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Payoff-driven migration promotes the evolution of trust in networked populations

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ABSTRACT

Establishing and maintaining trustworthy behaviors in large populations of self-interested individuals is a significant problem which received extensive attentions from research fields such as evolutionary biology, economics, sociology and engineering. As a well-known model that captures social trust dilemmas, the N-player trust game is adopted to investigate the evolution of trust in groups consisting of investors and trustees. In addition, to model real scenarios in dynamic environments, we introduce a novel migration mechanism, called adaptive environment-benefit-driven migration, which considers the influence of individuals' payoffs on migration. Through theoretical analysis and Monte Carlo simulations, we demonstrate the effectiveness of the migration mechanism on facilitating trust behaviors in the framework of evolutionary game theory. We find that the population density plays a crucial role in establishing trust. Simulation results reveal that trust can be fostered in a dynamic environment influenced by individual migration with the medium vacancy rate. This work significantly contributes to the understanding of mutual trust behaviors in networked social systems from a more realistic perspective.

1. Introduction

Trust in social and economic activities is crucial since it guarantees prosocial behaviors and the resilience of human societies [1–4]. From the perspective of evolutionary game dynamics [5], trust serves as a critical element for cultivating cooperation, fostering stability, and propelling social coherence [6–8]. As a catalyst to establish virtuous circle mechanism between or among individuals' interactions, trust can facilitate the normal operation of management systems, shape trustworthy economic behavior [9,10] and lay the fundamental foundation for the emergence of honesty, particularly cooperative behavior [11,12]. The establishment of a trusting relationship requires the tolerance, selflessness, and provident of an individual to provisionally allow a relative disadvantage in the decision-making process. This entails proactively exposing one's weaknesses and vulnerabilities, with the shared expectation of cultivating a deep sense of mutual trust and cooperation. In essence, this reflect the willingness of some agents who sacrifice their own benefits to facilitate the collective benefit [13,14].

The existence of such prosocial behavior contradicts the Darwinian concept of inherently competitive dynamics of biological evolution, or commonly referred to as "the survival of the fittest". Hence, how to understand the attraction of prosocial behaviors to selfish individuals at the cost of sacrificing the immediate interests is an intriguing question [15–17]. Besides, investigating the incentive mechanisms on the evolution of trust in agent-based systems has become a focal point of researchers from various fields [18–21], including cognitive neurology [22,23], behavioral science [24,25], economics [26], and control engineering [27], to name a few of them. As a well-established and classical theoretical tool, evolutionary game theory (EGT) is often employed to study the behavioral evolution of complex dynamical systems. Notably, the trust game (TG), as a relevant group of models within the framework of EGT, has been widely used to model the strategy evolution in the trust-based social dilemma games [28–32]. In the pioneering work of Abbass et al. [33], an N-player trust game (NTG) was developed, where individuals are categorized as investors, trusted trustees, and untrustworthy trustees within a well-mixed population. With the replicator dynamics, their study revealed that even there exist a small number of untrustworthy trustees, the trust relationship becomes vulnerable and can be completely destroyed.

How trust evolves in networked populations under the evolutionary dynamical rule is an important issue. Using EGT, researchers extended

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the two-player and multi-player trust games to networked groups, and investigated the evolution of trust and cooperation on social networks including lattice [34], small-word network [35] and the scale-free (SF) network [36,37]. For instance, Chica et al. [28,29] explored the N-player trust game on networks and found that network interactions can mitigate the negative impact of selfish behavior on the establishment of trust. They also emphasized the crucial role of different update rules in enhancing trust and group interests. To emphasize the importance of the trustee's reputation on influencing investors' investment behavior, Hu et al. [30] introduced an adaptive reputation mechanism. Furthermore, Li et al. [31] provided an extensive analysis of the second-order reputation mechanism, revealing that incorporating such mechanism can significantly decrease the prevalence of untrustworthy trustees. And, Liu et al. [32] investigated how the conditional investment strategy serves as a viable pathway to re-establish trust within a population engaged in repeated interactions. For more details, the readers can refer to the review articles related to trust and reputation [38–41].

In many real-life cases, people dissatisfied with the current job will seek to switch to a new company, even the suitable positions may not exist at the moment. In term of this, introducing migration to the evolutionary game dynamics provides a novel perspective for the investigations on the emergence of trust [42–44]. With abilities of self-perception and self-protection, selfish individuals' decision-making behaviors in the game are significantly influenced by the environment [45–47]. In previous works, the stochastic migration result show that [48], by modifying the interaction region among individuals during migration, the diffusion of cooperation can be facilitated in the whole population. By proposing a social norm-driven probabilistic migration model, Yang et al. [44] focused on factors including conformity and aversion to unfairness and found a novel strategy oscillation in two-strategy games. Moreover, the social self-organization was considered during migration and the Q-learning algorithm was adopted to formulate the adaptive migration process where individuals consistently achieve higher average payoffs [49–52]. On the new notions of labeling and migration, Dhakal's recent work [53] applied labels to guide migration decisions to promote cooperation. Besides, there also exists many other types of migration patterns with different migration rates [54–58].

In this work, we study the evolution of trust behaviors by proposing a novel migration mechanism: the adaptive environment-benefit-driven migration, which contains three inherent instincts of agents, i.e., crisis awareness, benefit-driven, and adaptability. Specifically, individuals autonomously assess whether their current environment is suitable (crisis awareness); when the current environment is unfavorable, they select a target location and assess whether it is better than the current position (benefit-driven); if the target location is more suitable, they migrate to it with a certain probability and imitate the new neighbors' strategies (adaptability). We investigate the N-player trust game by considering the social migration with vacancy rates, where effects of the migration and vacancy rates on the evolution of trust are analyzed. Main results and contributions include:

1. A novel adaptive environment-benefit-driven migration is proposed to model trust evolution. How migration and game parameter affect trust are studied.
2. Medium vacancy favors trust over whole range of dilemma strength, which differs from the case without migration [28].
3. Robustness of the migration mechanism is verified under different network typologies and vacancy ratios [44].

Remaining sections are organized as follows. Section 2 introduces the game model, including the environment-benefit-driven migration and strategy update rule. Theoretical analysis of the evolution dynamics is performed in Section 3. In Section 4, we provide detailed discussions of the simulations. Section 5 is a summary of conclusions and future works.

2. Model description

In this section, we provide a comprehensive definition of the networked N-player trust game, incorporating a dynamically adaptive environment-benefit-driven migration mechanism. In the trust game model, agents are randomly assigned to a structured network. Here, M represents the total number of nodes in the network, and α denotes the vacancy rate of the network. $M(1-\alpha)$ corresponds to the actual number of individuals.

2.1. Networked N-player trust game with vacancy

In the N-player trust game, each agent can select from the set with three strategies denoted by $S = \{I, T, U\}$. The investor (strategy I) who hold a certain amount of stake of value t_v will decide whether to keep or transfer it to the trustee. There are also two types of trustees: i) the trustworthy trustee (strategy T) will return the received payoff to the investor; ii) untrustworthy trustee (strategy U) defects the investor (does not return the received payoff). Given a random neighborhood where the numbers of investor, trustworthy trustee and untrustworthy trustee are denoted by K_I^*, K_T^* and K_U^*, respectively. While the strategy distribution of the total population with unchanged size ($K_I+K_T+K_U = M(1-\alpha)$) is assumed to K_I, K_T and K_U for the number of strategies I, T and U respectively. Correspondingly, $F_I = \frac{K_I}{M(1-\alpha)}$, $F_T = \frac{K_T}{M(1-\alpha)}$ and $F_U = \frac{K_U}{M(1-\alpha)}$ represent the proportions of agents adopting strategies I, T and U in whole network.

