Emotion-driven switching game environments facilitates general cooperation

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Abstract

Emotion is a fundamental driving force of individual behavior, decision-making, and social interactions. It determines our relations toward more and less successful partners, but it can also affects how we evaluate a specific relation with others. In particular, we tend to participate in high-value games with recognized persons and prefer low-value games with less reliable participants. To reveal the comprehensive consequences of individual emotions, we propose an extended model in which a "ternary interaction" among emotions, behaviors, and selected game environments determine the coevolutionary process in a social dilemma. Importantly, the proposed dynamical rule allows players to switch their game environment based on emotional indicators. Our results indicate that emotion-driven switching between the game environments can surprisingly promote cooperation even in the cases when neither high-value game environment nor low-value game environment is unable to do it. The key mechanism here is a nonlinear "feedback loop" among positive emotions, cooperative behavior, and a high-value game – characterized by threshold-dependent activation of emotional recognition and cluster-based cooperative amplification – which enables the formation of cooperative clusters. This nonlinear dynamics leads to a phase transition in emotional phenotypes, where "open-minded and kind people" gain evolutionary advantage beyond linear behavioral or environmental switching mechanisms. Our observations are broadly valid in spatial communities. Compared to random and scale-free interaction networks, regular networks are more conducive to the clustering of the mentioned individuals and have a lower threshold for achieving cooperation preference.

Key words: Cooperation, emotion, switching game environments, complex networks

1. Introduction

In repeated social games, the dynamical switching of actions can promote cooperation [1, 2, 3]. Evolutionary strategies [4, 5] based on the dynamic switching between cooperation (C) and defection (D), such as the Tit-for-tat (TFT) strategy [6, 7, 8] and the Win-Stay Lose-Shift (WSLS) strategy [5, 9], have revealed a direct reciprocity mechanism by which cooperation emerges. Social norms and behavioral guidelines based on reputation mechanisms (image scoring, shunning, stern judging, simple standing) have guided individuals to dynamically switch between cooperation and defection, explaining the indirect reciprocity mechanism underlying the emergence of cooperation [10, 11, 12, 13, 14].

Not only dynamic switching of actions can promote cooperation, but also dynamic switching of environments does [15, 16, 17, 18, 19]. There may be multiple interaction environments between individuals, which can be classified into the structural environment level (network carriers of interaction) and the game environment level (game benefits, game paradigms, etc.) based on the form and content of the interaction environment. For example, switching between densely connected networks (complete graph) and sparsely connected networks (star graph) can promote cooperation [20]. The game where there are differences in benefits corresponding to different interaction environments is switched to a relatively high-value game if they co-

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operate with each other, and to a relatively low-value game if there are betrayers. Such game transfer can promote cooperative evolution effectively [17, 18]. Game transfer not only occurs when the same game paradigm is maintained with different payoff parameters, but can also be extended to environments with different game paradigms (e.g Prisoner's Dilemma, Snowdrift, Stag-hunt, Harmony Game) [21, 22]. Therefore, dynamic switching, whether occurring at the level of structural environments, game environments, or both, may create incentive conditions that are conducive to cooperative development and stability.

Emotions are not only a comprehensive reflection of an individual's subjective experience and physiological responses, but also an important force driving individual behaviors, decisions, and social interactions. Emotions are a significant factor influencing individual cooperation [23, 24, 25, 26]. In the winning strategies of direct and indirect reciprocity, there exist "charitable" attributes such as hope, generosity, and magnanimity [27]. In the current emotion-driven evolutionary games, the relationship between emotion types, their intensities, and behaviors has been established. Sympathy for the weak and respect for the strong respectively correspond to the possibility of cooperating with them [28, 29]. Moreover, the emotional reputation of interacting individuals has an impact on the arousal of one's own emotional responses and even the reinforcement (or weakening) of actual behaviors. In reality, individuals show more sympathy for benign weak individuals and strengthen cooperation with them, while reducing the degree of respect for malicious strong individuals and weakening cooperation with them [30, 31]. Therefore, like evolutionary strategies, emotions can also fuel a dynamic switching of behaviors. This argument raises the question whether a dynamic switching of the game environment based on emotions promotes cooperation?

Previous studies have shown that the principle of dynamic switching in game environments depends on the historical behaviors of both parties (one-step memory). Due to past positive interaction experiences (mutual cooperation), both parties in a game may decide to "play bigger" next time, hence they tend to engage in higher-value games with acquaintances they have cooperated with before. Nonlinear dynamics of information diffusion in social networks that individuals also tend to play high-value games with recognized kind people of their own, where such kind people do not necessarily have to be "acquaintances", that is, there is no need to rely on behavioral history (repeated games). A recognized kind person is associated with an individual's emotions, which involves two emotional factors: first, an evaluation index for judging whether an individual is "kind" or "unkind", for which we adopt the emotional reputation index; second, the element of "recognition", as different individuals have different degrees of recognition towards "kind people", and the same individual may be recognized by some opponents but not by others. For this, we use an activation function to reflect the mechanism by which individuals recognize "kind people".

Cooperation in game systems is a typical nonequilibrium emergent phenomenon, characterized by nonlinear dynamics such as phase transitions, hysteresis, and sensitivity to initial conditions [32, 33]. Despite significant progress in understanding action switching and environment switching for cooperation promotion, traditional studies on cooperative evolution often simplified emotional and environmental interactions as linear feedback loops, failing to capture the complex nonlinear coupling between emotional dynamics, environmental switching, and cooperative behavior – gaps that nonlinear science is uniquely positioned to address [34]. Existing studies have two critical limitations that our work addresses. First, prior environment-switching mechanisms rely primarily on behavioral history (e.g., one-step memory of mutual cooperation or fixed game paradigms, ignoring the intrinsic emotional drivers that shape individuals' decisions to trust and select interaction stakes – a key nonlinear dimension of social complexity. Second, existing emotion-driven evolutionary games focus solely on the link between emotions and cooperative behaviors, failing to integrate emotions into the dynamic selection of game environments – creating a gap between emotional states and the risk/reward settings of non-equilibrium social interactions. Unlike previous models that treat emotions, behaviors, and environments as independent or pairwise coupled factors, our study proposes a ternary interaction framework where emotions simultaneously guide both behavioral choices (cooperation/defection) and the game environment selection (high/low value). This integration enables a unique nonlinear feedback loop between positive emotions, cooperation, and high-value games – an effect unattainable with single-factor or pairwise coupling models. Moreover, our mechanism does not require repeated interactions (i.e., no dependence on behavioral history) but instead relies on emotional reputation and recognition, expanding the applicability of cooperation-promoting strategies to non-acquaintance interactions in complex social networks. These novel contributions fill the existing research gap and provide a new paradigm for escaping the tragedy of the commons in nonlinear social systems [35].

2. Game implementation

In our extended model we express the emotional state of an individual in an N-member population by using three parameters α, β, h. Here $\alpha \in [0, 1]$ determines the probability to cooperate with a partner who has lower payoff, hence this parameter represents the degree of sympathy for the weaker associate. $\beta \in [0, 1]$ dictates the probability to cooperate with a stronger partner who has a higher payoff than the focal player. In this way parameter β characterizes the degree of individual unenvious (or servility). In sum, an individual's behavioral choice (to cooperate or defect) depends on their emotional parameters α (for the weak) or β (for the strong). Therefore intensity of emotions (the values of α and β) reflects the probability that the individual will cooperate with the weak and the strong, respectively.

