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An evolutionary game model with reputation threshold and reputation score to promote trust in the sharing economy

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This paper presents an evolutionary trust game model that sets a reputation threshold and implements a reward mechanism for participants whose individual reputation scores are above this threshold; conversely, a punishment mechanism is applied to those whose scores are below it, to investigate the formation of trust in the sharing economy. By conducting simulation experiments, we present the dynamic evolution of the proportion of four types of participants as the reputation threshold increases under five different initial scenarios. Additionally, we provide heatmaps to detailedly show the strategy and reputation score evolution of 10,000 participants over time steps when the reputation threshold is low, moderate, and high. Our results indicate that when the initial proportion of trustworthy participants is equal to that of untrustworthy participants, a higher reputation threshold facilitates the establishment of trust. Even if the initial proportion of trustworthy participants is lower than that of untrustworthy participants, there still exist some appropriate reputation thresholds that can promote the total proportion of trustworthy participants to reach 100% eventually. Furthermore, the heatmaps of strategy evolution indicate that a higher reputation threshold also results in untrustworthy participants, whether providers or consumers, eventually forming clusters of the same strategy, making it impossible for them to engage in transactions with their neighbors, thereby reducing the occurrence of untrustworthy transactions. In contrast, the two trustworthy strategies are found to be evenly interdependent.Additionally, it is observed that a higher reputation threshold gradually narrows the gap between the proportions of trustworthy providers and consumers during the evolution process, potentially reducing it to zero, which is conducive to achieving supply–demand balance.

Keywords Evolutionary game theory, Reputation threshold, Reward and punishment mechanism, Evolutionary of trust, Square lattice network

The sharing economy comprises a suite of software platforms that act as an intermediary to facilitate consumer to consumer (C2C) transactions of assets between private individuals[1,2]. Consumers share access to private resources with other users. In contrast to the more traditional for of C2C commerce, such transactions provide new opportunities for private individuals to:

(1) Act as providers and monetises their private assets in multiple transactions without loss of ownership;
(2) Act as consumers and get access to a broader range of rescouces, potentially at lower prices than by conventional modes of consumption[2–5].

In the sharing economy, the users can interchangeable provide or consume resources, or switch roles between a provide and a consumer. This flexibility enables the sharing economy to more efficiently match supply and demand, achieving optimal allocation of resources[2].

However, these sharing transactions typically take place within the provider's private domain, frequently involving personal interactions and carrying a significant degree of economic risk due to the potential for theft or damage to private assets. Therefore, the successful completion of a transaction hinges not only on the consumer's trust in the provider's integrity, but also on the provider's trust in the consumer's reliability.

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At the nexus of this mutual trusting constellation, previous researches aim to provide insights into how trust can be established in the sharing economy. Such researches are mostly in the form of surveys[4,6] and laboratory experiments[7,8], which is common to these studies, though, is that they focus on the perspectives of individual users. These studies fail to encompass the potential insights that might be gained by examining the evolution of trust and trustworthiness within the broader framework of the ecosystem as a whole.