An explanation for the game and payoff calculation process is made as follows. Investors offer investment t_v to trustees, where t_v ($t_v > 0$) reflects the degree of trust (in the trustee). Suppose that the trust game consists of K_I^* investors, the accumulated investment equals to $K_I^* t_v$. The trustees equally share the investment: $K_I^* t_v / K_{TU}^*$ (K_{TU}^* includes both trustworthy and untrustworthy trustees). A trustworthy trustee (Strategy T) will return the investment by multiplying R_T, i.e., $R_T K_I^* t_v / K_{TU}^*$; and each earns the same raised investment $R_T K_I^* t_v / K_{TU}^*$. However, the untrustworthy trustees (strategy U) get a free ride to the investment (no longer return) and multiply the acquired funds by R_U, resulting in $R_U K_I^* t_v / K_{TU}^*$. Here, $1 \le R_T \le R_U \le 2R_T$. The investment may bring reward, at the same time, the investors have to undertake risks of failed investments.

The payoff π_i for an agent i can be formulated using the following equation:

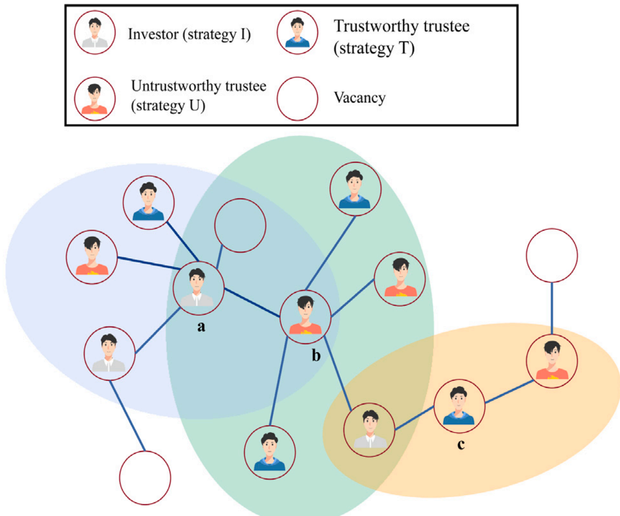
$$\pi_i = \begin{cases} \frac{R_T K_T^*}{K_{TU}^*} t_v - t_v & \text{Investor} \\ \frac{R_T K_I^*}{K_{TU}^*} t_v & \text{Trustworthy trustee.} \\ \frac{R_U K_I^*}{K_{TU}^*} t_v & \text{Untrustworthy trustee} \end{cases} \tag{1}$$

The intensity of the game dilemma is characterize by r_{UT}, which has the expression:

$$r_{UT} = \frac{R_U - R_T}{R_T} \quad \text{where} \quad r_{UT} \in (0, 1). \tag{2}$$

It is obvious that when r_{UT} increases, the payoff gap between untrustworthy (U) and trustworthy (T) trustees becomes larger. Higher value of r_{UT} (increased dilemma intensity) facilitates the evolution of untrustworthy behaviors.

In the gaming system, all individuals are located in a social network. Fig. 1 is a schematic representation for the payoff calculations in an N-player trust game on a network containing vacant positions. Each individual interacts with the current neighbors. If an adjacent position is vacant, no payoff can be obtained from the vacant neighbor. Additionally, when a group contains full-investors or full-trustees, the payoff is set to be 0.



Agent a: $\frac{R_T K_T^*}{K_{TU}^*} t_v - t_v = \frac{6*1}{3} * 1 - 1 = 1$

Agent b: $\frac{(1+r_{UT}) R_T K_I^*}{K_{TU}^* t_v} = \frac{1.33*6*2}{4} * 1 = 3.99$

Agent c: $\frac{R_T K_I^*}{K_{TU}^*} t_v = \frac{6*1}{2} * 1 = 3$

Fig. 1. A social network consists of 11 agents and three vacant positions. Each agent can choose strategy from the set I, T, U. The silver, blue, and red icons represent investors, trustworthy trustees, and untrustworthy trustees, respectively. Empty circles represent vacant positions. For individuals a, b and c, payoff calculations are available below the figure.
Parameters are set to be $R_T = 6$, $r_{UT} = 0.33$, $t_v = 1$.

2.2. Crisis-awareness escape process

The proposed migration mechanism combines individual awareness of the crisis with the motivation to pursue higher interests. After the game, individuals start to assess the environment. An isolated individual will directly move to other positions, i.e., the escape probability is 1. If there is no empty neighbor, the probability to escape ($Pro(E)$) is calculated based on the proportion of untrustworthy trustees among all neighbors. Whether to escape or not is determined by $Pro(E)$. The escape not only happens to strategy types I and T individuals, but also the U trustees. This mechanism reflects people's crisis awareness in real-life contexts, who always tend to escape from the unreliable and exploitative interactions. The probability $Pro(E)$ is calculated by:

$$\text{Pro(E)} = \begin{cases} \frac{K_U^* - 1}{K_{TU}^* + K_I^* - 1} & \text{Strategy } U \\ \frac{K_U^*}{K_{TU}^* + K_I^* - 1} & \text{Other cases.} \end{cases} \tag{3}$$

2.3. Environment-benefit migration mechanism

The individual's decision to escape the current environment does not necessarily guarantee that a better situation can be found. Hence, in our model, there is a virtual gaming and comparing process, where agents engage in a game with the new neighbors of the target vacant position. The probability of successful migration is calculated based on the difference between the current position's payoff and the target position's payoff in the virtual game according to Eq. (1). The probability ($Pro(M)$) of successful migration is listed as follows:

$$Pro(M) = \frac{1}{1 + \exp[(\pi_i - \pi_{aim}) * \theta]}, \tag{4}$$

where π_i represents the individual's payoff at position i, π_{aim} is the expected payoff by moving to the target location. Parameter θ denotes the extent of the information asymmetry, which characterizes individual's capability to acquire information of the target position.

In the real-life scenarios, it is difficult for individuals to grasp full information about the new spaces (new job, habitat, etc.). Therefore, we assume that nodes cannot acquire the complete information about the new position before migrate to the targeted location (θ is large). Parameter θ is set within the range of $[0, 100]$. When $\theta = 0$, $Pro(M) = 1/2$, once the individuals decide to escape, the migration is independent of payoff differences, they will migrate with probability $1/2$. If $\theta = 100$, more accurate information of the target position can be acquired. There are two cases: i) $\pi_i > \pi_{aim}$, $Pro(M) \to 0$ (almost do not migrate); ii) $\pi_i < \pi_{aim}$, $Pro(M) \to 1$ (migrate with high probability).

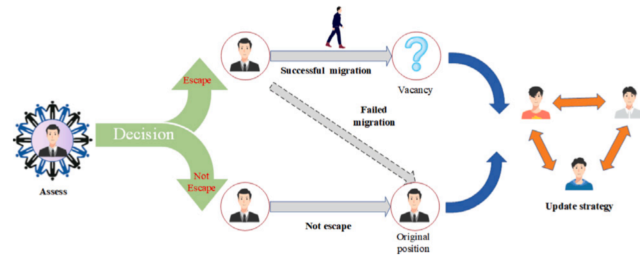


Fig. 2. The N-player trust game with environment-benefit-driven migration mechanism. At time t, an individual i and all neighbors participate the N-player game (excluding vacancies).
Each agent evaluates the current environment after the game to decide whether to escape. If they decide to escape, then calculate the probability of successful escape by estimating the obtained payoff at the selected vacant position. After all individuals complete the migrations, they update strategies.

