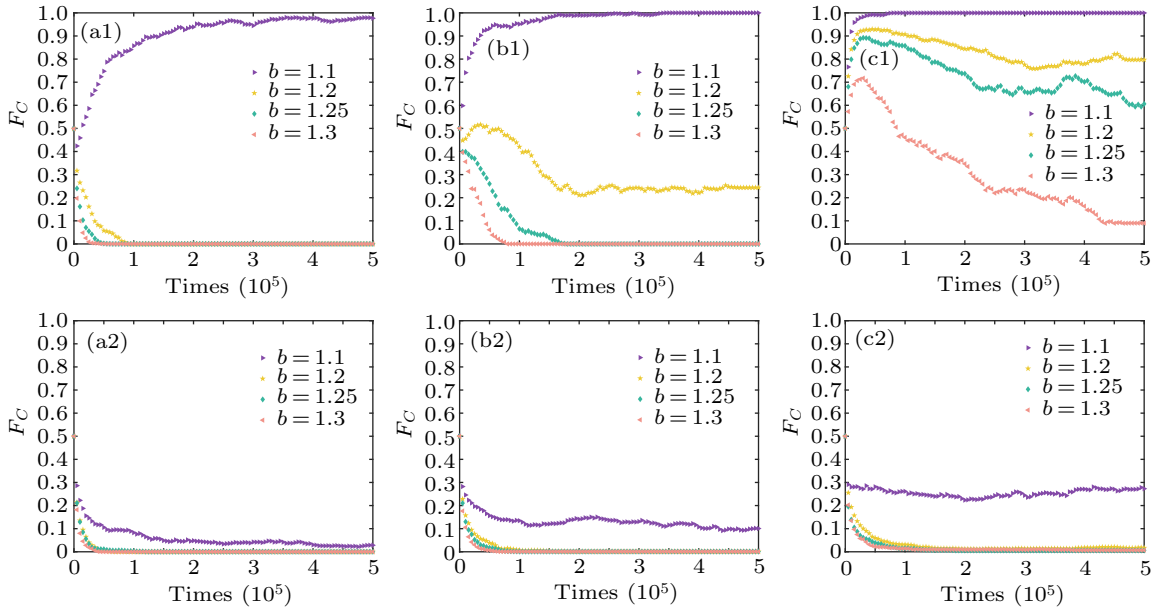


Fig. 4. Under different proportions of vacant nodes and temptation factors, and considering the impact of the migration mechanism, the proportion of cooperators evolves over time. From (a1) to (c1), when individuals are influenced by the migration mechanism, the proportion of cooperators changes over time. In contrast, from (a2) to (c2), when individuals are not influenced by the migration mechanism, the proportion of cooperators also evolves over time. From left to right, the proportions of vacant nodes are 0.1, 0.2, and 0.3, with the other parameters set as $\alpha = 0.2$, $\beta = 0.5$, $\gamma = 0.5$, and $r = \sqrt{2}d$.

Building on this, Fig. 5 further explores the impact of the proportion of vacant nodes and peer pressure intensity on the level of cooperation, revealing how they jointly influence the evolution of cooperative behavior. Specifically, under the migration mechanism, as shown in Figs. 5(a1), 5(b1), and 5(c1), as the intensity of peer pressure increases, the proportion of cooperators in the system increases significantly. This phenomenon suggests that the intensity of peer pressure plays a key role in promoting cooperative behavior. Higher peer pressure intensity significantly inhibits the spread of defection by reducing opportunities for defectors to interact with cooperators, making individuals more likely to adopt coop-