Recently, limited studies have used evolutionary game theory(EGT) to model trust on the rewards and punishments mechanism to promote trust. Manuel Chica et al[2]. proposed an evolutionary trust game model that considers punishment and protection, to evaluate the dynamic changes of the population under different initial group settings, as well as the effects of implementing punishment and insurance measures;Raymond Chiong et al[9]. provided an evolutionary trust game model in the context of the sharing economy, targeting participants with fixed provider or consumer roles. They simulated the evolution of trust among different roles under various initial population ratio scenarios and compared it with previous studies where roles were not fixed;Shijia Hua and Linjie Liu[10] introduced a reward mechanism into the public goods game, developing a class of coevolutionary game models to investigate the coevolutionary dynamics between group states and reward systems. In this model, rewards adaptively adjust according to the group's state, rather than remaining idealized and constant values as in traditional models. Simulation results indicate that an internally stable coexistence state, where cooperation levels and reward intensities remain constant, can emerge within the model. 2; Qianxi Yang and Yanlong Yang[11] proposed a social monitoring mechanism to mitigate the impact of third-party arbitrator corruption on cooperation levels. Monte Carlo simulation results reveal that when the earnings of third-party arbitrators are influenced by the proportion of cooperators, the new social monitoring mechanism can effectively promote cooperation and curb corruption; Shijia Hua, Mingquan Xu, and Linjie Liu[12] addressed the coevolution of human behavioral decision-making and dilemma intensity, proposing a coevolutionary game model based on collective-risk social dilemmas. The research demonstrates that the introduction of institutional reward mechanisms can not only facilitate the emergence of optimal system states but also effectively avoid the occurrence of the worst system states; Qianxi Yang and Yanlong Yang[13] proposed an updating mechanism based on composite memory and high-reputation learning objects. Numerical simulations show that considering both composite memory and high-reputation learning objects in the updating rules is more effective in promoting cooperation than considering either factor alone.

In these studies, penalties and rewards are mostly presented in the form of fixed vales, without considering the differences in the personal reputation of the participating parties. To bridge this gap, this paper dynamically adjusts the traditional reward-punishment mechanism, using the difference between a participant's individual reputation score and the reputation threshold as the basis for rewards and punishments. If a participant's individual reputation score exceeds the reputation threshold, they are rewarded; otherwise, they are punished. A participant's individual reputation score is dynamically adjusted based on their strategy in the previous time step. Furthermore, this paper improves the Fermi update rule by adopting an equivalent representation of the larger of two functions to prevent high-earning participants from imitating low-earning participants. The new adaptive reputation mechanism integrates the joint influence of a participant's individual reputation score and the reputation threshold on the formation of trust. By adjusting the reputation threshold, we can alter the pattern of rewards and punishments for participants, and simultaneously shorten or widen the gap between a participant's reputation score and the reputation threshold, thereby changing their payoffs. This incentivizes participants to continuously improve their reputation scores to receive rewards, thus promoting the establishment of trust.

In our model, players can either be providers or consumers, and they can choose to be either trustworthy or untrustworthy. Thus, the model is a game between four possible strategies: trustworthy provider (TP), untrustworthy provider(UP), trustworthy consumer(TC),and untrustworthy consumer(UC); and players can switch from being a provider to a consume,or vice-versa.

We prefer agent-based modelling to a purely analytical approach to model the game and its players' interactions. In this modeling, agents(or players) represent individuals in the population. Each of them is given an opportunity to act autonomously based on a set of rules. In our study,this trust game model is located in a square lattice network with periodic boundaries. Network topology restricts the game's interaction to local neighborhoods[14,15]. Update rules, such as proportional imitation[16], are employed to evolve the strategies of players based on the net wealth they have received in previous simulation step.

Background and motivation

Evolutionary game theory (EGT)

EGT is a branch of game theory that integrates ideas from biology about evolution and adaptation, aiming to study the evolutionary progress of interactions among individuals within a population.It typically employs mathematical modeling and numerical simulation methods, involving steps such as constructing game models, analyzing replicator dynamics equation methods, and solving evolutionary equilibrium points, to investigate the strategy evolution process within a group. Unlike traditional game theory, which typically focuses on single interactions between specific individuals, evolutionary game theory studies repeater interactions and the process of strategy evolution among individuals within a population. Evolutionary game theory offers us a research framework that is more aligned with reality, providing insights into the process and outcomes of strategy evolution within a group.

Over the past decades, EGT has been widely adopted as a fundamental framework for comprehending the emergence and sustenance of cooperation. Based on the development and study of different social dilemma models, significant progress has been achieves not only in the field of evolutionary biology, but also across diverse disciplines including anthropology, computer science, economics, operations research, physics, political science, social science, psychology and so on[17].