Fig. 2 illustrates the migration mechanism. The individuals choose not to migrate, or migrate after evaluating the new environment. Then, individuals who achieve the condition to migrate will move to new locations. Particularly, considering the diversification of new information and the convenience of transportation, suppose that the migration area covers the whole network, allowing the agents' moves to all unoccupied sites. When all individuals decide to migrate (or not migrate), strategy updates will take place.

2.4. Strategy update rule

After the migration, all agents start to update strategies by interacting with the new neighbors after the migration of the social network, based on their current payoff (before the migration). This strategy update rule conforms to the classical evolution mechanism combining the neighborhood-based imitation and global information acquisition in the social learning process. The updating of an agent's behavior follows the Fermi conditional imitation rule: a random neighbor is chosen, and the focal agent conditionally imitates the neighbor's action in the current game round, proportional to their payoff difference. The probability of imitating a randomly selected neighbor is calculated by the Fermi rule shown below:

$$Pro_{S_i \leftarrow S_j} = \frac{1}{1 + \exp\left[\frac{(\pi_i - \pi_j)}{\beta}\right]} \tag{5}$$

where S_i and S_j respectively represent the strategies of the focal individual and the selected neighbor in the current round; π_i and π_j denote their payoffs obtained at the current game round. Parameter β is related to the traditional intensity of selection of the Fermi rule, which characterizes irrational degree in individuals' decision-making behaviors.

To sum the above four aspects, the adaptive environment-benefit-driven migration focuses on whether individuals migrate and to which position they would migrate. Except for the payoff optimization, our model takes individuals' perception of the surrounding environment into account. There are many practical applications for this setting,

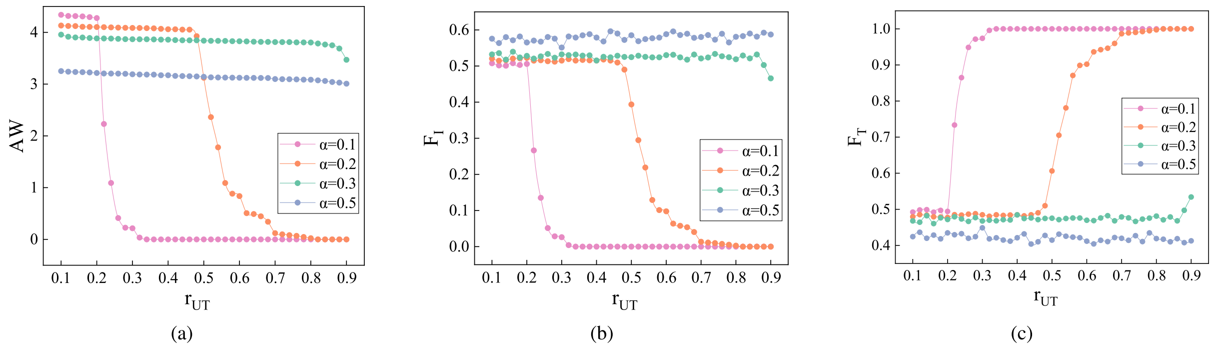


Fig. 3. Given a lattice network consists of 1024 nodes with different values of α, evolutionary curves of global average wealth AW and the average proportions of investors F_I and trustworthy trustees F_T as functions of the dilemma strength r_{UT}. The results for AW, strategies F_I and F_T correspond to panels (*a*), (*b*) and (*c*). For different settings of α, the value of r_{UT} is adjusted between the range of 0.1 to 0.9 with increments of 0.02. Other parameter settings: $t_v = 1$, $R_T = 6$, $\beta = 0.1$, $\theta = 100$. Initial proportions: $F_I = 0.3$, $F_T = 0.3$, and $F_U = 0.4$.

such as job hopping and biological migration, where individuals unsatisfied with current environment will seek new positions/habitats [59, 60]. The crisis-awareness escape and benefit-driven migration equipped with information asymmetry consider individual's ability to perceive environmental information, which is conducive to solve the above questions in social or economic systems.

3. Theoretical analysis

We assume that the multi-player trust game is played within an infinitely large, well-mixed population, which can modeled by replicator dynamics. Accordingly, the payoffs of investors π_I, trustworthy trustees π_T, and untrustworthy trustees π_U can be respectively written as

$$\pi_I = \begin{cases} \frac{R_T N_T}{N-N_I-1} t_v - t_v, & \text{if } N_I \neq N-1 \\ 0, & \text{otherwise} \end{cases}$$
$$\pi_T = \begin{cases} \frac{R_T N_I}{N-N_I} t_v, & \text{if } N_I \neq N \\ 0, & \text{otherwise} \end{cases} \tag{6}$$
$$\pi_U = \begin{cases} \frac{R_U N_I}{N-N_I} t_v, & \text{if } N_I \neq N \\ 0, & \text{otherwise} \end{cases}$$

where N_I, N_T and N_U represent the number of investors, trustworthy trustees and untrustworthy trustees among other $N-1$ co-players in the group, respectively.

In the large infinite population, x is the probability of an individual choosing strategy I; y is the frequency of strategy T; and z is the frequency of choosing strategy U. With the expected payoff f_j for strategy j ($j = I, T, U$) and $\phi = x f_I + y f_T + z f_U$, evolution of trust can be characterized by the replicator dynamics equation:

$$\begin{cases} \dot{x} = x(f_I - \phi) \\ \dot{y} = y(f_T - \phi) \\ \dot{z} = z(f_U - \phi) \end{cases}. \tag{7}$$

To approximate the migration process, we then consider following adjustments on the distributions of the three strategies. That is, introducing the vacancy rate α, the actual proportions of strategies in the population are denoted by $\hat{x} = (1-\alpha)x$, $\hat{y} = (1-\alpha)y$, $\hat{z} = (1-\alpha)z$; relevant payoffs are $\hat{f}_I$, $\hat{f}_T$, $\hat{f}_U$. Dynamic equation could be rewritten as follows in equation:

$$\begin{cases} \dot{\hat{x}} = \hat{x}[(1-\hat{x})(\hat{f}_I - \hat{f}_T) + \hat{z}(\hat{f}_T - \hat{f}_U) + \alpha \hat{f}_T] \\ \dot{\hat{z}} = \hat{z}[(1-\hat{z})(\hat{f}_U - \hat{f}_T) + \hat{x}(\hat{f}_T - \hat{f}_I) + \alpha \hat{f}_T] \end{cases}. \tag{8}$$

Specifically, the expected payoff of strategy I is calculated as in Eq. (9):

$$\begin{aligned} \hat{f}_I = & \sum_{N_I=0}^{N-1} \sum_{N_T=0}^{N-1-N_I} \binom{N-1}{N_I} \binom{N-1-N_I}{N_T} \\ & \times \hat{x}^{N_I} \hat{y}^{N_T} \hat{z}^{N-1-N_I-N_T} \pi_I \\ = & t_v\left[\frac{R_T(1-\hat{x}-\hat{z})}{1-\hat{x}} - 1\right](1-\hat{x}^{N-1}). \end{aligned} \tag{9}$$

In the same way, we can obtain payoff of strategy T and strategy U from Eqs. (10) and (11), respectively.

$$\hat{f}_T = \frac{R_T t_v \hat{x}}{1-\hat{x}}(1-\hat{x}^{N-1}) \tag{10}$$

$$\hat{f}_U = \frac{(1+r_{UT}) R_T t_v \hat{x}}{1-\hat{x}}(1-\hat{x}^{N-1}). \tag{11}$$