erative strategies. Based on Figs. 5(a1)–5(c1), it can be observed that, under the same peer pressure intensity, as the proportion of vacant nodes increases, the cooperation effect improves significantly. This suggests that vacant nodes provide individuals with more buffering space and migration options, allowing cooperators to cluster more flexibly and form cooperative groups. This spatial advantage helps cooperators resist the erosion of defectors, thereby accelerating the spread and stabilization of cooperative behavior. In contrast, in the absence of the migration mechanism, as observed in Figs. 5(a2), 5(b2), and 5(c2), although the intensity of peer pressure gradually increases, the proportion of cooperators in the system shows little fluctuation, indicating that the intensity of peer pressure has a minimal effect on the frequency of cooperation. From Figs. 5(a2)–5(c2), it can be seen that, under the same peer pressure intensity, an increase in the proportion of vacant nodes does not significantly improve cooperation levels; instead, it increases the number of evolutionary steps required for the system to reach a stable state. This suggests that, in the absence of the migration mechanism, although the increase in vacant nodes reduces direct competition between individuals, it does not promote the clustering of cooperators, but rather delays the system's evolution. Additionally, by comparing Figs. 5(a1) with 5(a2), 5(b1) with 5(b2), and 5(c1) with 5(c2), we observe that the migration mechanism significantly promotes cooperative behavior. Through this mechanism, individuals can adjust their positions, with cooperators migrating to areas of higher cooperator density, forming stable clusters. This reduces opportunities for direct interactions with defectors, thereby reducing the erosive effect of defection strategies on cooperation strategies, allowing cooperators to maintain higher stability when facing the temptation to defect. By contrast, in the absence of the migration mechanism, the spread and stability of cooperation remain limited, even with a high intensity of peer pressure or a large proportion of vacant nodes. This indicates that the migration mechanism plays an indispensable role in promoting cooperative behavior, thereby confirming the analysis results in Fig. 4.

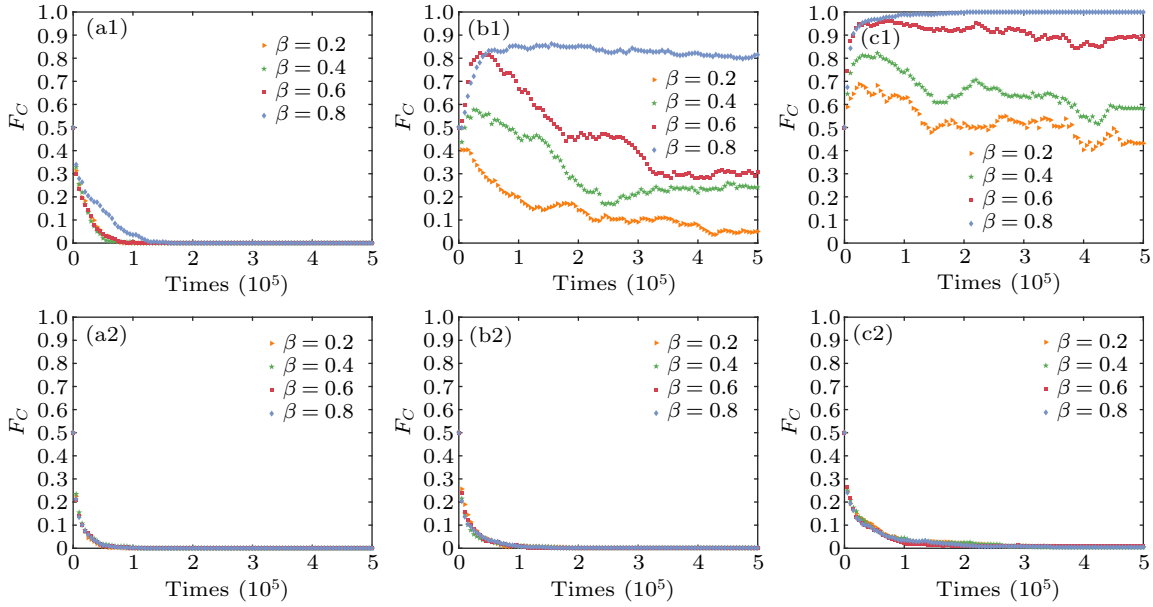


Fig. 5. Under different proportions of vacant nodes and peer pressure intensities, and considering the impact of the migration mechanism, the proportion of cooperators evolves over time. From (a1) to (c1), when individuals are influenced by the migration mechanism, the proportion of cooperators changes over time. In contrast, from (a2) to (c2), when individuals are not influenced by the migration mechanism, the proportion of cooperators also evolves over time. From left to right, the proportions of vacant nodes are 0.1, 0.2, and 0.3, with other parameters set as $O = 0.2$, $\alpha = 0.2$, $\beta = 0.5$, and $r = \sqrt{2}d$.