Importantly, an individual's choice of game environment is related to their recognition of the interacting individual. If the opponent is a "recognized kind person" in their eyes, they will choose the high-value game. We first step to construct an individual emotional reputation index to evaluate a partner whether "kind" or "unkind". This emotional reputation is composed of emotions towards the weak and emotions towards the strong and defined as $E = \alpha + \beta$. Accordingly, a larger $E(0 \leq E \leq 2)$ indicates a larger likelihood to be a "kind person". To reflect individual i's recognition of interacting with individual j, we define an activation function

$$f(h_i, E_j) = E_j^{h_i}/2^{h_i} , \quad (1)$$

which is the emotional reputation of individual j. This probability characterizes the willingness of player i to play a high-value game with player j. Evidently, a higher emotional reputation leads to a higher recognition of player j by player i. Here, parameter h_i characterizes a so-called emotional conservatism of individual i. A larger h_i means that positive emotions are more difficult to activate (i.e., harder to be "motivated"), resulting in a lower chance of recognition of the interacting partner. The recognition of individual j by individual i corresponds to the $f(h_i, E_j)$ probability that individual i chooses Game A (a high-value game) (and vice versa when facing with individual j). It is a natural assumption that Game A is only established between players i and j when they both select this scenario. In this way they mutually "recognize each other as kind people". In all other cases, in the absence of mutual trust, a lower-value Game B is played between the partners. For simplicity, consider two Prisoner's Dilemma (PD) game environments with payoff parameters:

- (1) High-value Game A: Payoff parameters (b_1, c) where $b_1 > c > 0$ (temptation to defect $>$ cost of cooperation > 0).
- (2) Low-value Game B: Payoff parameters (b_2, c) where $b_2 > c > 0$ and $b_1 > b_2$.

The benefit $b_1 > b_2$ are different for Game A and Game B respectively, while the c cost of cooperation is identical.

The dynamical steps of our emotion-driven evolutionary game, which is summarized in Fig. 1, are as follows:

- (1) In the initial stage, each individual is randomly assigned a parameter combination of $\{\alpha, \beta, h\}$ representing their emotional profile and an initial payoff U_0.
- (2) In each round, an individual i is randomly selected from the population to play a game with each of its neighbors.

  (2a) It involves to select the game environment for each bond which determines the actual payoff values. There are two forms of games between individual i and its neighbor j: a high-value Game A and a low-value Game B. Individual i (and its neighbor j similarly) calculates the activation probability defined by Eq. 1. If both players i and j choose Game A, Game A is conducted; otherwise, Game B is performed.

  (2b) Next we determine the behavior mode. The "strong" and "weak" partners are identified according to the payoffs of individual i and neighboring individual j in the current

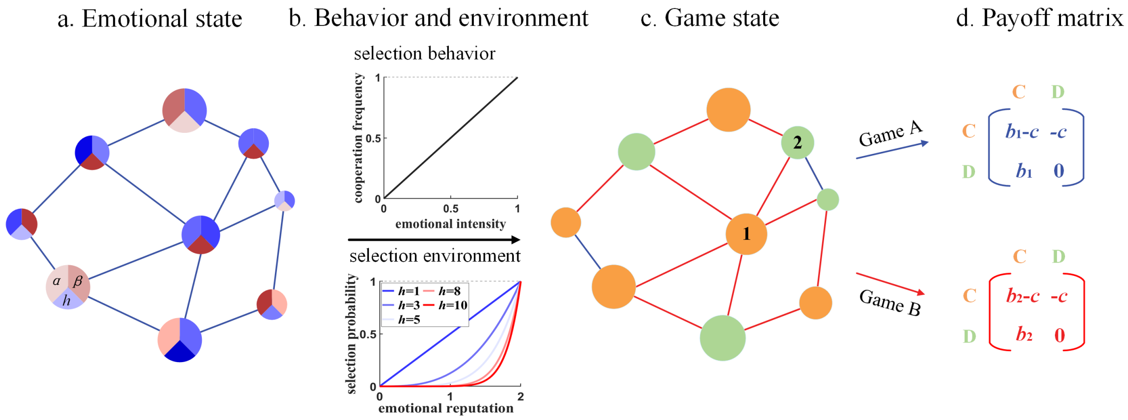

Figure 1: Emotional-driven switching of game environment. (a) Each player occupies a node of an interaction graph where the individual emotional state is represented by a triplet of parameters α, β, and h. The color change from blue to red indicates the parameter values increasing from small to large. The size of a node represents the current payoff values, which determine the relative strength of focal player and its neighbors. The top of panel (b) illustrates the probability of an individual to cooperate determined by its own emotional intensity (via the values of parameters α and β). The bottom of panel (b) shows the willingness of focal player to select high-value game environment in dependence of the opponent's emotional reputation. Here the value of h characterizes the the emotional conservatism of focal player. Different h values correspond to different curves, with the color changing from blue to red indicating h values increasing from small to large. Accordingly, the larger the h the more reluctant focal player to select the high-value game. (c) In the light of emotional profiles and payoff values players choose a strategy and a game environment along an edge. The color of a node represents the behavior (cooperation or defection), and the color of an edge represents the game environment (Game A or Game B). Taking the game between node 1 and node 2, as an example, node 1 cooperates, node 2 defects in a social dilemma represented by Game B. (d) According to the simplest scenario, both game represent a Prisoner's Dilemma situation where parameters b_1 and b_2 represent different game environments. Because of $b_1 > b_2$, Game A represents a high-value environment.

game round. In the light of actual payoff values, their strategies (cooperation or defection) are determined based on the probabilities characterizing their emotional profiles α, β. Based on the selected game environments and interaction behaviors, the updated U_i payoff is calculated for individual i. It is the average of the payoffs obtained by individual i after playing games with all neighbors. This payoff value replaces the previous payoff value of individual i.

- (3) Individual i updates its three emotional parameters via an imitation process. The target player j is randomly selected from the neighborhood and payoff values are compared. Individual i adopts the emotional parameter of individual j with probability $q = \{1 + \exp[(U_i - U_j)/\kappa]\}^{-1}$, where κ is a noise parameter, taken as 0.1 in this paper. Notably, the values of α, β and h are adopted independently to avoid artificial propagation of certain combinations of emotional profiles.

- (4) Repeat steps (2)-(3) for N rounds, so that on average each individual has a chance to update its emotional characteristic parameters and payoffs probabilistically.

- (5) The above process establishes a full Monte Carlo step, and the iteration process is repeated until the evolution reaches a stationary state (usually judged by the stability of the distribution of group emotional profiles).

In a spatial population the players are distributed on a square lattice (size 200×200 with periodic boundary conditions), which determine the neighborhood of players. Importantly, however, we also tested alternative interaction graphs, including random graph and highly heterogeneous scale-free graph, to explore the robustness of our findings. (The details are given in the Appendix.)

3. Evolutionary Dynamics

Our key findings are shown in Figs. 2-5. For comparison, we also used the traditional evolutionary method from Ref. [28], where simulations were performed by using only Game A or only Game B. The results (Figs. 2a and 2b) indicate that both the

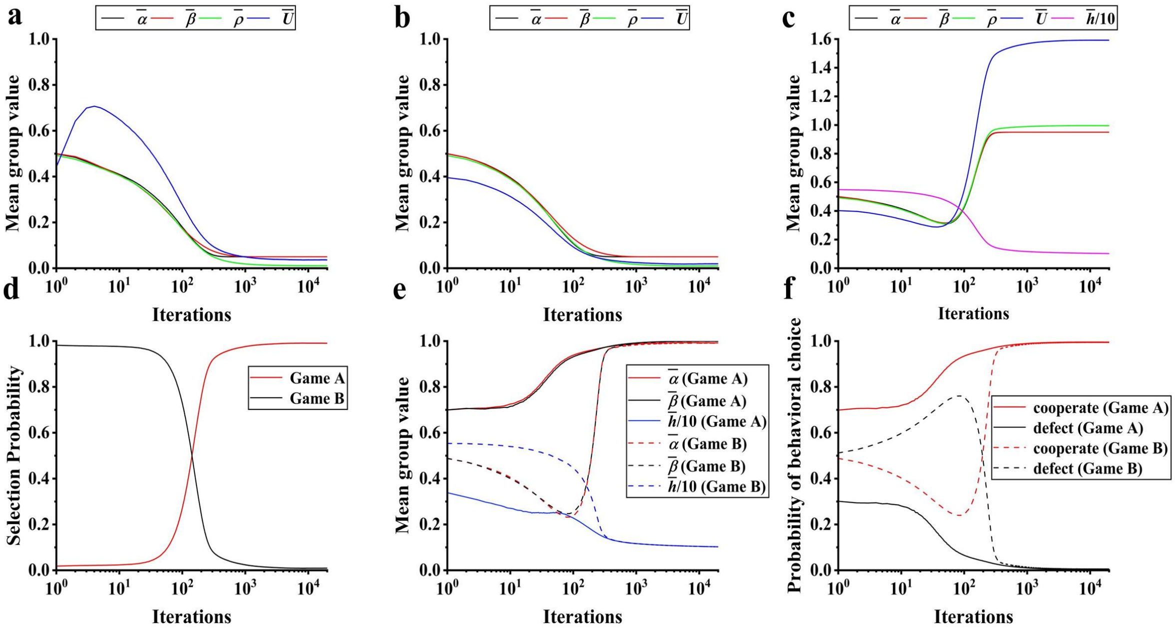

Figure 2: Evolutionary dynamics of indicators on a square lattice. (a) Evolution of the average emotional profile $(\overline{\alpha}, \overline{\beta})$, cooperation level $(\overline{\rho})$ and payoff $\overline{U}$ when only Game A is played. (b) The same values when only Game B is used. (c)-(f) Dynamic switching between Game A and Game B is allowed via the coevolutionary process described in Sec. 2. (d) Frequency of participants playing Game A and Game B during the evolution. (e) Evolution of emotional profiles dedicated to different game environments as indicated in the legend. (f) Behaviors adopted by participants during the coevolutionary process involving environment switching. Parameter values: $b_1 = 1.9$, $b_2 = 1.1$, $c = 0.3$.