Equilibria of the gaming system can be obtained by assuming $\dot{\hat{x}} = \dot{\hat{y}} = \dot{\hat{z}} = 0$. Solving Eq. (8), we deduce the border equilibria for the networked system: $(x^*, y^*, z^*) = (1,0,0)$, $(0,1,0)$, $(0,0,1)$, $(0, \frac{\alpha \hat{f}_U}{(1-\alpha)(\hat{f}_T - \hat{f}_U)}, 1 - \frac{\alpha \hat{f}_U}{(1-\alpha)(\hat{f}_T - \hat{f}_U)})$, $(\frac{1}{1-\alpha} - \frac{\hat{f}_U}{\hat{f}_I - \hat{f}_U}, 0, \frac{\hat{f}_U - \alpha \hat{f}_I}{\hat{f}_I - \hat{f}_U})$, $(\frac{1}{1-\alpha} - \frac{\alpha \hat{f}_T}{(1-\alpha)(\hat{f}_T - \hat{f}_I)}, \frac{\alpha \hat{f}_I}{(1-\alpha)(\hat{f}_T - \hat{f}_I)}, 0)$; and the possible interior equilibria solved by: $(x^*, y^*, z^*) = \{(x,y,z) | \hat{f}_I = \hat{f}_U\}$, $(x^*, y^*, z^*) = \{(x,y,z) | \hat{f}_I = \hat{f}_T\}$ and $(x^*, y^*, z^*) = \{(x,y,z) | \hat{f}_I = \hat{f}_T = \hat{f}_U\}$. With Eqs. (7) and (9)–(11), evolution of investors and trustworthy trustees would be inhibited by larger f_U which is positively correlated with r_{UT}. For the influence of vacancy rate α, consider the equilibrium of coexisting I and T individuals, medium vacancy rate promotes the coexistence of I and T strategies, which give rise to higher trust level.

4. Simulation results

To further explore the strategy evolution on network, we perform Monte Carlo simulations. Algorithm 1 provides the details for the simulation experiment, where all individuals simultaneously participating in a decision-making process, but migrate asynchronously. To ensure accuracy, each steady state of the network game is obtained by the maximum time step of 10,000; all simulation experiments are repeated by 20 independent Monte Carlo runs; and the network size is $M = 1024$. For the game parameters in the simulation, the default payoff rate for trustworthy trustees is set to be $R_T = 6$; the cost of investment for investors is 1; the dilemma intensity $r_{UT} = 0.66$ is chosen to be larger than the value adopted in literature [28] to highlight the robustness of the migration mechanism. With $r_{UT} = 0.66$, the payoff rate for untrustworthy trustees is calculated by $R_U = 6 \times (1 + 0.66) = 9.96$.

4.1. Global average wealth and dilemma intensity

(1) Global average wealth. With the migration mechanism, payoff calculation will naturally skip the empty nodes who do not participate in the games. Therefore, we employ the average payoff AW: the total payoff of the network averaged by all participants. In the steady state of the network, the average payoff can be used to characterize the level of trust and reciprocity. As shown in Eq. (12), M represents the total number of nodes in the social network and α denotes the vacancy rate. Payoff AW is calculated by

$$AW = \frac{\sum_{i=1}^{M(1-\alpha)} \pi_i}{M(1-\alpha)}. \tag{12}$$

Algorithm 1: Strategy updates and migration process of the trust game

```
Initialize social network, all agents
Assign (M ∗ α) vacancies to nodes in the network
Assign M ∗ (1 − α) non-vacant nodes in the network
for each agent i ∈ {1, M(1 − α)} do
    Employ a strategy S_i ∈ {I, T, U}
end
for time step t ∈ [1, T] do
    for each agent i ∈ {1, M(1 − α)} do
        Calculate the payoff π_i
    end
    for each agent i ∈ {1, M(1 − α)} do
        Calculate the Escape Probability Pro(E)
        Take a random number P ∈ [0, 1]
        if P < Pro(E) then
            Select a vacant position randomly
            Conduct a virtual game
            Calculate migration probability Pro(M)
            Take a random number Q ∈ [0, 1]
            if Q < Pro(M) then
                Move to new position
            end
        end
    end
    for each agent i ∈ {1, M(1 − α)} do
        Update strategy
    end
end
```

We study evolutionary game dynamics on regular lattice network with 1024 nodes by investigating values of AW, F_I and F_T with an increase of dilemma strength (r_{UT}) ranges from 0.1 to 0.9, as illustrated in Fig. 3. For a higher dilemma intensity, the average payoff AW decreases significantly. As depicted in the panel (a), higher vacancy rate corresponds to higher ability or robust of the individuals to survive more severe cooperative dilemma. Lower density of individuals means that there are more available vacancies for the migrants; the changing connecting topology can make individuals playing different strategies mixed more evenly.

(2) Influence of the dilemma intensity. The adaptive environment-benefit-driven migration mechanism stipulates that all individuals with the escape awareness are benefit-pursuing, under which a stable alliance between investors and reliable trustees can be established. With the escape mechanism, neighboring positions with altruistic strategies become more favorable, hence the untrustworthy trustees will be isolated. This explains why the trust behaviors can evolve among the benefit-oriented, selfish and rational populations. By taking the migration mechanism into consideration, the increase of the dilemma strength r_{UT} flattens the reduction of the strategy U, especially for lower vacancy cases. When the dilemma strength is high, untrustworthy trustees inhibit the evolution of investors; although the migration suppresses (even at a low level) untrustworthy trustees, lower vacancy rate (with more untrustworthy trustees) causes investors decrease. When the fraction of investors in the network decreases to 0, that is, the network merely consist of trustworthy trustees and untrustworthy trustees, the migration mechanism continues to inhibit the evolution of untrustworthy trustees; the network eventually evolves to a state composed of full trustworthy trustees. Despite the trustworthy trustee is altruistic, lack of investors leads to $AW = 0$, which results in a lower trust level.

Although the increase of r_{UT} promotes the evolution of trustworthy trustees in some special cases ($\alpha = 0.1, 0.2$), the average payoff decreases along with the increase of the r_{UT}, as a result of the decrease of