Evolutionary trust games

The trust game is sequential in nature. In a standard trust game,there are usually two participants: the investor and the trustee[18]. The investor first choose to invest some of all of their endowment to the trustee based on the level of trust in the trustee. Then the trustee decides whether to return the investment (i.e., to act trustworthily) or not.

Recently, trust games have begun to gain attention from the EGT community. McNamara et al[19] demonstrated that permitting investors to acquire information regarding trustees' past behavior, albeit at a cost, can effectively enhance trust and trustworthiness. Manapat et al[20] examined a situation where information on trustees is not consistently available and discovered that this can modify the dynamics of game interactions, resulting in the emergence of behavior characterized by complete trust but only marginal trustworthiness. Tarnita[21] investigated non-random interactions within a structured environment utilizing the classical evolutionary trust game and revealed that the population structure tends to favor the selection of strategies that exhibit both trust and trustworthiness.

Abbass et al[22] introduced an N-player trust game and demonstrated that in a well-mixed environment, the presence of even a single untrustworthy player in the initial population can rapidly lead to the proliferation of untrustworthiness, ultimately resulting in the extinction of investors. Notably, they also observed that a portion of the population consistently remains trustworthy, even in the absence of investors. Chica et al[23] extended the N-player trust game by investigating the effects of various social network topologies. They found that trust can be fostered when players are connected through a social network. More intriguingly, they showed that the heterogeneity of a network topology influences the evolution of trust, depending on the difficulty level of the game. Furthermore, they subsequently studied the effects of different update rules based on the extended N-player trust game[24].

Reputation

Reputation is intimately linked to people's daily lives. An individual with a tarnished reputation often finds it hard to secure cooperation from others, whereas those with a good reputation are more readily sought after. People are more inclined to emulate their behavior and collaborate with them. Numerous scholars have delved into the influence of reputation on various facets of evolutionary games, including reputation-based investment strategies[25], the incorporation of delayed information[26], Reputation-based weighted network[27], the impact of reputation on updating rules[28]. Additionally, scholars have explored the impact of reputation on the Spatial Public Goods Game[29] and the Prisoner's Dilemma Game[30]. Nowak and May[31] first record an individual's historical behavior in a reputation, and then build a credit system based on personal reputation to find that spatial reciprocity can effectively facilitate the realization of a transaction. Nowak and Sigmund[32] introduce reputation to the indirect reciprocity model and found that individual reputation has a significant impact on transaction. Quan et al[33]. investigated how reputation evaluation with tolerance and reputation-dependent imitation affect cooperation, concluding that reputation facilitates the enduring presence of cooperation. Furthermore, Quan et al[34]. examined the effect of reputation discounting on cooperation, discussing both relative and absolute reputation, and discovered that discounting based on absolute reputation was more favorable for fostering cooperation. Consequently, the reputation mechanism, recognized as an indirect reciprocity rule, play a pivotal role in promoting trust within the game.

Trust evolutionary game model in sharing economy

Game definitions and classical payoff matrix

Our trust evolutionary game model consists of a finite set of players that occupy the nodes of a square lattice network (Fig. 1), with each node having four neighbors up and down, left and right. And the edges denote the interactions or transactions between them.Transactions in the sharing economy are facilitated through the matching of individuals who share a mutual interest in exchanging resources, typically via an online network. The underlying intuition behind this modeling approach is that each player maintains relationships with:

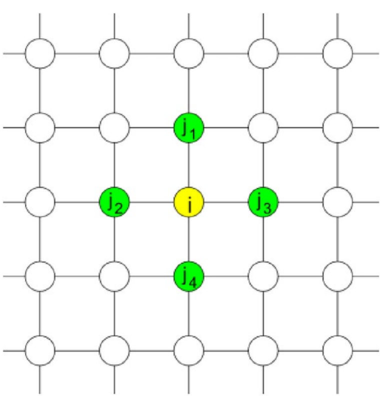

Fig. 1. Square lattice network with periodic boundary (Each Player *i* can only interact with its four neighbors (j_1, j_2, j_3, j_4) through the network's connections).