population emotional parameters $\overline{\alpha}$ and $\overline{\beta}$ tend to zero, where $\alpha \to 0$ suggests that individuals have no willingness to cooperate with a weak partner, and $\beta \to 0$ indicates that individuals have no willingness to cooperate with the stronger one. Consequently, the average cooperation level $\overline{\rho}$ and the average payoff $\overline{U}$ tend to zero and the system becomes trapped in the tragedy of the common state.

In the coevolutionary case, when dynamically switching between Game A and Game B is possible, the direction of the evolution can be reversed completely. This is illustrated in Fig. 2c where both the population emotional parameters $\overline{\alpha}$ and $\overline{\beta}$ tend to 1, suggesting that individuals are willing to cooperate both with weaker and stronger partners. Consequently, the average cooperation level $\overline{\rho}$ also tends to 1. Comparing the evolutionary processes of dynamic switching (Fig. 2c) with those of only playing Game A (Fig. 2a) or only playing Game B (Fig. 2b), the most significant difference is that both emotional parameters $\overline{\alpha}$ and $\overline{\beta}$ exhibit an upward transition after 100 Monte Carlo steps, which is completely missing when only playing Game A or only playing Game B is used. To understand how the switching of game environments promotes the development of mutual cooperation, we recorded the frequency of participants playing Game A or Game B (Fig 2d), their corresponding emotional profiles (Fig. 2e), and the behaviors they adopted (Fig. 2f). It can be seen from Fig. 2d to Fig. 2f that at the initial stage of the evolution, only a small proportion of individuals (accounting for about 2%) select Game A environment. Moreover, these individuals show high level of sympathy toward weaker fellows and respect for stronger ones (both around 0.7). In parallel, it has a high probability of adopting cooperative behaviors (around 0.7). The high payoff from mutual cooperation (in the Game A environment, it yields $b_1 - c = 1.6$) allows individuals to build high emotional reputation and kind trait, hence enjoy an evolutionary advantage. Additionally, the chance of emotional imitation makes them possible to spread their emotional profiles among their neighbors, thereby forming a positive cycle. As a result, with the progress of evolution, the frequency of choosing Game A continued to rise, with a particularly significant jump after 100 Monte Carlo steps, and finally reaching the maximal value of 1. Simultaneously, the population emotional parameters and the probability of adopting cooperative behaviors also approach 1.

It is instructive to monitor how emotional profiles evolve during the evolution for different cases. It is shown in Fig. 3 where we plot the time dependence of $P(\alpha, \beta)$ probability distribution for the traditional and the coevolving cases. To classify individual emotion profiles, both $\alpha \in [0, 1]$ and $\beta \in [0, 1]$ are divided into 10 intervals, respectively. Individuals are considered to belong to the same emotional phenotype if their α and β values fall into the same interval, resulting in a total of $10 \times 10 = 100$ different emotional phenotypes in the population. Accordingly, $P(\alpha, \beta)$ represents the proportion of individuals belonging to a certain emotional profile phenotype in the whole population.

Since unkind individuals (with high bullying, $\alpha \to 0$, and high envy, $\beta \to 0$) are similar to the ALLD strategy, the cooperation of other individuals provides opportunities for these unkind individuals to "free-ride". This makes their payoff (at this point, the game environment is highly likely to be Game B, with the payoff for successful betrayal being b_2) higher than that of other individuals. The high payoff increases the probability that neighbors will imitate the emotional characteristic parameters of these unkind individuals, leading to a gradual rise in the number of individuals with emotional profile of high-bullying and high-envy in the initial stage of evolution. As time proceeds, populations using only Game A or only Game B are eventually dominated by individuals with emotional phenotypes of high bullying and high envy (Panel V in Figs. 3a and 3b). However, in the case of dynamic switching between game environments, the final evolutionary outcome is completely different. The population is finally dominated by individuals having high level of sympathy ($\alpha \to 1$) and high respect ($\beta \to 1$) (Panel V in Fig. 3c). In agreement with our observation about alternative indicators, a clear divergence between evolutionary trajectories emerges after 100 Monte Carlo steps: in a population that only use Game A (Panel III in Fig. 3a) or only Game B (Panel III in Fig. 3b) parametrization, the population is dominated solely by unkind emotional profiles characterized by high bullying toward a weaker ($\alpha \in [0.0, 0.1)$) and high envy toward a stronger ($\beta \in [0.0, 0.1)$). In contrast, the population with dynamic switching between games is dominated by two emotional phenotypes (Panel III in Fig. 3c). These are an unkind emotional profile with high bullying toward weak partners ($\alpha \in [0.0, 0.1)$) and high envy toward stronger fellows ($\beta \in [0.0, 0.1)$), and the other is a kind emotional profile with high sympathy toward a weaker ($\alpha \in [0.9, 1.0)$) and high respect toward a stronger ($\beta \in [0.9, 1.0]$). Individuals having the latter profile are capable to "cluster together for mutual benefit". This phenomenon is clearly demonstrated in the bottom row of Fig. 4 where the emerging yellow islands at stage III indicate these supporting clusters. The participant players are likely engaged in the high-value Game A with high reward for mutual cooperation (Figs. 2e and 2f). As evolution proceeds further, the portion of individuals with the kind emotional profile gradually increases and eventually dominates the entire population.

The dynamic switching mechanism of the game environment provides a niche for the survival and development of individuals with benign emotions. Indeed, for kind individuals (with high corresponding emotional reputations), there is a chance to meet with unkind individuals (with low corresponding emotional reputations) among their neighbors, and their interactions may lead to "exploitation" by the betrayal. However, the game environment between them is more likely to be a low-value game since unkind individuals, with low emotional reputations, are hardly recognized. As a result, unkind individuals can only obtain the low-value betrayal payoff b_2, while kind individuals gain a payoff of $-c$. However, the final fitness is the consequence of more subtle process: the survival adaptability of kind individuals depends not only on their interactions with unkind individuals but also on their interactions with other kind individuals. Because of the clustering, there is a high probability that kind individuals engage in high-value games with each other and choose mutual cooperation (when choosing to play the high-value game, the requirement for the other party's emotional reputation inherently includes the expectation that the other party will choose to cooperate), enabling both sides to enjoy the high cooperative reward $b_1 - c$. As long as this cooperative reward is sufficient, it can make up for the loss of evolutionary advantages caused by being "exploited" by unkind individuals. Similarly, the survival adaptability of unkind individuals depends not only on their interactions with kind individuals but also on their interactions with other unkind individuals. The payoff from mutual betrayal among unkind individuals is 0. Accordingly, unkind indi-