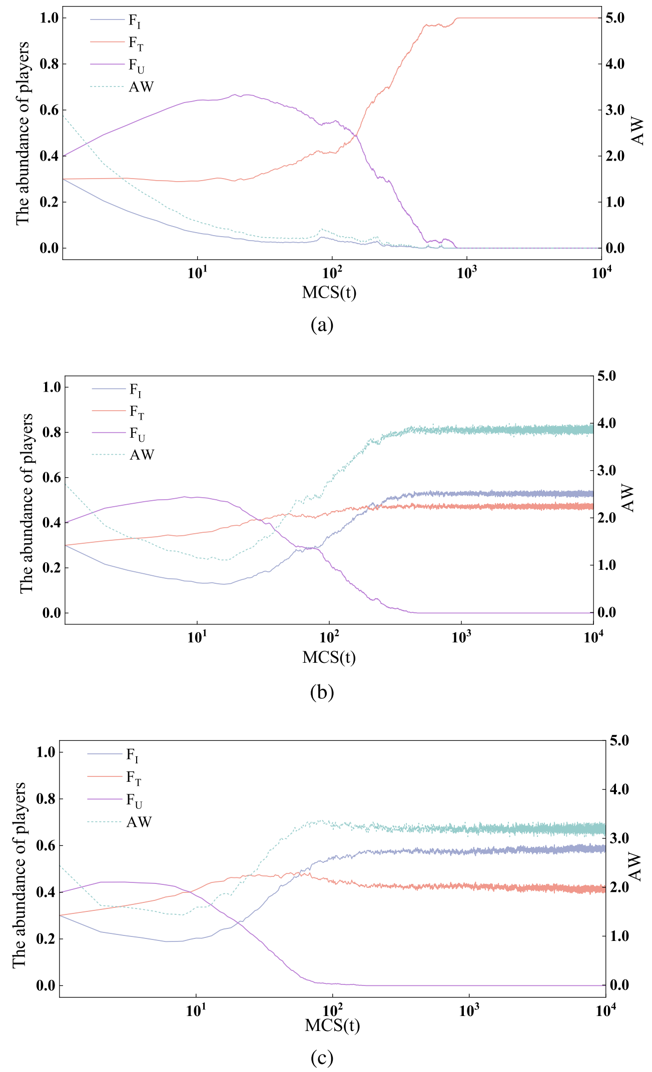


Fig. 4. On regular lattice with $L \times L = 1024$, evolution curves of the three strategies (I, T and U) and the average wealth AW are presented given different α. For the double Y-axis: left axis is the abundance of the three players I, T, U; right axis describes AW. Blue, orange, and purple solid lines denote F_I, F_T and F_U; the cyan dashed line is AW. The sub-graphs (a), (b) and (c) correspond to vacancy rates of $\alpha = 0.1$, $\alpha = 0.3$ and $\alpha = 0.5$, respectively. Other parameters: $\beta = 0.1$, $\theta = 100$, $r_{UT} = 0.66$, $R_T = 6$, $t_v = 1$. Initial distributions of the three strategies in the network are: $F_I = 0.3$, $F_T = 0.3$ and $F_U = 0.4$.

investors. To be specific, as depicted in Fig. 3, panel (a), at low dilemma strength ($r_{UT} < 0.2$), a lower vacancy rate corresponds to higher global average payoff. When $\alpha = 0.1$, the global average payoff approximately equals to 4.3. If the intensity of dilemma is low, investors can get chances to survive. When the vacancy rate α is set to be 0.1 and 0.2, a significant reduction on the trust level will be observed if the dilemma strength increases to 0.2 and 0.46, respectively. To sum up, with the environment-benefit-driven migration mechanism, influence of the dilemma intensity includes: i) larger r_{UT} will lead to the reduction of the average payoff AW; ii) higher dilemma intensity level means that the situation is unfavorable for evolution of investors (especially for cases with low vacancy rates); iii) higher dilemma intensity level promotes the evolution of trustworthy trustees.

4.2. Discussion of the vacancy rate

By introducing the migration mechanism and the vacancy rate, we can investigate how the population density affect the evolution of trust behaviors. Depending on the exact value of vacancy rate, there are three real-life situations: the evolution of trust behaviors in large cities (low vacancy rate), medium-sized cities (medium vacancy rate) and rural areas (large vacancy rate).

(1) Evolution curves and convergence time. We explore how the trust level be affected by different vacancy rates α, from the perspective of the system evolution. According to Fig. 3, we adopt larger dilemma strength $r_{UT} = 0.66$ to show different outcomes of the strategy evolution under vacancy rates of $\alpha = 0.1, 0.3, 0.5$. The evolutionary process of the network is illustrated in Fig. 4 where all results on the curves are averaged over 50 independent runs, with the total evolution time steps of 10,000. In Fig. 4, panel (a), even the self-interest-driven migration mechanism has been introduced, when the vacancy rates are extremely low, untrustworthy trustees rapidly reproduce in the early stages of evolution. The prosperity of untrustworthy trustees leads to investment failure and reduces investors' payoffs, thus inhibits evolution of investors.

Notably, in Fig. 4, panel (a), $\alpha = 0.1$ indicates that in large cities, the untrustworthy behaviors are largely inhibited, while trust is difficult to be established due to the lack of investors. During evolutionary process, though there are small growth for F_I, each happens after small decline of the untrustworthy trustees F_U. When the vacancy rate is low, such minor increment is insufficient to form a stable alliance between I- and T-individuals. Whereas, under the migration mechanism, untrustworthy trustees U will be suppressed, since rational investors will escape from an unfavorable position, leading to small payoffs of U-individuals. Eventually, untrustworthy trustees are eliminated and trustworthy trustees dominate the whole population.

Then, we pay attention to the evolution of trust behaviors in the moderately densely populated environment, which stands for the medium-sized cities or biological populations. As illustrated in Fig. 4, panel (b), the vacancy rate α is increased to 0.3. Different from (a), when the population becomes sparse with more vacant positions, a considerable number of investors can successfully get rid of untrustworthy trustees and reach a more suitable investment environment. Thus a stable alliance between trustworthy trustees and investors forms over time, which in turn resist the invasion of untrustworthy trustees. Apparently, sparse populations provide individuals with more vacancies to escape untrustworthy individuals. Hence migration plays a critical role in fostering trustworthy behaviors and an interesting phenomenon is found: medium sparse population environment is more conducive to building trust between individuals.

When the vacancy rate becomes large, which corresponds to the real-life scenarios: the city (or biological habitat) contains small number of individuals. As depicted in panel (c) with $\alpha = 0.5$, the network converges to the steady state consisting of investors and trustworthy trustees faster and collects smaller overall average wealth AW than panel (b). Above result indicates that small cities stabilizes faster; however, the level of trust is lower than the medium-sized city (also reflected by the decreased total average payoff).

According to the system time evolution curves, effect of the vacancy rate can be summarized by three aspects: the migration mechanism with vacancy promotes trust; higher vacancy rate accelerates the system convergence process; higher vacancy rate leads to reduction in the public welfare (limit the overall collaboration level). In the practical applications, maintaining an appropriate population size (moderate group size) can effectively establish trust and acquire more public welfare.

(2) Migration process on square lattice. To figure out how the vacancy and migration affect individuals' decision-making behaviors from a microscopic perspective, we simulate the strategy dynamics on a square lattice with $L = 32$ and obtain the evolutionary snapshots of strategies I, T and U at different time steps, as illustrated in Fig. 5. In Fig. 5, significant differences between the evolutionary dynamics of strategies I, T and U can be observed in cases of high ($\alpha = 0.1$), medium ($\alpha = 0.3$) and low population densities ($\alpha = 0.5$).

In the first row $\alpha = 0.1$, the density of game players in the network is high, which facilitates the untrustworthy trustees in the early stages of evolution (e.g., MCS=50). Since there are large number of untrustworthy trustees, investors face great risks and receive lower returns. Thus, investors are dissatisfied with their current states and tend to migrate. In fact, dense population means that getting rid of the situation surrounded by a large number of untrustworthy trustees is extremely difficult for investors; we come to time step 100, where trustees T and U coexist and the trustee U dominate. In the following, due to the escape mechanism stipulated by the adaptive environment-benefit-driven mechanism and the Fermi rule (5), only trustworthy trustees survive ultimately (MCS=500). In scenarios without untrustworthy trustee, the migration will stop; and the network reaches a steady state with pure T trustees. To sum up, even with the migration mechanism, when the network is densely populated, the evolution of the investors will be largely inhibited.