(1) Providers who can furnish the resources they require;
(2) Consumers who seek the assets that the players can offer[2].

In essence, the network embodies a matching of complementary provider-consumer relationships among private individuals, as opposed to traditional social relationships.

All players play the game over a fixed number of time steps. Each Player *i* can only interact with its four neighbors (j_1, j_2, j_3, j_4) through the network's connections as either a provider or a consumer, and as either trustworthy of untrustworthy. Therefore, the model can be considered a game among the following strategies:

(1) *TP*: A trustworthy provider who offers an asset as promised;
(2) *UP*:An untrustworthy provider who offers assets with markedly lower levels of product/service quality compared to what was promised beforehand;
(3) *TC*: A trustworthy consumer who uses an asset facilitated by a provider in a dependable, socially and economically appropriate manner;
(4) *UC*: An untrustworthy consumer who uses an asset facilitated by a provider in an excessive, socially or economically inappropriate manner.

Each player's initial strategy is randomly generated with the above four strategies. The net wealth of each individual agent is calculated based on their payoffs and is determined by the strategy they adopt as well as the strategies of those they interact with. Table 1 is the classical payoff matrix without considering punishments and rewards.

Reward and punishment mechanism via reputation score and reputation thresholds

In the classical payoff matrix , there is an unstable state of Pareto optimality, under which both the provider and the consumer enjoy the benefits of B. Nevertheless, if a consumer choose to defect against a trustworthy provider, the latter will incur a penalty of $-S$,while the untrustworthy consumer will reap an income of $Temp$ .Conversely, if a provider opts to defect against a trustworthy consumer, the consumer will face a penalty of $-X$, and the untrustworthy provider will gain an income of X.This demonstrates that untrustworthy players have the potential to exploit trustworthy participants, thereby making untrustworthy strategies more advantageous than trustworthy ones.

Therefore, platform operators employ a variety of mechanisms or tools to :

(1) Protect users from indecent and mischievous behaviour by installing means of punishment;
(2) Encourage players to engage in transactions in a trustworthy manner by using rewards .

For instance, most platforms allow their users to denounce and hence punish misbehavior. Negative reviews for providers will thus lead to a worse reputation. A bad reputation, in fact, represents a great threat to any platform user's aspiration to future transactions and is therefore a powerful means to ensure compliance and good behavior. Moreover, providers with positive reputation are able to attract more demand and to impose higher prices for their goods and services in the market.

In our evolutionary game model, we introduce reputation scores and reputation thresholds to construct a new payoff matrix as Table 2.

Here,k_{TP},k_{UP}, k_{TC} and k_{UC} represent the numbers of trustworthy providers, untrustworthy providers, trustworthy consumers, and untrustworthy consumers among each player's neighbors, respectively. The summation of k_{TP},k_{UP}, k_{TC} and k_{UC} must always equal 4 in our square lattice network. S_i is the strategy of player i and R_i is its reputation score .By taking this notation and the payoff matrix into account, we can define the net wealth π_i of agent i as follows:

$$\pi_i = \begin{cases} k_{TC}B\frac{(R_i-Z)B}{Z}k_{UC} - S\frac{(R_i-Z)S}{Z} & if S_i == TP \\ k_{TC}X\frac{(R_i-Z)X}{Z}k_{UC} - X\frac{(R_i-Z)X}{Z} & if S_i == UP \\ k_{TP}B\frac{(R_i-Z)B}{Z}k_{UP} - X\frac{(R_i-Z)X}{Z} & if S_i == TC \\ k_{TP}Temp\frac{(R_i-Z)Temp}{Z}k_{UP} - X\frac{(R_i-Z)X}{Z} & if S_i == UC \end{cases} \tag{1}$$

The total revenue for all agents is calculated as follows:

	Consumers	
Providers	**TC**	**UC**
TP	B, B	$-S, Temp$
UP	$X, -X$	$X, -X$

Table 1. Payoffs in the sharing economy trust game. B is the benefit for transactions if both the provider and the consumer are trustworthy; S is the sucker punishment for a trustworthy provider who is exploited by an untrustworthy consumer; $Temp$ is the temptation for a consumer to be untrustworthy towards a trustworthy provider; and X is the value an untrustworthy provider keeps and a consumer pays after a transaction has been initiated. Here, *Temp*, *B* , *S* and *X* can be any values greater or equal to zero.