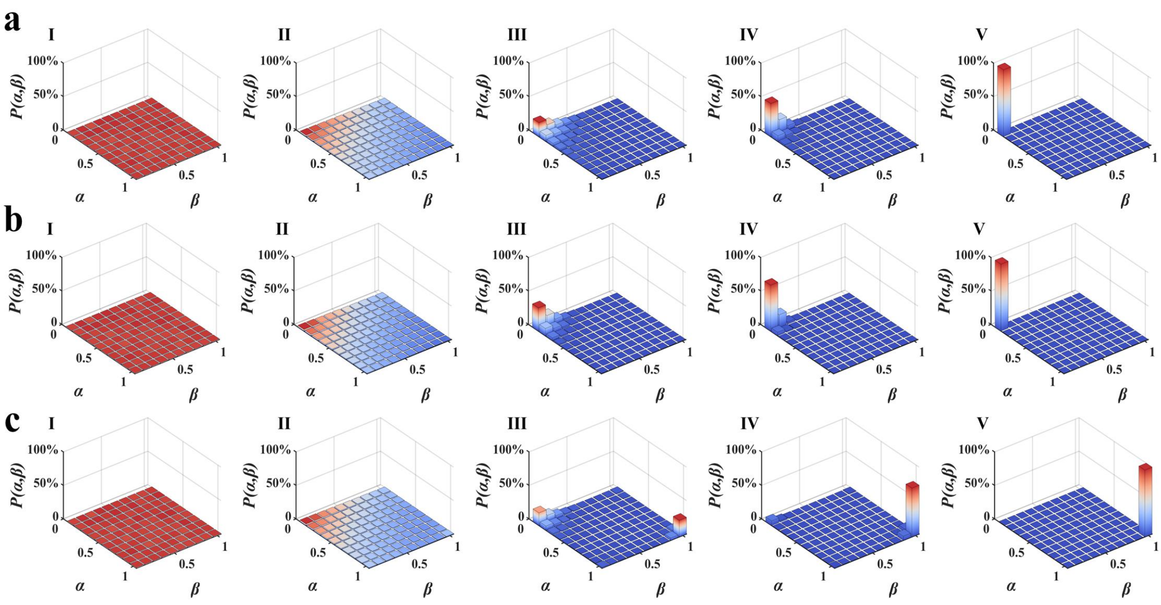

Figure 3: Evolution of emotional profile in a square lattice population. The time evolution of $P(\alpha, \beta)$ probability distribution is shown for different cases. (a) Only Game A is used. (b) Only Game B is applied. (c) Dynamic switching between Game A and Game B. Parameter values: $b_1 = 1.9$, $b_2 = 1.1$, $c = 0.3$. Emotional profiles are recorded at (I) 1, (II) 10, (III) 100, (IV) 200, and (V) 20000 full Monte Carlo steps.

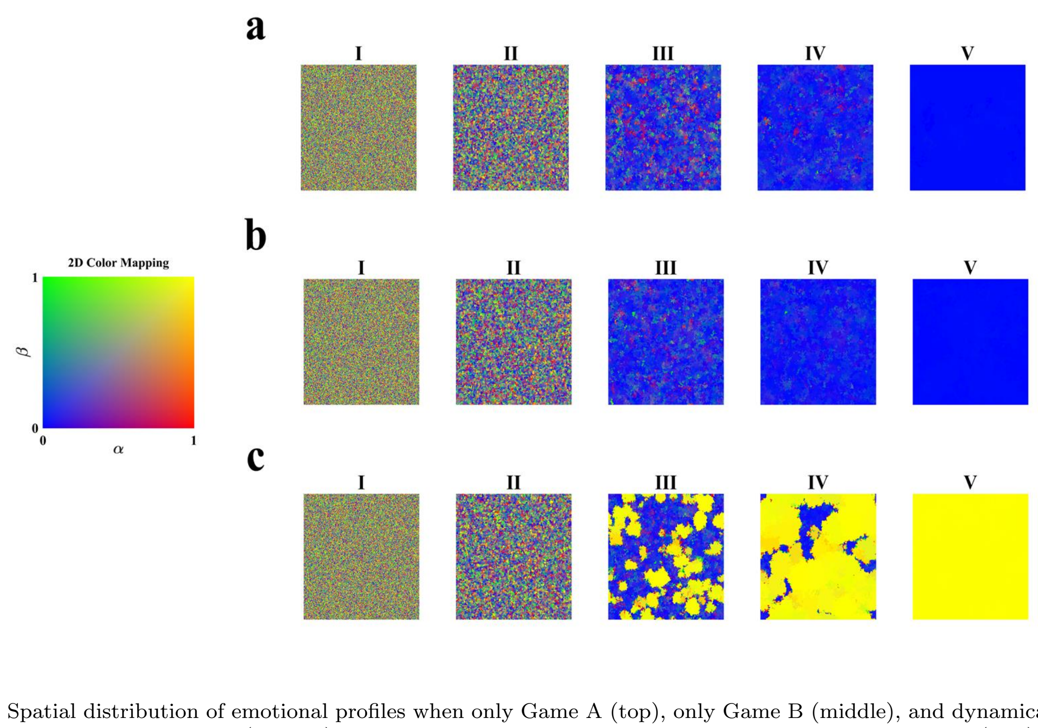

Figure 4: Spatial distribution of emotional profiles when only Game A (top), only Game B (middle), and dynamical switching between these games are allowed (bottom). Panel in left-hand side indicates how we link a specific pair of (α, β) profile to a certain color. Parameters are $b_1 = 1.9$, $b_2 = 1.1$, $c = 0.3$. The spatial distribution of emotional profiles are recorded at (I) 1, (II) 10, (III) 100, (IV) 200, and (V) 20000 full Monte Carlo steps.

viduals will lose the evolutionary advantages they seized from kind individuals. In summary, the cooperative rewards that kind individuals enjoy by "clustering together" are sufficient to make up for the losses caused by being "exploited" by unkind individuals. Therefore, kind individuals gain evolutionary advantages until they dominate the entire population.

The above described phenomenon is clearly demonstrated in Fig. 4 where we compare the spatial distribution of parameter profiles between the traditional and coevolutionary models. Let us stress that here a color does not mean a strategy or a specific value of a parameter. Instead, it marks a particular emotional profile, a pair of α, β that a player possesses. Accordingly, the different combination of α and β values are linked to a color, as it is shown on the left-hand side of Fig. 4. On the right-hand side of this figure we present the link between a color and a specific pair of (α, β) profile. For example, blue indicates unkind players who have low α and low β values, or red marks those players who has high sympathy toward weaker partners but envious of more stronger neighbors. The comparison of the traditional and the coevolutionary models has revealed that there is a strong clustering, becomes visible after 100 Monte Carlo steps, in the latter model, which is completely missing in the single-game versions. More precisely, some small red or green islands emerge in the top and in the middle row due to fluctuations, but these formations are not sustainable. Neither high α - low β, nor low α - high β combination is viable in a social dilemma situation. The only winner combination is the yellow high α - high β emotional profile, hence kindness becomes dominant if actors have a chance to adjust the stake of their interaction according to the emotional reputation of their partners.

In the emotional evolution considering dynamic switching of game environments, not only "kind people" have evolutionary advantages, but "openness" also gains such advantages. While the population emotional parameters $\overline{\alpha}$ and $\overline{\beta}$ undergo an upward transition, the parameter $\overline{h}$, which reflects the population's emotional conservatism, gradually decreases (Fig. 2c) and eventually converges to around 1. The distribution of individual h values in the population also gradually changes from an initial uniform distribution to a power-law distribution, and finally arrives to a δ-distribution with a value of 1 (Fig. 5a). The evolution of the spatial distribution (Fig. 5b) presents the same characteristics, where $h \to 1$ means that individuals' conservatism decreases, tending to be open and easily recognizing the "goodness" of others, which makes the high-value game the final choice.

4. Alternative topologies

To explore the robustness of our findings, we have also checked alternative interaction topologies for the population. They are the standard random network and Barabási-Albert scale-free networks. The results are shown in the Appendix. Heterogeneous networks (random networks in Figs. A1-A3 and BA scale-free networks in Figs. A4-A6) show conceptually the same evolutionary results as homogeneous networks, that is, emotion-driven game switching can significantly promote cooperation. In addition, when only a high-value game (Game A) is played on scale-free networks, the group emotion shows a relatively high degree of respect for stronger neighbors (with $\overline{\beta}$ around 0.7, shown in Fig. A4a and Fig. A5a), which is consistent with the conclusion in Ref. [29] that heterogeneous networks lead to low sympathy and high respect (low envy).

5. Parameter regions

As we pointed out dynamic switching between two game environments can effectively support cooperation even in the case when a single game environment is unable to do it. The explanation of this phenomenon is based on the fact that parameters characterizing emotional profiles can evolve toward the desired direction via a coevolutionary process. Another important ingredient is the payoff difference between the two game environments should reach a certain level. In other words, there must be a significant difference between the stakes related to low-value and high-value dilemmas.