The medium vacancy scenario ($\alpha = 0.3$) is illustrated in the second row of Fig. 5, which means that there exist more potential vacant positions for the migration activity. The increased vacancy rate provides investors more opportunities to get rid of the unfavorable relationships with U trustees under the adaptive environment-benefit-driven migration mechanism. In the case of MCS=100, there is a significant growth in the number of trustworthy trustees, which creates a reliable environment for the future investments of I individuals. As a result, the investors and trustworthy trustees will forge a stable alliance (MCS=500). As a consequence, untrustworthy trustees are isolated, which in turn diminishes individuals' need to migrate. The two sub-graphs MCS=500 and MCS=5000 in the second row shows the co-evolutionary results of strategies and network topology: migration stops (fixed distribution of vacancies); and there is an equilibrium with stable coexistence of investors and trustworthy trustees.

The sparse case $\alpha = 0.5$ is illustrated in the third row of Fig. 5. We can observe similar the evolutionary process to $\alpha = 0.3$ scenario: untrustworthy trustees gradually disappear and trust behavior get promoted. However, in sparsely populated areas (high vacancy rates), there are small clusters of single strategy type, which reduces the total average payoff and suppress the evolution of trust. In particular, at MCS=5000, there still exist isolated nodes. Owing to the large number of vacancies, the probability to find a more suitable gaming environment that has more I-players (or T-players) decreases, so the population converges more quickly (conforms to Fig. 4, (c)). Although there is a stable coexistence of the two strategies I and T in the network, the game scenario with large number of empty positions suppresses the formation of strategy pair of $I - T$, thus reduce the network average payoff.

(3) Comparison of theoretical and simulation results. Based on above simulation results, we find that trust level can be improved when the numbers of I and T strategies are consistent and: (i) under medium vacancy rates (e.g., $\alpha = 0.3$) and dilemma intensity (e.g., $0.2 < r_{UT} < 0.5$); (ii) under low vacancy rates (e.g., $\alpha = 0.1$) and intensity (e.g., $r_{UT} \leq 0.2$). This conclusion conforms to the theoretical results of Eqs. (9), (10) and (11). Since $r_{UT} \in (0, 1)$ means $\hat{f}_T < \hat{f}_U$, the trustworthy trustee is at a disadvantage in competition with untrustworthy trustee. Therefore, we can only seek the condition for investor winning the game of untrustworthy trustee: $\hat{f}_I > \hat{f}_U$. Assuming that proportion of U is low, i.e, $z \approx 0$, the inequality becomes to following equation:

$$x < \frac{R_T - 1}{(1-\alpha)(r_{UT}+2)R_T - (1-\alpha)}. \tag{13}$$

Based on this, there are some qualitative conclusions. When α is large, e.g., $\alpha > 1 - \frac{1}{2+r_{UT}}$, we have $(1-\alpha)(2+r_{UT}) < 1$, which indicates that R_T largely affects the fraction of I. If α is small, e.g., $\alpha < 1 - \frac{1}{1+r_{UT}}$, the effect of coefficient $(1-\alpha)(2+r_{UT})$ is more significant, showing that smaller r_{UT} facilitates the evolution of I. That is, given certain ranges of α and r_{UT}, the result suggests that as α increases, r_{UT} also increases. As a theoretical explanation for above middle vacancy rate effect, the influence factor for parameter α is multiple: if $z > 0$, the system dynamics can only be predicted by studying the interior equilibria, which means the nonlinear relationships between α and I (or T).

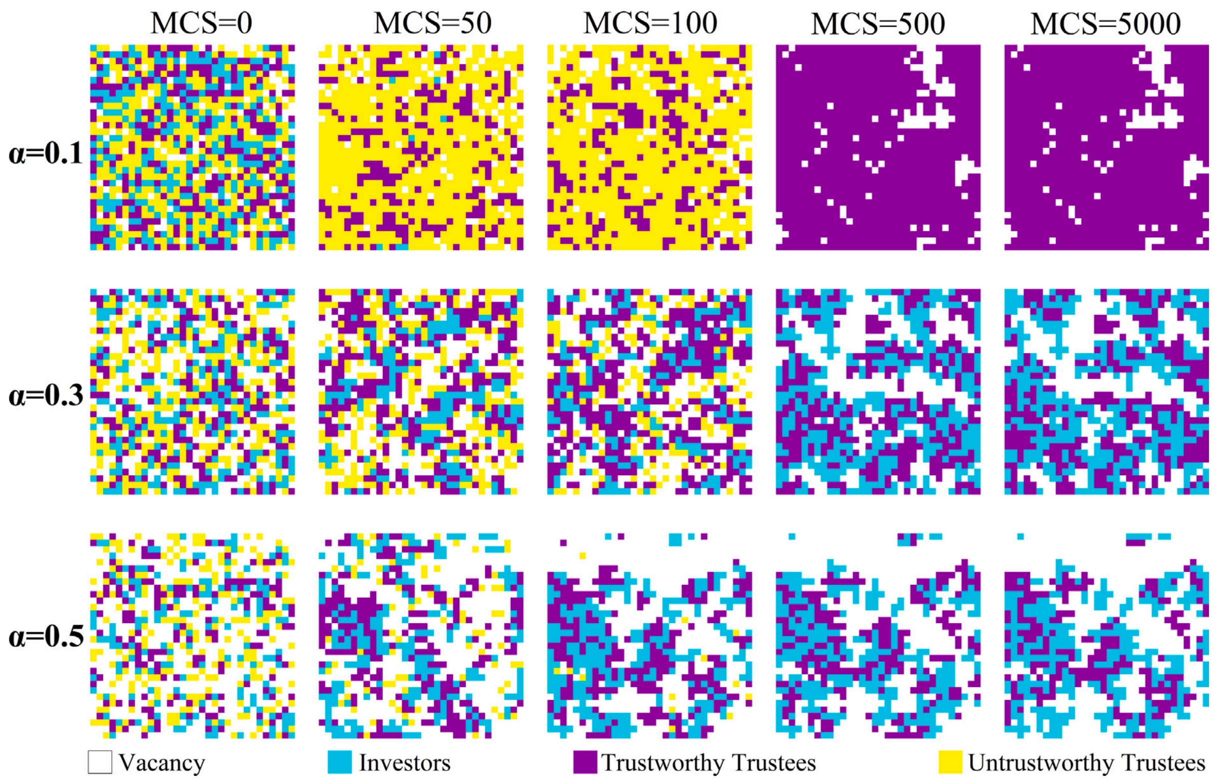


Fig. 5. Snapshots of strategies under the adaptive environment-benefit-driven migration mechanism with different vacancy rates α and dilemma strength $r_{UT} = 0.66$. Rows correspond to the vacancy rates α of 0.1, 0.3 and 0.5, from top to bottom. The columns illustrate different time steps: 0, 50, 100, 500 and 5000, from left to right. In all panels, white represents vacant positions in the network, cyan represents investors (strategy I), purple represents trustworthy trustees (strategy T), and yellow represents untrustworthy trustees (strategy U). Other parameters are consistent with those of Fig. 3.

4.3. Effect of initial distributions

To investigate the impact of initial distribution of strategies I, T and U, we perform simulations and relevant results are illustrated in Fig. 6. Horizontal and vertical axes represent the initial frequencies of trustworthy trustees and investors. We study the equilibrium average wealth AW^*, proportion of investors F_I^*, and proportion of trustworthy trustees F_T^*, under vacancy rate settings $\alpha = 0.1$, $\alpha = 0.3$ and $\alpha = 0.5$.

In the case of $\alpha = 0.1$ (first row of Fig. 6), only when the untrustworthy trustees F_U start from low initial fraction does the average wealth AW^* be in the non-zero state. This suggests that when the vacancy rate α is at a low level (dense populations), the introduction of the environment-benefit-driven migration is not enough to promote trust level. This is because that update sequence in the asynchronous migration will affect who can move to the available empty position. It is possible that the advantageous positions be occupied by early migrants; nodes who migrate later are unable to get away from the untrustworthy trustees neighbors, even they are unsatisfied with the current environment, so investors vanish.