	Consumers	
Providers	TC	UC
TP	$B\frac{(R-Z)B}{Z}, B\frac{(R-Z)B}{Z}$	$-S\frac{(R-Z)S}{Z}, Temp\frac{(R-Z)Temp}{Z}$
UP	$X\frac{(R-Z)X}{Z}, -X+\frac{(R-Z)X}{Z}$	$X\frac{(R-Z)X}{Z}, -X\frac{(R-Z)X}{Z}$

Table 2. Payoffs in the sharing economy trust game. *R* represents player's reputation score, which is a quantitative result based on the player's past transaction behavior. *Z* represents the reputation threshold. When a player's reputation score is higher than the reputation threshold, their payoff will be rewarded; otherwise, they will be punished. The specific reward or punishment is added as a multiple of *(R–Z)/Z* to the original payoff result.

$$W = \sum_{i=1}^{N} \pi_i \tag{2}$$

where N is the total number of players.

Since sharing economy platforms employ insurance mechanisms (for both consumers and providers) to alleviate potential harms arising during transactions, thereby diminishing the costs associated with engaging with untrustworthy parties. In this study.,the magnitude of these payment parameters is interrelated as follows: $2B > temp > B > S > X$.

In our model, we run the simulation synchronously up to the maximum number of time steps. At each time step t, all players in the population decide which strategy to choose based on the population state at the previous time step. In other words, the decision of any player at time step t is not influenced by the actions of other players within the same time step.

Reputation update rules

The reputation score of a player is dynamic and continuously adjusted throughout the game according to specific rules. The reputation score at a given time step t is contingent upon its strategy during that time step $t-1$. If a player demonstrates trustworthiness, his reputation score will rise by one unit. Conversely, if he opts to behave untrustworthily, his reputation score will diminish by one unit. Let $R_i\left(t\right)$ represent the reputation score of player i at time t. Consequently, the process of updating player 's reputation can be outlined as follows:

$$R_i\left(t\right) = \begin{cases} R_i\left(t-1\right)+1, if S_i\left(t\right) = TPorTC \\ R_i\left(t-1\right)-1, if S_i\left(t\right) = UPorUC \end{cases} \tag{3}$$

Without loss of generality, in the simulation, we set the reputation scores within the range of 0 to 20. Specifically, when the calculated reputation value according to the reputation update rule is less than zero, it is set to zero; when it is greater than 20, it is set to 20. At the beginning of the simulation, each participating player is randomly assigned a reputation score within this range.

Strategy update

The strategy of each player, denoted as S_i, has the potential to evolve throughout the game, as every player is granted the opportunity to refine its strategy through an evolutionary update mechanism. This process of strategy updating can be seen as a form of information exchange within a social learning framework, whereby players within the population adopt the strategies of their peers. Strategy imitation[35] takes place at every time step of the game. At time step t, a focal player i, regardless of its current strategy, assesses its net wealth π_i from the previous time step $t-1$ and determines whether to imitate the strategy of a neighboring player by applying an evolutionary update rule. Imitative update rules embody scenarios where agents, constrained by bounded rationality or a lack of information, are compelled to replicate the strategies of their neighbors. These update rules are extensively utilized in the pertinent literature to model the dynamics of evolution.