This criterion is justified in Fig. 6 where we show the stationary values of parameters in the coevolutionary model compared to the values obtained in the traditional single-game scenario. For a more complete insight, we present these values for different interaction graphs. Notably, the parameter region where the above described mechanism is effective is larger for regular network than that of the random graph and the scale-free network. For comparison, in the Appendix we present the same plot obtained at a significantly larger cost of cooperation c (Fig. A7). Importantly, as the

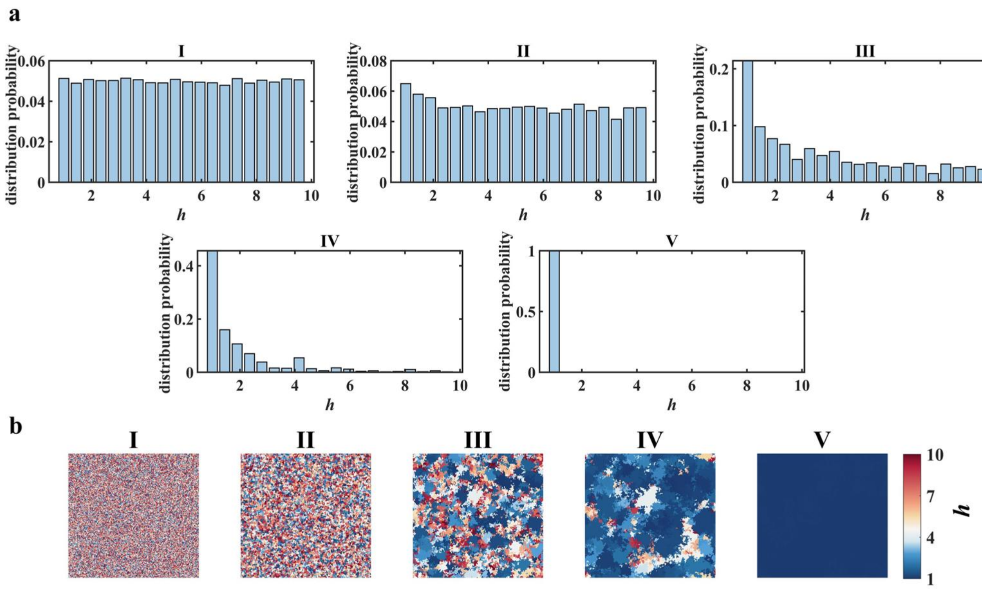

Figure 5: Evolutionary dynamics of emotional parameter h in a population distributed on a square lattice. (a) Probability distribution of h obtained at different time. (b) Spatial distribution of the same parameter. Histograms and snapshots were taken at (I) 1, (II) 10, (III) 100, (IV) 200, and (V) 20,000 full Monte Carlo steps. Parameter values: $b_1 = 1.9$, $b_2 = 1.1$, $c = 0.3$.

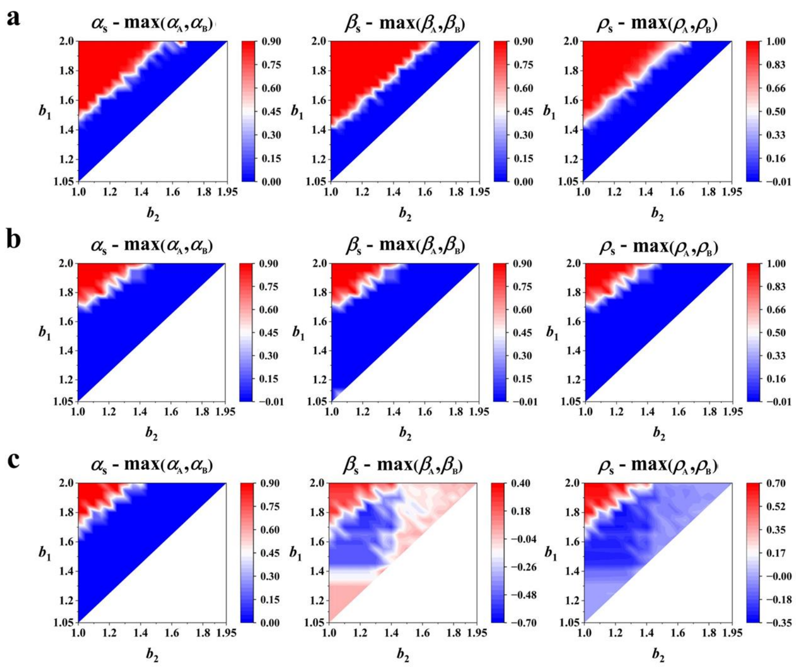

Figure 6: Color-coded parameter values for different topologies when cost values is $c = 0.3$. (a) Square lattice. (b) Random graph. (c) BA scale-free network. α_S , β_S and ρ_S are the population averages of emotional parameters and cooperation level considering dynamic switching; α_A, β_A, ρ_A and α_B, β_B, ρ_B are the population averages of emotional parameters and cooperation level when only Game A or only Game B is used. Note that $b_1 \in [1.05, 2]$, and $b_2 \in [1.0, 1.95]$, by keeping $b_1 > b_2$.

cost of cooperation increases, a larger payoff difference $b_1 - b_2$ between the two game environments is required to achieve the requested positive result. Consequently, the red region of the lattice network shrinks (Fig. A7a), while the red regions of the random graph (Fig. A7b) and the scale-free network (Fig. A7c) practically disappear.

The key element to reach cooperation through emotion-driven game environment switching is the formation of self-supporting spatial clusters where kind individuals have evolutionary advantage. We can assume that the average payoff of kind individuals in the mentioned cluster is higher than that of unkind individuals.The requested conditions can be identified in the following way:

- (1) Payoff Threshold Condition: The kind-person clustering coefficient r (the spatial probability that kind individuals are neighbors of each other) satisfies: $rb_1 - (1-r)b_2 > c$, where r is called as the "kind-person clustering coefficient".
- (2) Imitation Condition: The emotional imitation probability q ensures high-payoff kind individuals are imitated: $q = \{1 + \exp[(U_k - U_u)/\kappa]\}^{-1}$, where $U_k = r(b_1 - c) + (1-r)(-c)$ (The average payoff of kind individuals), $U_u = (1-r)b_2$ (the average payoff of unkind individuals), $\kappa = 0.1$ is a noise parameter.

Here, the parameter r is related to the network structure and topological characteristics. A larger r is more conducive to kind individuals enjoying cooperative rewards from the high-value game through "clustering", which reduces the required payoff difference between the two game environments and expands the parameter region where cooperation is favored. Based on the boundaries of the red regions in Fig. 6 and in Fig. A7, the kind-person clustering coefficient of the square lattice is approximately 0.54, and that of heterogeneous networks (random and scale-free networks) is approximately 0.49. Therefore, we can argue that homogeneous interaction graphs, such as lattices, are more conducive to boost kind-person clustering, hence to promote the evolution of cooperation [36].

6. Discussion

Many decisions in the real world depend on emotional states, including not only choices between cooperation and defection but also choosing between playing "big" or "small". For example, we may give more donations to less successful people, or willing to follow morally noble influencers in important matters, and tend to engage in major business with benevolent and more prosperous citizens. Therefore, considering the impact of emotions in the field of social interaction is crucial for understanding the driving factors behind the evolution of cooperation [28, 29].

To explore the comprehensive consequences of emotional-driven evolutionary dynamics we generalize and extend a basic model where emotions not simply influence how to behave in a certain situation but also determine how large risk an actor is willing to take. For this reason employ three emotional parameters: a probability α which determines the willingness to cooperate with weaker partner (sympathy), a probability β describing the cooperation willingness with a more successful neighbor (unenvious or servility), and a parameter h describing individual emotional conservatism. The latter parameter characterizes a sort of inertia to choose a high-value interaction in dependence of the partner's emotional reputation. Accordingly, the emotion-driven mechanism is reflected in two aspects: first, the choice of behavior, determining the probability of cooperating with a weaker (α)or stronger fellow (β), second, the choice of game environment based on the other party's emotional reputation (α+β) and one's own emotional conservatism h. If both parties in the game are "recognized kind people" by each other, a mutual trust is established [37, 38], hence a high-value game (Game A) is conducted. In all other cases, in the absence of mutual trust, a low-value game (Game B) is performed.