Then we focus on the cases with higher vacancy rate $\alpha = 0.3$. For the special equilibrium that the untrustworthy trustee is eliminated, this does not mean that the group has high public benefit. For example, when $\alpha = 0.3$, $F_I \leq 0.02$, $F_I^* = 0$, $F_T^* = 1$, the average wealth $AW^* = 0$ and trust cannot be established in this case. When the vacancy rate α is 0.3 (second row of Fig. 6), even if the initial proportion of investors F_I is small (e.g., $F_I = 0.2$), when the proportion of trustworthy trustees F_T is greater than 0.25, investors form an alliance with trustworthy trustees. This demonstrates that the adaptive environment-benefit-driven migration mechanism has strong robustness and can promote trust for most initial distribution conditions of strategies I, T and U.

As the vacancy rate increases to $\alpha = 0.5$ (third row of Fig. 6), the migration mechanism can also be able to facilitate the trust alliance $I-T$ for an unfavorable environment. However, the average wealth for the higher vacancy rate case is lower than the medium vacancy rate ($\alpha = 0.3$) case, over the initial distribution range of $F_T > 0.2$. Thus, the effectiveness for the migration mechanism on promoting trust is robust to initial strategy distributions, especially for medium vacancy rate case.

4.4. Influence of network topology

To validate the robustness of the networked games, we extend our model to scale-free networks and compare the differences in trust levels between these two different network typologies (as shown in Fig. 7). The scale-free (SF) network is constructed using the Barabasi–Albert algorithm [36]. (1) Growth: starting from a connected network of m_0 vertices and M_0 edges, each time a new vertex is added and connected to m existing vertices ($m \leq m_0$). (2) Priority Connection: probability of generating an edge between the new vertex and an existing vertex i is proportional to degree of i. (3) Iteration: after time step t, the SF network with $t + m_0$ vertices and $mt + M_0$ edges can be obtained. For density of the generated network, here we choose the parameter $m = 3$ and obtain average degree of $\langle k \rangle \approx 4$ to consist with results on lattice network (similar to the network model in [28]).

In the scale-free network, it can be observed that when the vacancy rate α reached 0.3, the environment-benefit-driven migration mechanism promotes trust behaviors and offers a high level average wealth AW, approximately to 3.24. Notably, there exists a significant difference in trust levels as compared with the lattice network: when the vacancy rate $\alpha < 0.5$, the trust level on the SF network is significantly lower than the lattice. Moreover, the conclusion that medium vacancy rate (e.g., $\alpha = 0.3$) is most conducive to trust evolution still be true for the SF network.

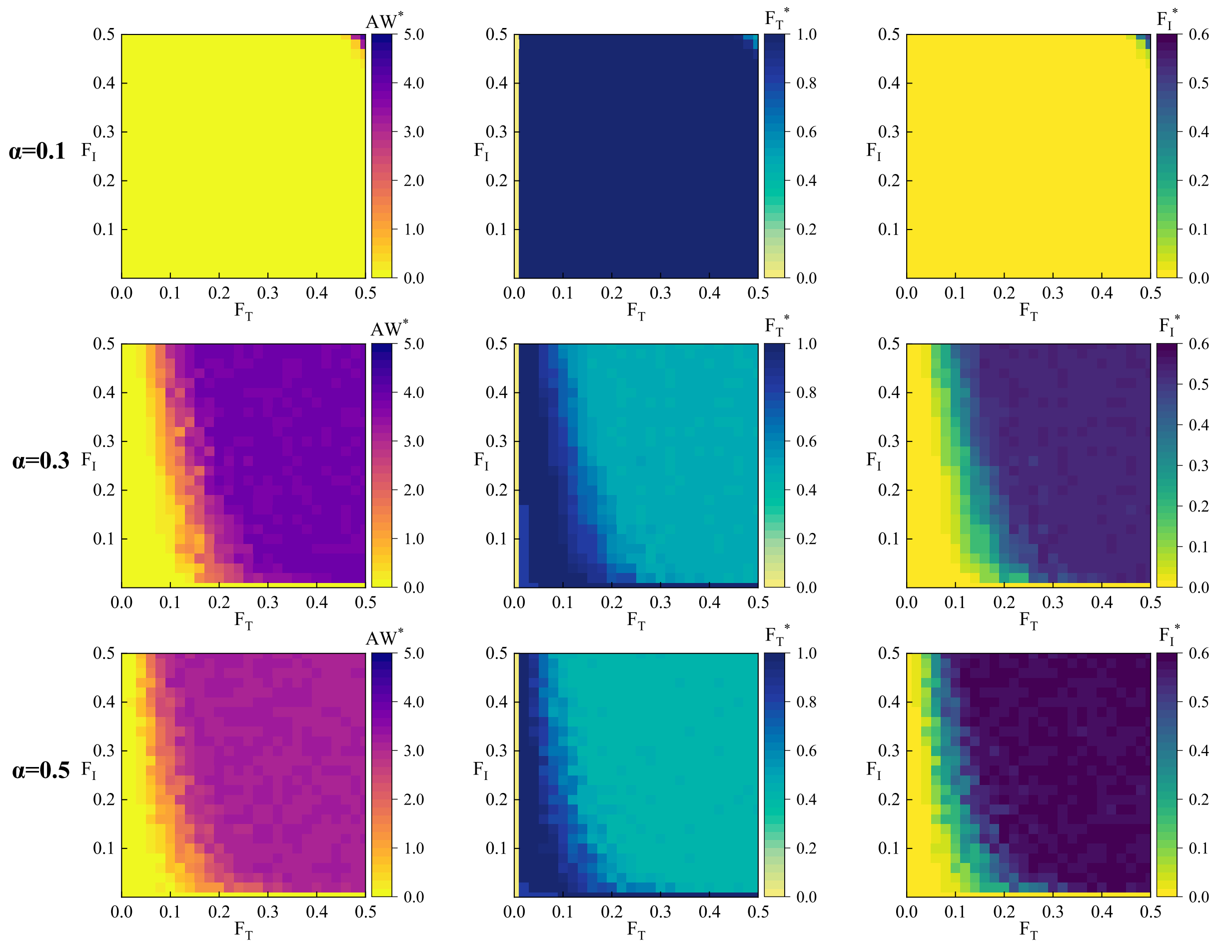


Fig. 6. Analysis of how initial distributions of the three strategies F_I, F_T, F_U affect the evolution of the trust in a lattice network with $L \times L = 1024$. The three columns represent equilibrium values of average wealth (AW^*), equilibrium proportions of trustworthy trustees (F_T^*) and investors (F_I^*), respectively. Besides, value of the three quantities are investigated under different vacancy rates of $\alpha = 0.1$ (the first line), $\alpha = 0.3$ (the second line) and $\alpha = 0.5$ (the third line). Each data point is averaged by 20 independent Monte Carlo simulations, where each simulation running for 10,000 steps. The horizontal axis (F_I) and vertical axis (F_T) range from 0 to 0.5, with an increment of 0.02. Other parameters are set as follows: $\beta = 0.1$, $\theta = 100$, $r_{UT} = 0.66$, $R_T = 6$, $t_v = 1$.