In our study, we use a proportional imitation[16] rule which is pairwise and stochastic and similar to Fermi's rule[36]. Under this rule, at each time step, players can imitate the strategies of their neighbors with a certain probability to achieve strategy updating. The specific approach is as follows: On the one hand, assuming all players are rational participants, to reduce computational complexity, we set the noise parameter in the Fermi rule expression to a constant value of 1. On the other hand, to avoid the irrational behavior in the Fermi rule where high-payoff players may imitate low-payoff players, we propose the following new update rule based on the Fermi rule:

$$P\left(S_i\left(t\right) \leftarrow S_j\left(t\right)\right) = \left|\frac{1}{1+\exp\left[\left(\pi_i\left(t-1\right)-\pi_j\left(t-1\right)\right)\right]} - \frac{1}{2}\right| + \left(\frac{1}{1+\exp\left[\left(\pi_i\left(t-1\right)-\pi_j\left(t-1\right)\right)\right]} - \frac{1}{2}\right) \tag{4}$$

where, the above function expression not only ensures that the probability of imitation falls within the interval [0,1], but also ensures that high-payoff players will never imitate low-payoff players,which increases the likelihood of strategies with higher net wealth being replicated.

Experiment and results

Monte carlo method

We adopt the Monte Carlo method to simulate our shared economy trust model, with the specific steps as follows:

Step 1: Model and strategy setup. We construct a sharing economy game model, build a square lattice network with periodic boundaries, and propose reputation score update rules and strategy update rules.
Step 2: Parameter Initialization . We set the initial values for various parameters, including the edge length of the network, the proportion of the initial population, and the strategies and payoff of each participant.
Step 3: Game Initiation. Iterate through all nodes in the network so that the current node plays a game with each of its four surrounding neighbors and calculates the sum of the current node's payoffs.
Step 4: Strategy update. Once the game round is complete, each node updates its policy and reputation score in accordance with the predetermined rules.
Step 5: Record Parameter Changes. We document the changes in revenue, reputation score, and strategy for each, as well as the variations in the number of participants in each category.
Step 6: Iteration Until Stability. Steps 2 through 5 are repeated until the system reaches a stable state. This is characterized by the stabilization of the number of participants adopting each strategy type and the convergence of the system's total return to a fixed point.
Step 7: Experimental Result Analysis. Organize the experimental results, create relevant graphs, and conduct a thorough analysis to draw meaningful conclusions.

Experimental setup

We set the edge length L = 100, there are10000 agents in our square lattice network. Initially, players are randomly distributed via predetermined probabilities.We set the simulations to 10,000 time steps, and all of them were repeated for 10 independent Monte Carlo runs to ensure the accuracy and stability. Reported results were calculated by averaging in the last 1,000 time steps (i.e., the last 10%) of each run. Each plays the game iteratively with four neighbors and decides whether to change its own strategy.

We set reputation thresholds Z ranging from 0 to 20, covering three trust scenarios ranging from lower, moderate to higher and set $Temp = 40, B = 25, S = 20, and X = 10$. Five scenarios with different initial distributions of strategies were considered as follows.

- Scenario 1: Equal proportions of the four strategies ($k_{TP} \approx k_{UP} \approx k_{TC} \approx k_{UC} \approx 0.25N$).
- Scenario 2: More consumers than providers ($k_{TP} \approx k_{UP} \approx 0.05N, k_{TC} \approx k_{UC} \approx 0.45N$).
- Scenario 3: More providers than consumers ($k_{TP} \approx k_{UP} \approx 0.45N, k_{TC} \approx k_{UC} \approx 0.05N$).
- Scenario 4:More untrustworthy than trustworthy ($k_{TP} \approx k_{TC} \approx 0.05N, k_{UP} \approx k_{UC} \approx 0.45N$) .
- Scenario 5: More trustworthy than untrustworthy ($k_{TP} \approx k_{TC} \approx 0.45N, k_{UP} \approx k_{UC} \approx 0.05N$).