Importantly, the choice of behavior and the choice of game environments are both independent (choices are made separately based on their respective rules) and coupled (the mechanism for selecting "recognized kind people" can greatly increase the probability of mutual cooperation between both parties in high-value games). This coupling enables high-value cooperation among "kind people" (with high sympathy $\alpha \to 1$ and high respect $\beta \to 1$) to emerge and gain evolutionary advantages through a spatial "clustering" process. The proposed evolutionary dynamic model embodies a "tripartite interaction" among emotions, behaviors, and game environments: individual emotions and the comparison of payoffs between interacting parties determine the behavior (cooperation or defection) at the current time step; the emotional reputations of both interacting parties and their emotional conservatism determine the game environments (a high-value or a low-value game) at the current step; then, individuals obtain game payoffs at the current step based on both parties' interaction behaviors and the game environments. Subsequently, individuals update their emotions for the next time step based on the payoff relationship with their neighbors. Ultimately, a "feedback loop" is formed among kind emotions, cooperative behaviors, and high-value games [39].

A defining nonlinear insight of our study is the threshold-dependent feedback loop between emotional recognition, cooperative behavior, and game environment selection – core to non-equilibrium complex systems. Unlike linear models where cooperation increases proportionally with environmental value or emotional intensity, our framework exhibits a phase transition: cooperation remains low until the proportion of kind individuals (high α, β) and open-minded individuals (low h) exceeds a critical threshold, after which cooperative clusters expand rapidly (Figs. 2c, 3c). This aligns with recent observations in nonlinear social systems, where small changes in key parameters trigger drastic shifts in collective behavior [40]. The nonlinear amplification of cooperative clusters via high-value game interactions further demonstrates that emotion-driven environment switching [40, 41] is a powerful mechanism for escaping the tragedy of the commons in complex networks—advancing nonlinear science applications to social dynamics [42].

As we stressed, a high-value game can only be conducted when both parties are "recognized kind people" by each other, and being a "recognized kind participant" requires two elements. First, the other party must be significantly "kind" (with a high emotional reputation), which is jointly composed of the emotion towards a weaker (α) and the positive emotion towards stronger (β). Only when both values are relatively high can the so-called the emotional reputation be significantly "kind". Therefore, the evolution of α and β among "clustered" kind individuals shows certain synchronicity (shown at stage III and IV in Fig. 4. Second, one should not be too conservative. Kind individuals with low conservatism (h) are more likely to recognize each other, thus engaging in high-value games and obtaining high-value cooperative rewards $b_1 - c$. In contrast, although kind individuals with high conservatism (h) cooperate with each other, they are more likely to engage in low-value games (due to high conservatism, they are less likely to recognize each other), hence only gaining a low-value cooperative reward $b_2 - c$. Such low-value reward may be insufficient to compensate the loss caused by being "exploited" by unkind individuals. Hence, kind individuals with low conservatism (i.e., being open) have evolutionary advantages. Just as the dynamic switching of games gives rise to the evolution of moral norms of cooperation, our model evolves an emotional phenotype of cooperation, "open benign people", who are kind and easily moved.

Information influences the dynamic switching of game environments and the evolution of cooperation. Our analysis is based on the premise that individual emotional reputations are accessible public information. In reality, emotions are harder to obtain than behaviors. We can only assess underlying emotions through actions. For example, we judge an individual's respect for a stronger and sympathy for a weaker based on their behaviors toward these groups, thereby forming an overall understanding of their emotional reputation. However, such understanding is vague and difficult to quantify. Moreover, assessment errors may arise from factors like cognitive abilities, whether behaviors truly reflect emotions, and the dynamic variability of emotions under different environments and moods. Thus, the difficulty in quantitatively acquiring emotional reputations limits the selection and dynamic switching of game environments in real interactions. Due to the implicit nature of emotional reputations, people attempt to use easily obtainable markers as substitutes for emotional reputations. For instance, we refer a Chinese saying, "People from one's hometown are approachable". Commercial groups in China, such as Huizhou merchants, Shanxi merchants, and Zhejiang merchants, formed "mutually recognized benign people" with fellow townsmen as the emotional bond, thereby cooperating in clusters to engage in high-value games (conduct large-scale business). Accents and dialects are explicit features of fellow townsmen. People can quickly and effectively identify them through linguistic factors, reducing assessment errors. Therefore, our model offers a stimulating starting point for exploring the impact of alternative markers of emotional reputations – such as region, culture, education, beliefs, and language – on behaviors in social interactions and economic exchanges.

Our findings align with key physics experiments and real-world observations of nonlinear cooperation in complex systems. In laboratory experiments on spatial PD games [43], researchers observed that cooperative clusters emerge and expand only when a critical density of cooperators is reached—mirroring the threshold-dependent phase transition in our model (Figs. 2c, 3c). This experimental result confirms that nonlinear clustering is a universal feature of spatial cooperation, regardless of whether the driver is spatial proximity (experiments) or emotional recognition (our model). Field observations of human cooperation in economic exchanges [44] further show that individuals dynamically adjust interaction stakes (analogous to our game environment switching) based on perceived trust—leading to clustered cooperation among trusted partners. This aligns with our result that mutual emotional recognition drives high-value game selection and cooperative clustering. Additionally, recent physics studies on nonlinear social systems have demonstrated that feedback loops between individual traits and environmental selection induce collective behavior shifts—our ternary interaction framework (emotions-behaviors-environments) provides a concrete mechanism for this nonlinearity in cooperation evolution. While direct experiments on emotion-driven environment switching are limited, our model's predictions (e.g., phase transition in cooperation level, clustering of kind individuals) are testable via controlled behavioral experiments on online platforms (e.g., Amazon Mechanical Turk), where emotional reputations can be quantified and game environments adjusted dynamically—offering a path to validate our nonlinear framework experimentally.

Our current research mainly focuses on emotion-driven dyadic interactions and dynamic switching at the game environment level. Since higher-order networks (hypergraphs, simplicial networks) [45, 46] and multilayer networks [36] can reflect the impact of multivariate interactions and multiple domains of social interactions on the evolution of cooperation, they can be used to study the application of emotion-driven game environment switching in multiplayer game models (such as public goods games [47]) and the switching of structural environments [48] (network carriers) in multichannel games [49]. This may reveal the influence of emotions on group cooperation in higher-order interaction relationships and dynamically coupled environments. Simutanously, a key limitation of this study is the reliance on computational simulations, with relatively limited analytical formalization. While simulations excel at capturing the nonlinear, spatial, and stochastic dynamics of emotion-driven cooperation, they are less effective at generalizing results to arbitrary network topologies or game paradigms. Future work could address this by adopting mean-field theory to derive approximate analytical solutions for the evolutionary dynamics. Mean-field approximations would enable simplifying the complex spatial interactions into population-level equations, potentially yielding formal theorems for the existence and stability of cooperative equilibria across different network structures. Additionally, integrating pairwise approximation methods could further bridge the gap between simulation results and theoretical generalizability, enhancing the study's contribution to nonlinear evolutionary game theory.

Acknowledgment

This work was supported by The Excellent scientific research and innovation team of Anhui Provincial Education Department of China under the award number 2022AH010027, Anhui University Collaborative Innovation Project of China under the award number GXXT-2022-082, The Open Fund of Key Laboratory of Anhui Higher Education Institutes under the award number CS2025-ZD02, and by the National Research, Development and Innovation Office (NKFIH) under Grant No. K142948.