Figure 6 explores the impact of different proportions of vacant nodes and migration costs on cooperative behavior under the influence of the migration mechanism. Specifically, in Figs. 6(a)–6(c), as migration costs increase, the proportion of cooperators shows a significant decreasing trend. This is because higher migration costs significantly inhibit individuals' migration behavior. When considering the cost of migration, individuals tend to remain in their original positions rather than actively migrating to environments that offer higher utility. This limitation makes it difficult for cooperators to cluster in areas that are more conducive to cooperation, thereby weakening the evolutionary advantage of cooperative behavior. However, as observed in Figs. 6(a)–6(c), with an increase in the proportion of vacant nodes, the proportion of cooperators shows an upward trend. This phenomenon suggests that, even with migration restrictions, the increase in vacant nodes creates a more favorable environment for cooperators' survival. The presence of vacant nodes effectively reduces direct interactions between cooperators and defectors, thereby lessening the negative impact of defectors on cooperative behavior and indirectly supporting the maintenance of cooperation.

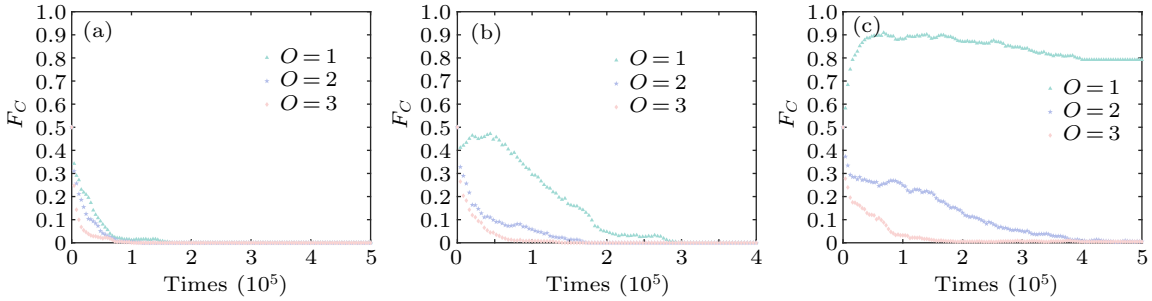


Fig. 6. Under different proportions of vacant nodes and varying migration costs, considering the effect of the migration mechanism, the proportion of cooperators evolves over time. From (a) to (c), the vacancy ratios are 0.1, 0.2, and 0.3, respectively, while other parameters set as $b = 1.2$, $\alpha = 0.5$, $\beta = 0.5$, and $r = \sqrt{2}d$.

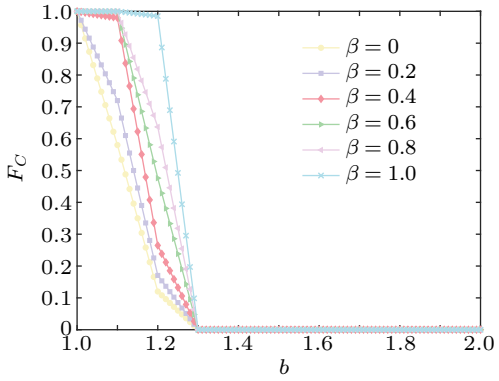


Fig. 7. When times = 400000, the relationship between the proportion of cooperators and the temptation parameter is analyzed under different levels of peer pressure intensity, while also considering the impact of the migration mechanism. All results were obtained under the conditions of $f_0 = 0.2$, $O = 0.2$, $\alpha = 0.5$, and $r = \sqrt{2}d$.

Figure 7 illustrates the impact of different peer pressure intensities and defection temptation on the cooperative evolution process under the influence of the migration mechanism. As shown in the figure, with an increase in the temptation parameter, the proportion of cooperators generally decreases. This phenomenon clearly reflects that a higher temptation value offers greater short-term rewards for defection strategies, making defection a more attractive option. This trend is particularly pronounced in the absence of peer pressure or when peer pressure is low ($\beta = 0$ or $\beta = 0.2$), indicating that individuals are more easily tempted to adopt defection strategies. However, the increase in peer pressure intensity plays a significant protective role in maintaining the proportion of cooperators. Specifically, when the defection temptation is 1.2 and the peer pressure intensity is 1, the proportion of cooperators remains high. This suggests that peer pressure effectively inhibits defection through social norms and group identity, while also providing spatial advantages for cooperators through the migration mechanism, thereby facilitating the consolidation and spread of cooperative behavior within local regions. This result aligns with the conclusions presented in Fig. 5 and further supports the positive role of peer pressure intensity in promoting cooperative behavior. Additionally, when the temptation parameter is $b = 1.1$, the proportion of cooperators under different peer pressure intensities ($\beta = 0.4$, $\beta = 0.6$, $\beta = 0.8$, and $\beta = 1$) tends to converge. This suggests that higher peer pressure intensity can, to some extent, mitigate the negative impact of defection temptation on cooperative behavior.