Impact of different reputation thresholds on the establishment of trust in different initial states

Figure 2 presents polyline graphs of sensitivity analysis for reputation thresholds ranging from 0 to 20 in different scenarios. Each row of the polyline graphs contains four polylines, representing the changes in the average proportion of four strategies over the last 1000 steps of the simulation as the reputation threshold varies. It needs to be specially noted here that, for comparing with the initial state, when the reputation threshold Z is set to zero, the y-axis in the figure corresponds to the initial proportions of the four strategies.

In this section, We analyze the trust evolution process in Fig. 2 under different reputation threshold .Firstly, when the initial proportion of trustworthy participants is equal to that of untrustworthy(i.e.,(a),(b),(c) in Fig. 2), it can be observed, as the reputation threshold increases, the total proportion of trustworthy participants also increases and eventually stabilizes at 100%, regardless they are providers or consumers, which is because a higher reputation threshold results in a greater degree of punishment for untrustworthy individuals, prompting them to transition into trustworthy. Specifically, the more balanced the initial proportions of the four strategies are, the easier it is for trust to be established at a lower reputation threshold (i.e., (a) in Fig. 2).

Secondly, in Scenario 4, although the initial total proportion of trustworthy participants is 10%, significantly less than that of untrustworthy participants, there still exist some relatively small reputation thresholds that allow the proportion of trustworthy participants to reach 100% in the final evolved state. This is because when the reputation threshold is low, the model rewards participants, and untrustworthy participants can increase their earnings simply by improving their reputation scores, thereby facilitating the establishment of trust. Conversely, when the reputation threshold is high, untrustworthy providers dominate, and trust cannot be established. This is because under a higher reputation threshold, the model is more likely to impose penalties on all participants. In such a situation where untrustworthy participants dominate and there is no reward incentive, trustworthy participants, who are not numerically advantageous, are easily assimilated by untrustworthy participants and transformed into untrustworthy ones,and the proportion of untrustworthy providers ultimately reaching 100% is simply because, in such a market saturated with untrustworthy behavior, untrustworthy providers, who hold ownership of the goods, end up with the highest returns.

Thirdly, in Scenario 5, even if the initial proportion of trustworthy participants is much higher than that of untrustworthy ones, the untrustworthy participants will not disappear ultimately. As the reputation threshold increases, the final proportion of untrustworthy participants stabilizes at around 20%. This is because, in a market where honesty prevails almost everywhere, There are always untrustworthy participants who try to take shortcuts and gain higher benefits through dishonest behavior.