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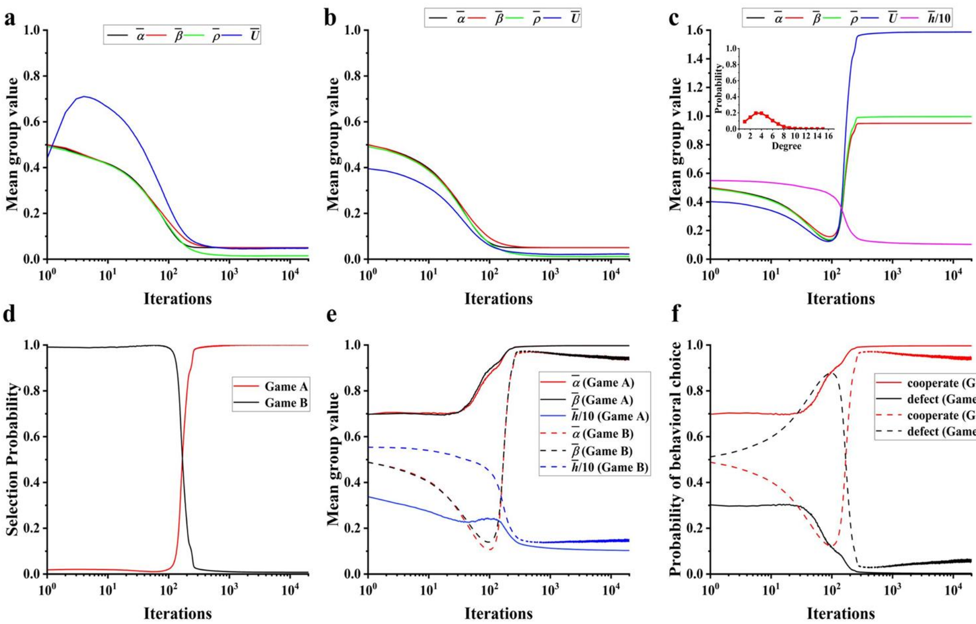

Figure A1: Time evolution of parameters in a population distributed on a random graph. (a) Only Game A is used. (b) Only Game B is applied. (c-f) Dynamic switching between Game A and Game B is allowed. (d) Frequency of participants playing Game A and Game B during game environment switching. (e) The corresponding emotional characteristics of these subsets during game environment switching. (f) Behaviors adopted by participants during game environment switching. $\overline{\alpha}$ and $\overline{\beta}$ are the population averages of emotional parameters α and β, respectively; $\overline{\rho}$ is the population cooperation level; $\overline{U}$ is the population average payoff; $\overline{h}$ is the population average of emotional parameter h. Parameter values: $b_1 = 1.9$, $b_2 = 1.1$, $c = 0.3$. The evolutionary method is adopted for the scenarios of only playing Game A or Game B from Ref. [29], while the evolutionary method considering dynamic switching is referred to Sec. 2 of this study. The random graph has a total of 40,000 nodes with an average node degree of 4, and the node degree distribution is shown in the inset of panel (c).

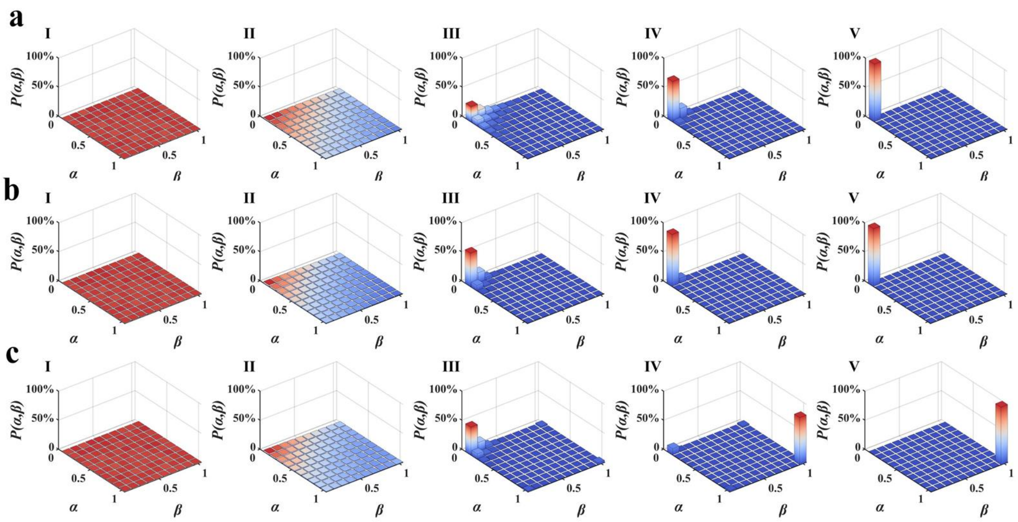

Figure A2: Time evolution of emotional profile distribution in a population arranged in a random graph. (a) Only Game A is used. (b) Only Game B is applied. (c) Dynamic switching between Game A and Game B. To classify individual emotion profiles, both $\alpha \in [0, 1]$ and $\beta \in [0, 1]$ are divided into 10 intervals respectively. Individuals are considered to belong to the same emotional profile if their α and β values fall into the same interval. This classification results in a total of $10 \times 10 = 100$ emotional profiles. $P(\alpha, \beta)$ represents the proportion of individuals belonging to a certain emotional profile in the total population. Parameter values: $b_1 = 1.9$, $b_2 = 1.1$, $c = 0.3$. The distribution of profiles is recorded at (I) 1, (II) 10, (III) 100, (IV) 200 and (V) 20,000 full Monte Carlo steps.

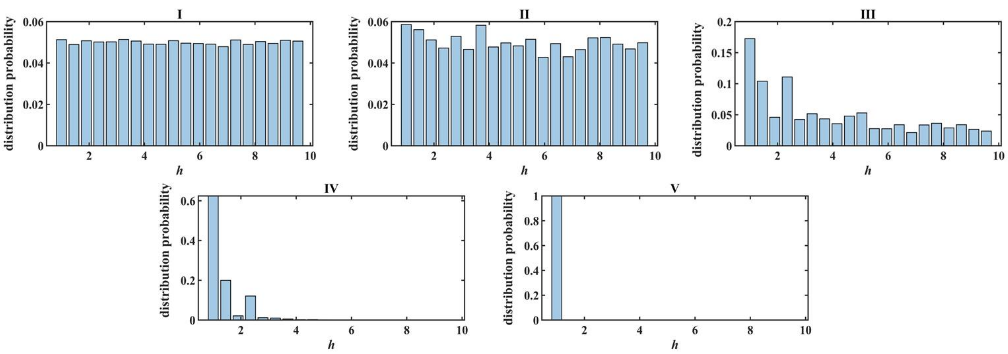

Figure A3: Evolutionary dynamics of the distribution of emotional parameter h in a population based on a random graph. Parameter values: $b_1 = 1.9$, $b_2 = 1.1$, $c = 0.3$. Histograms were taken at (I) 1, (II) 10, (III) 100, (IV) 200 and (V) 20,000 full Monte Carlo steps.

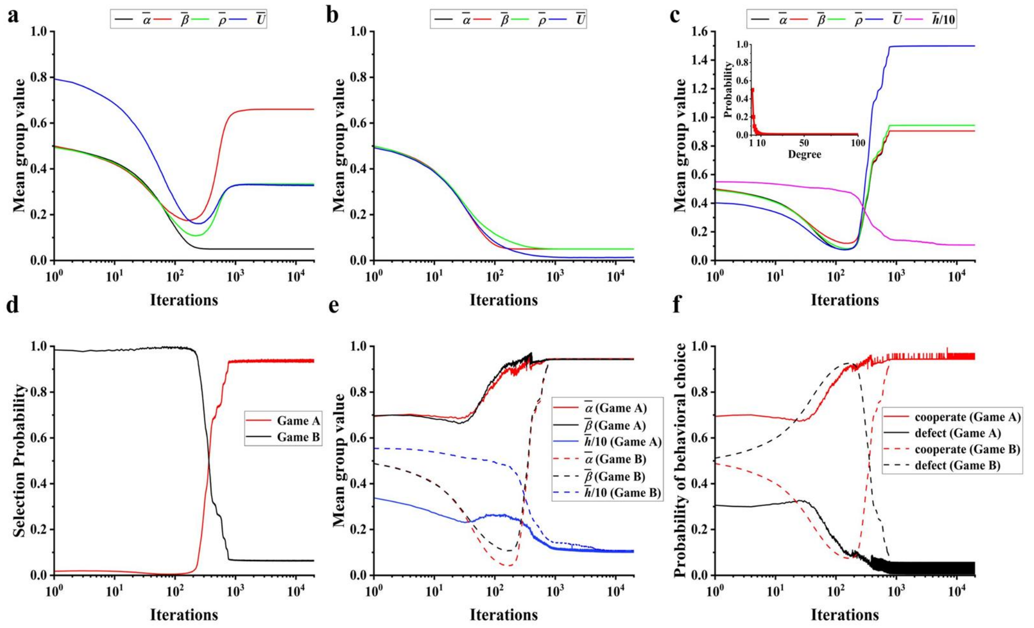

Figure A4: Time evolution of parameters in a population distributed on a scale-free network. (a) Only Game A is used. (b) Only Game B is applied. (c-f) Dynamic switching between Game A and Game B is allowed. (d) Frequency of participants playing Game A and Game B during game environment switching. (e) The corresponding emotional characteristics of these subsets during game environment switching. (f) Behaviors adopted by participants during game environment switching. $\overline{\alpha}$ and $\overline{\beta}$ are the population averages of emotional parameters α and β, respectively; $\overline{\rho}$ is the population cooperation level; $\overline{U}$ is the population average payoff; $\overline{h}$ is the population average of emotional parameter h. Parameter values: $b_1 = 1.9$, $b_2 = 1.1$, $c = 0.3$. The evolutionary method is adopted for the scenarios of only playing Game A or Game B from Ref. [29], while the evolutionary method considering dynamic switching is referred to Sec. 2 of this study. The scale-free network has a total of 40,000 nodes with an average node degree of 4, and the node degree distribution is shown in the small window in panel (c).