To visually observe the impact of peer pressure intensity on the overall evolutionary process, Fig. 8 presents a heatmap displaying the variation in the proportion of cooperative strategies under different defection temptations and peer pressure intensities at a time step of 400000. From the figure, it is evident that as the defection temptation increases, the effectiveness of promoting cooperation progressively diminishes. This suggests that, under higher defection temptations, maintaining cooperative behavior becomes increasingly difficult, even with higher peer pressure intensity. This is reflected in the heatmap, where in regions with higher b, the color gradually transitions from red (indicating a high cooperation rate) to blue (indicating a low cooperation rate), even when β is high. This suggests that the frequency of cooperation decreases significantly as the defection temptation increases. The high payoff associated with defection makes individuals more inclined to choose defection. Even with higher peer pressure and the migration mechanism, it is difficult to fully counteract the attraction of defection, thereby weakening the stability of cooperative behavior. When the defection temptation is low ($b < 1.3$), the cooperation rate in the system increases significantly with the increase in peer pressure intensity and eventually stabilizes. This is reflected in the heatmap, where, in regions with low defection temptation, the color gradually transitions from blue (indicating a low cooperation rate) to red (indicating a high cooperation rate) as β increases. However, as β increases further, the color change becomes less pronounced, indicating that the cooperation rate has reached a high level and no longer changes substantially with further increases in β. This suggests that an increase in peer pressure encourages cooperators to migrate to regions with a higher density of cooperators, while defectors are more inclined to migrate to areas with a higher density of defectors. This migration strategy enables cooperators to avoid defectors, thereby forming cooperation clusters in local regions and enhancing the stability and diffusion efficiency of cooperative behavior. Consequently, as peer pressure intensity increases, the cooperation rate gradu-

ally rises and stabilizes. However, when peer pressure intensity increases further, its effect on enhancing the cooperation rate diminishes. For example, when the defection temptation is 1.1, we observe that when $0.3 < \beta \leq 1$, the proportion of cooperators tends to become consistent, nearly achieving global cooperation. In the heatmap, this is reflected by minimal color differences for different values of β (where $0.3 < \beta \leq 1$) when $b = 1.1$. This observation is consistent with the conclusions drawn from Fig. 7.

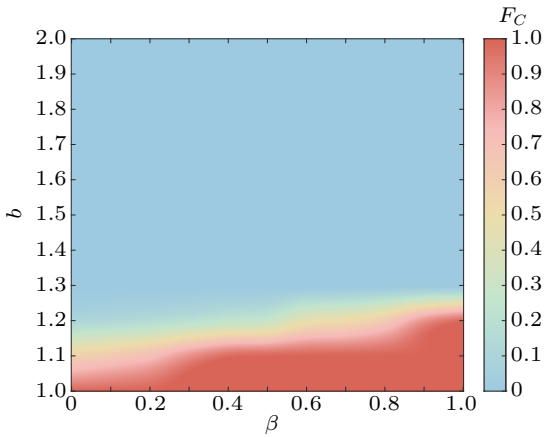


Fig. 8. When times = 400000, the heatmap of the cooperation level on the b–β plane under the influence of the migration mechanism is shown. All results were obtained under the conditions of $f_0 = 0.2$, $O = 0.2$, $\alpha = 0.5$, and $r = \sqrt{2}d$.

The heatmap in Fig. 9 intuitively illustrates the distribution pattern of the cooperation level under different migration costs and peer pressure intensities. When the migration cost is low and the peer pressure intensity is high, the proportion of cooperators increases, as reflected in the heatmap with deeper red regions. This indicates that cooperative behavior is more easily maintained under these conditions, as low migration costs allow individuals to migrate more frequently in search of environments that are more beneficial to their utility. At the same time, high peer pressure intensity encourages individuals to migrate towards regions with more cooperators, while defectors are more inclined to move to regions with more defectors in order to avoid social exclusion and gain social recognition. This migration strategy enables cooperators to avoid defectors, thereby forming clusters of cooperation in local areas, which enhances the stability and diffusion efficiency of cooperative behavior. However, as migration costs increase, individual mobility becomes restricted, and the proportion of cooperators gradually decreases, with the colors in the heatmap becoming progressively lighter. This