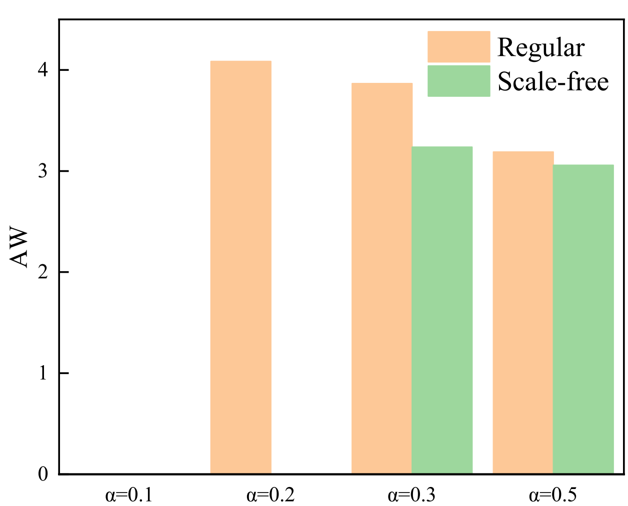
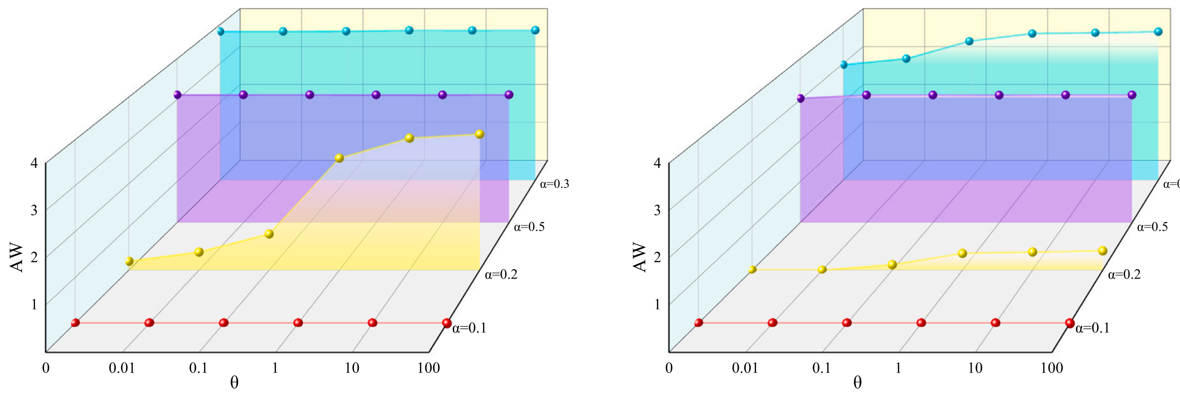


Fig. 7. Value of the average wealth AW in scale-free and regular networks with the migration mechanism. Parameters are set to be: $\beta = 0.1$, $\theta = 100$, $R_T = 6$, $r_{UT} = 0.33$, $k = 0.1$; and the initial proportions of the three strategies are $F_I = 0.3$, $F_T = 0.3$, and $F_U = 0.4$.

4.5. Impact of the information asymmetry

Influence of information θ is discussed under different vacancy rates: $\alpha = 0.1, 0.2, 0.3, 0.5$. As shown in Fig. 8, panel (a), the dilemma strength r_{UT} is set to 0.5, while in panel (b), there is a higher dilemma strength $r_{UT} = 0.66$, other parameters (e.g., t_v, R_T) adopt the same value as the previous scenarios. Note that for the sake of clarity, in Fig. 8, the order of cases $\alpha = 0.3$ and $\alpha = 0.5$ has been exchanged. In panel (a) with $r_{UT} = 0.5$, similar conclusion can be observed for $\alpha = 0.1$: the benefit-driven migration is ineffective for θ belongs to the range of $[0, 100]$ (AW is 0). When the vacancy rate increases to $\alpha = 0.2$, the information accuracy start to play an important role: as θ increases (more accurate information of target positions), the trust level will be positively correlated with parameter θ. However, when $\theta > 10$, the increase of θ almost have no influence on the trust levels.

For panel (b), given larger dilemma strength value, in the case of $\alpha = 0.2$, trust level facing significant decrease, as compared with panel (a) (consistent with the conclusion in Fig. 3). When the vacancy rate α reaches 0.3 and 0.5, even with $\theta = 0$, random migration still promote trust; and θ has almost no effect on the final result. When $\alpha = 0.3$ and $r_{UT} = 0.66$, trust levels become sensitive to θ in the range from 0 to 1. Hence, both dilemma strength r_{UT} and vacancy rate α shape the network environment collectively. With the benefit-driven migration, the evolution of trust can be largely promoted, especially on networks with low dilemma intensity and medium density.



(a) (b)

Fig. 8. Impact of the information accuracy θ of target positions on trust levels under varying vacancy rates α is investigated. The values of θ are chosen as 0, 0.01, 0.1, 1, 10 and 100, while the vacancy rates α are set to 0.1, 0.2, 0.3 and 0.5, respectively. The panel (*a*) corresponds to the strength of the dilemma of $r_{UT} = 0.5$, while panel (*b*) represents $r_{UT} = 0.66$, with all other parameters be constant: $\beta = 0.1$, $t_v = 1$, $R_T = 6$, the initial strategy proportions $F_I = 0.3$, $F_T = 0.3$, and $F_U = 0.4$. The lattice network consists of $L \times L = 1024$ nodes.

Above results could be used to analyze the evolution of trust behaviors in urban and rural areas, where urban/rural area corresponds to lower/higher vacancy ratio case. The dilemma intensity represents the social environment. In large, densely populated cities, the level of trust is more vulnerable, that is, largely influenced by the social environment. Although larger vacancy ratios (i.e., medium-sized city, rural areas) bring more stable level of trust, the sparsely populated area (extremely large vacancy rate) is unable to maintain high global average wealth. To sum up, it is the medium-sized city that can bring people a sustained and high level of trust to maintain the global revenue. At this point, density of population is an important factor affecting the evolution of trust, where the medium-sized city may be the optimal result for job hopping and habitat seeking.

5. Conclusions and future works

Trust and being trusted among self-served individuals is the foundation for the long-term maintenance of all relationships. We proposed the adaptive environment-benefit-driven migration mechanism by combining the inherent instincts of three-strategy of agents: crisis-awareness escape process, environment-benefit migration, and strategy updating. We analyzed the migration mechanism in the context of the N-player trust game. Theoretical analysis and simulation experiments were conducted based on different vacancy rates α, dilemma strengths r_{UT}, initial distributions of F_I, F_T, F_U and the accuracy of environmental information θ. Main results are summarized as follows:

1. The adaptive environment-benefit-driven migration mechanism facilitates the evolution of trust and enhances global average wealth in networked populations.
2. There exists an optimal medium vacancy α for the migration mechanism facilitates the alliances between I and T individuals, which offers most suitable environment for trust.
3. Simulation results on scale-free networks and different initial states verified the robustness of the migration mechanism on promoting trust behaviors.

Future researches can consider more realistic factors: cost of migration, heterogeneous population density, effect of escape on agents' reputations and social norms during the migration. Besides, taking the self-learning mechanisms (e.g., reinforcement learning [61,62]) into the migration and strategy update processes is another important direction.

CRediT authorship contribution statement

Yuying Zhu: Writing – original draft, Visualization, Software, Methodology, Funding acquisition, Conceptualization. **Wenbo Li:** Visualization, Software, Methodology. **Chengyi Xia:** Writing – review & editing, Methodology, Funding acquisition, Conceptualization. **Manuel Chica:** Writing – review & editing, Funding acquisition, Conceptualization.

Declaration of competing interest

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

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Data availability

No data was used for the research described in the article.

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