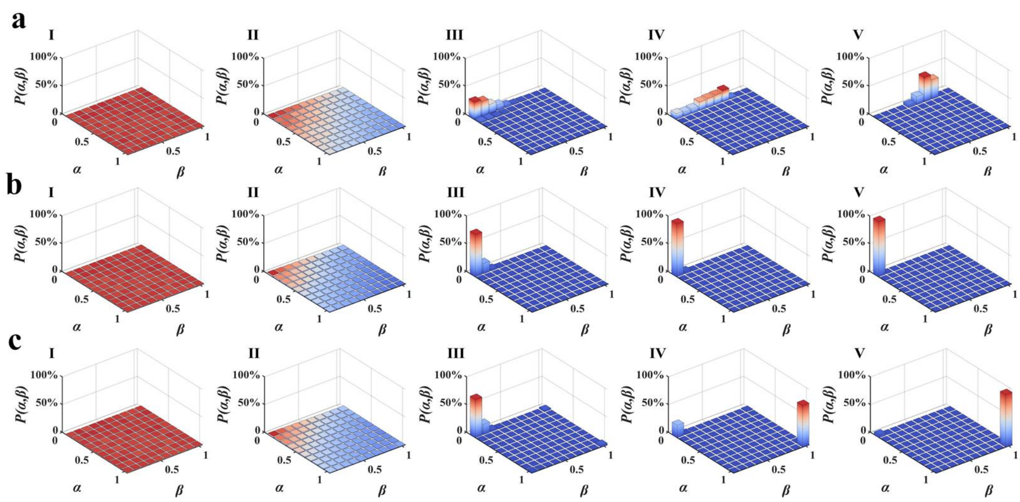

Figure A5: Time evolution of emotional profile distribution in a scale-free networked population. (a) Only Game A is used. (b) Only Game B is applied. (c) Dynamic switching between Game A and Game B. To classify individual emotion profiles, both $\alpha \in [0, 1]$ and $\beta \in [0, 1]$ are divided into 10 intervals respectively. Individuals are considered to belong to the same emotional profile if their α and β values fall into the same interval. This classification results in a total of $10 \times 10 = 100$ emotional profiles. $P(\alpha, \beta)$ represents the proportion of individuals belonging to a certain emotional profile in the total population. Parameter values: $b_1 = 1.9$, $b_2 = 1.1$, $c = 0.3$. The distribution of profiles is recorded at (I) 1, (II) 10, (III) 100, (IV) 200 and (V) 20,000 full Monte Carlo steps.

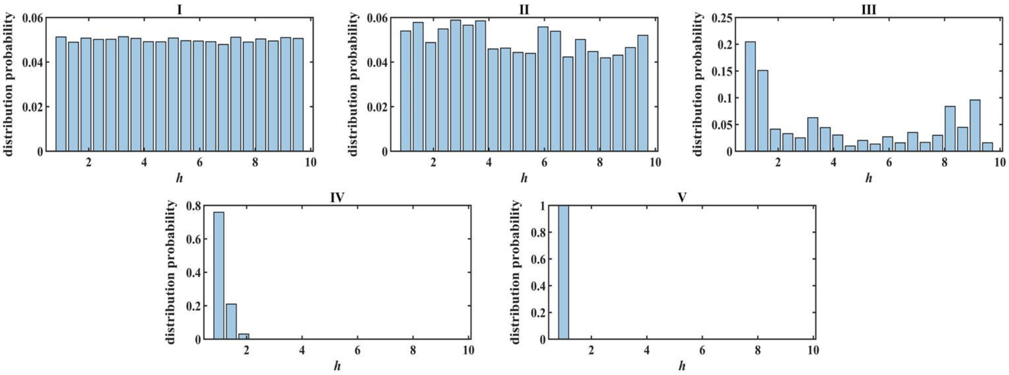

Figure A6: Evolutionary dynamics of the distribution of emotional parameter h in a population based on a scale-free network. Parameter values: $b_1 = 1.9$, $b_2 = 1.1$, $c = 0.3$. Histograms were taken at (I) 1, (II) 10, (III) 100, (IV) 200 and (V) 20,000 full Monte Carlo steps.

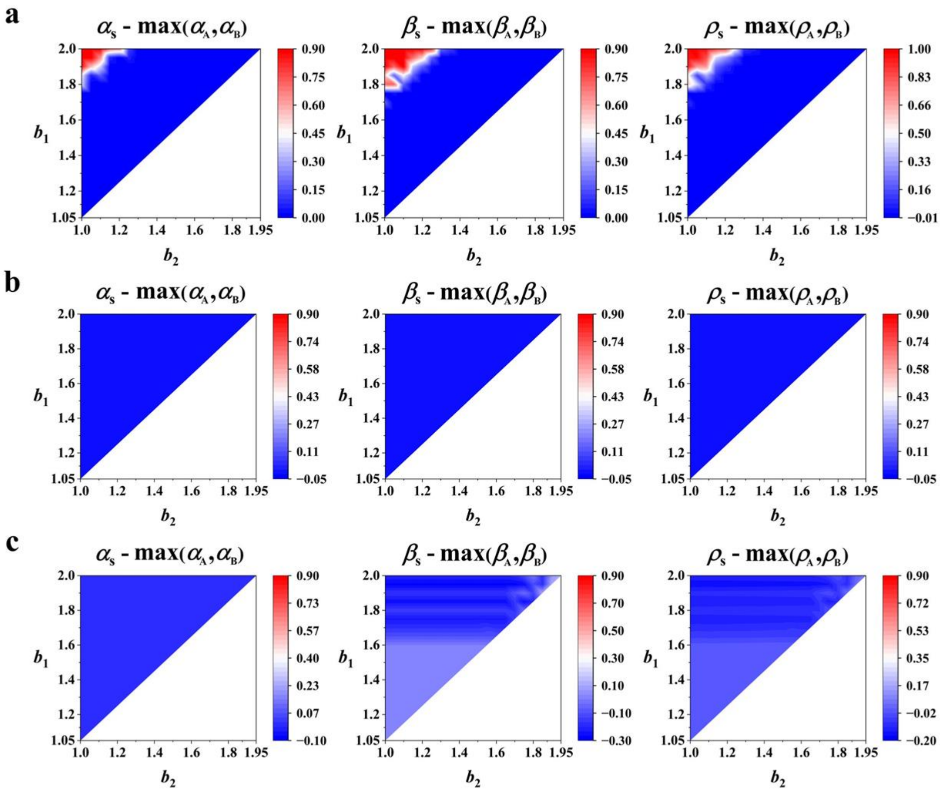

Figure A7: Color-coded parameter values for different topologies when cost value is $c = 0.5$. (a) Square lattice. (b) Random graph. (c) BA scale-free network. α_S , β_S and ρ_S are the population averages of emotional parameters and cooperation level considering dynamic switching; α_A, β_A, ρ_A and α_B, β_B, ρ_B are the population averages of emotional parameters and cooperation level when only Game A or only Game B is used. Note that $b_1 \in [1.05, 2]$, and $b_2 \in [1.0, 1.95]$, by keeping $b_1 > b_2$.