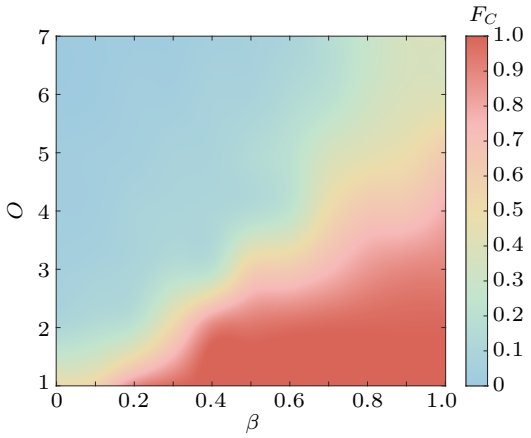


Fig. 9. When times = 400000, the heatmap of the cooperation level on the O–β plane under the influence of the migration mechanism is presented. All results were obtained under the conditions of $f_0 = 0.2$, $b = 1.1$, $\alpha = 0.5$, and $r = \sqrt{2}d$.

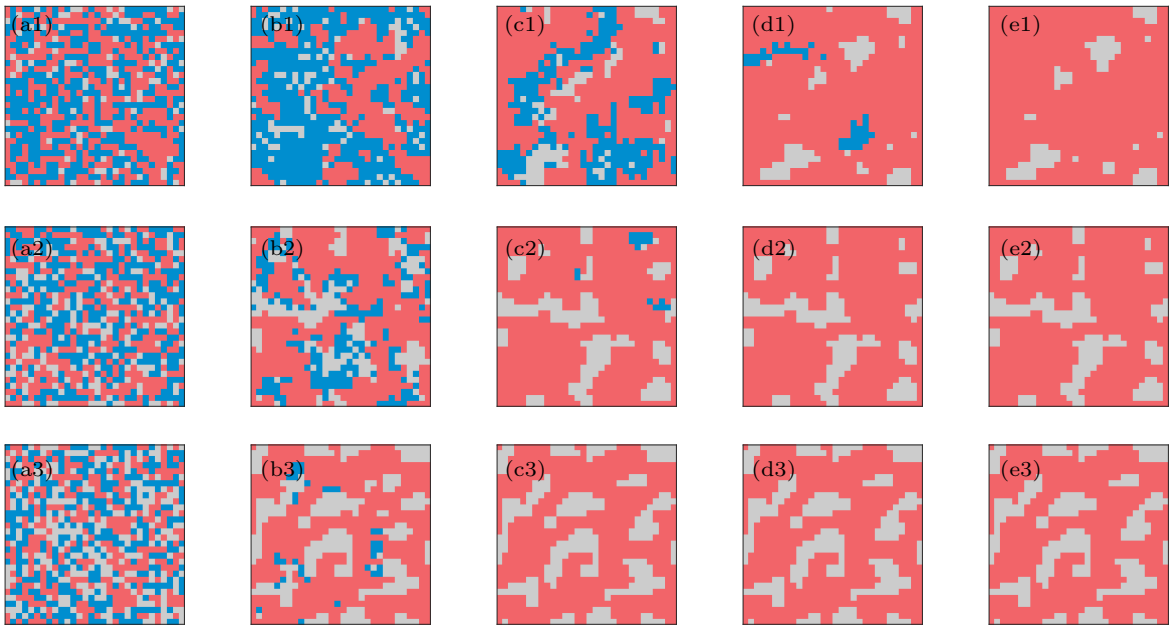


Fig. 10. The snapshots of strategy distribution under the influence of the migration mechanism, for different time steps and varying proportions of vacant nodes. Red indicates cooperative strategies, blue indicates defective strategies, and gray indicates vacant nodes. From top to bottom, the values of f_0 are 0.1, 0.2, and 0.3, respectively. Snapshots were taken at times = 0, 10000, 50000, 200000, and 400000 from left to right. All results were obtained with $b = 1.1$, $O = 0.2$, $\alpha = 0.5$, $\beta = 0.5$, and $r = \sqrt{2}d$.

suggests that higher migration costs may hinder individuals from forming clusters of cooperators through migration, thereby weakening the sustainability of cooperative behavior. Furthermore, the heatmap reveals a critical region that may exist in the O–β plane, where the proportion of cooperators decreases rapidly as migration cost increases. However, once the peer pressure intensity reaches a certain level, the rate of decrease slows down and may even stabilize at a higher level. This suggests that peer pressure can, to some extent, mitigate the negative impact of migration costs on cooperative behavior.

Finally, Fig. 10 illustrates the snapshot of the strategy distribution under the conditions of defection temptation $b = 1.1$, migration cost $o = 0.2$, individual sensitivity $\alpha = 0.5$, peer pressure intensity $\beta = 0.5$, and radius $r = \sqrt{2}d$. From the figure, it can be observed that the proportion of blank nodes in the system's initial structure significantly impacts the evolutionary path and final pattern of cooperative strategies. Specifically, when the initial proportion of blank nodes is 0.1 (Figs. 10(a1)–10(e1)), cooperative clusters are initially dispersed, and their diffusion is slow. However, in contrast, when the proportion of blank nodes increases to 0.2 (Figs. 10(a2)–10(e2)) and 0.3 (Figs. 10(a3)–10(e3)), cooperative strategies form larger and more stable clusters in a shorter time, exhibiting higher diffusion speed. Specifically, when the proportion of blank nodes is 0.3, the cooperative region expands rapidly, and the system reaches a cooperation-dominated state more quickly. In addition, a comparison of evolutionary times further confirms the positive role of vacant nodes. This suggests that a higher proportion of vacant nodes provides cooperators with greater buffering space and more opportunities for interaction, enabling them to form stable clusters and resist invasion by defectors. Overall, increasing the proportion of vacant nodes significantly enhances both the propagation efficiency and the stability of cooperative strategies.

4. Conclusion

This study, based on the framework of evolutionary game theory and integrated with simulation modeling, provides an in-depth study on the impact of peer pressure under the migration mechanism on the evolution of cooperative behavior in the networked PDG. By constructing a model that incorporates migration mechanisms and peer pressure in the networked PDG, we investigate how various factors, such as the migration mechanism, individual sensitivity, peer pressure intensity, the proportion of vacant nodes, migration costs, and the temptation to defect, affect the evolutionary dynamics of individual cooperation. The study finds that the migration mechanism, by allowing individuals to migrate according to the principle of utility maximization, enables cooperators to flexibly join cooperative groups and form stable cooperation clusters. Moreover, smaller migration ranges promote cooperation more effectively than larger ones, as they limit individuals' choice space, increase the opportunity to connect with local cooperators, and thereby foster the stability and expansion of cooperative behavior. Secondly, higher individual sensitivity, which reflects a stronger perception of external pressure, leads to an increase in the level of cooperation, as such individuals can adapt to the environment more rapidly and adjust their strategies accordingly. At the same time, higher peer pressure intensity can encourage defectors to cluster together, reducing the erosion of cooperative strategies by defection, and highlighting the significant influence of social norms and group identity on individual decision-making. In addition, an increase in vacant nodes provides individuals with more opportunities for migration and greater buffering space, thereby facilitating the maintenance and dissemination of cooperative behavior. This effect becomes particularly evident under a low temptation to defect, where vacant nodes enable cooperation to emerge and spread more rapidly. Finally, the combination of low migration cost and high peer pressure intensity is most conducive to the stabilization and expansion of cooperative behavior. A low migration cost encourages individuals to adjust their positions more frequently in search of favorable cooperative environments, while high peer pressure intensity reduces interactions between defectors and cooperators, promoting the clustering of defectors. This spatial segregation weakens the erosion of cooperation by defection and strongly supports the long-term maintenance of cooperation. The findings of this study provide valuable insights for social network design and organizational management. For instance, in social network design, the scope of user connections can be limited, and initially, members with similar interests or geographical proximity can be recommended to foster stable cooperation. In organizational management, companies can implement an "internal job rotation" program, allowing employees to move between different departments or project teams based on their interests and abilities. Specifically, companies can establish a "mobility platform" that enables employees to apply for short-term project rotations. This mobility not only supports employees' diverse development but also encourages them to collaborate with different members across various teams, thereby fostering a broader sense of cooperation and teamwork skills. At the same time, it reduces the cost of mobility, encourages employees to move between teams, enhances peer pressure, and helps maintain cooperation among members.

Future research could consider integrating multiple games into this model to further investigate how individuals balance and adjust their strategies across different game environments. In reality, individuals often participate in multiple interrelated games rather than just a single game, such as price games, reputation games, and others. The interactions

among these games may have a profound impact on the evolution of cooperative behavior. Incorporating multiple games would provide a more comprehensive understanding of how cooperative behavior evolves and is sustained under the influence of multiple competing and cooperative pressures in complex decision-making environments.

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