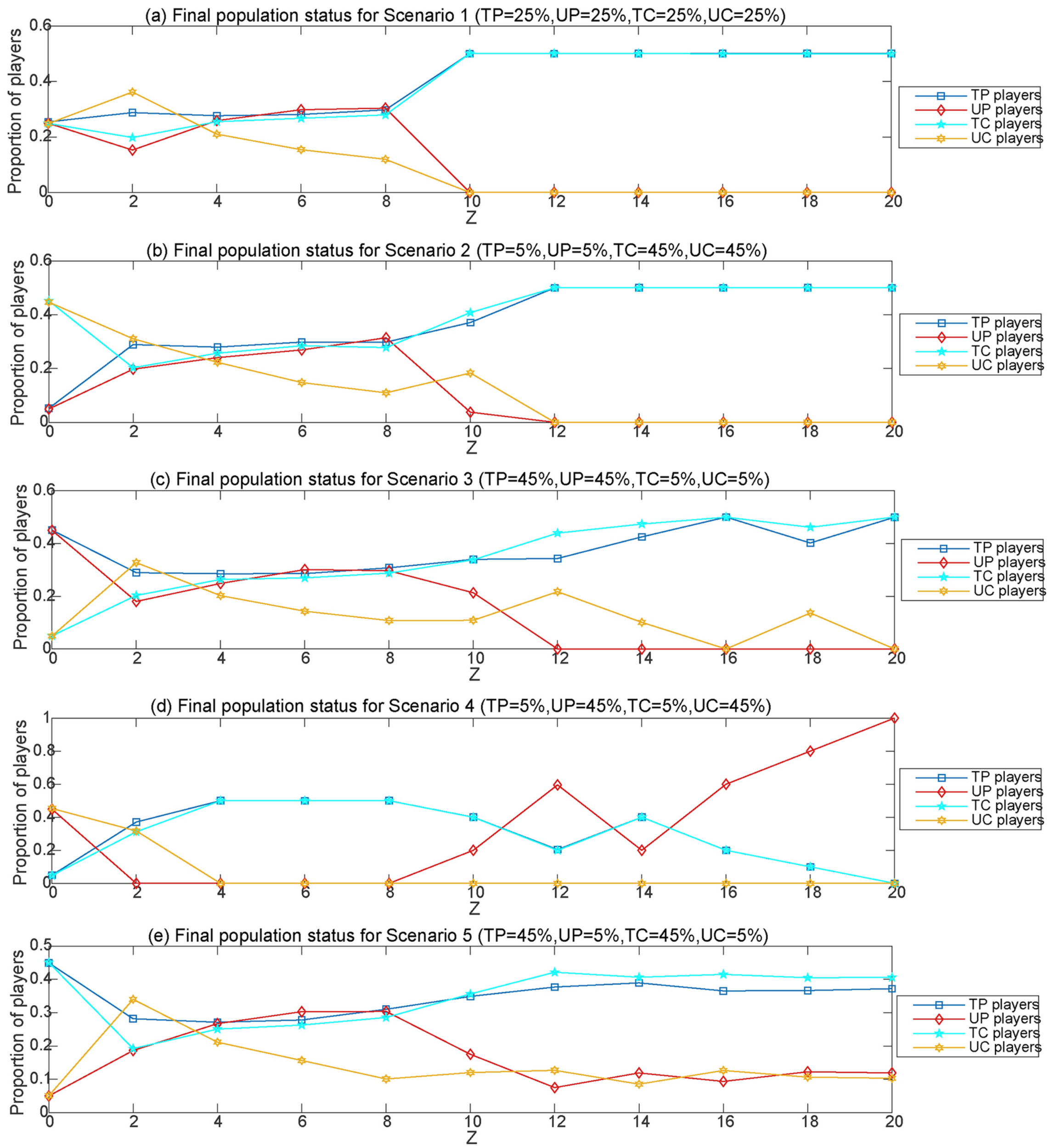

Fig. 2. Line graph showing the evolution process of the final proportion of different strategies with respect to the reputation thresholds in five different scenarios.The first to the fifth lines represent the evolution process of scenarios 1 to 5, respectively, with reputation thresholds $Z \in [0, 20]$.

Total revenue under reputation thresholds in different initial states

In this section, we will analyze how the total revenue changes with the reputation threshold in different scenarios. Figure 3 below presents the polyline graph of total revenue for five scenarios under different reputation thresholds.

In Fig. 3, regardless of the initial scenario, the total revenue exhibits an overall decreasing trend as the reputation threshold increases. This is because a higher reputation threshold makes players more susceptible to punishment. Upon closer observation, we will find that each total revenue curve exhibits a local maximum point during its decreasing process. For example, the curve corresponding to Scenario 1 reaches its local maximum when Z equals 10, while the curve for Scenario 2 reaches its local maximum when Z equals 12. In conjunction with Fig. 2, it is clear that Z equals 10 and 12 are the minimum reputation thresholds that enable the proportion of trustworthy participants to reach 100% in Scenarios 1 and 2, respectively. In the sharing economy, while honest transactions are crucial, ensuring high returns for participants is equally important. We can set appropriate reputation thresholds for different scenarios based on Figs. 2 and 3 to ensure participant satisfaction.

Figures 2 and 3 serve as valuable tools in providing effective theoretical insights for tackling practical problems. Considering that the total payoff diminishes as the reputation threshold rises, we can opt for the minimum reputation threshold that achieves the highest overall proportion of trust, thereby determining the

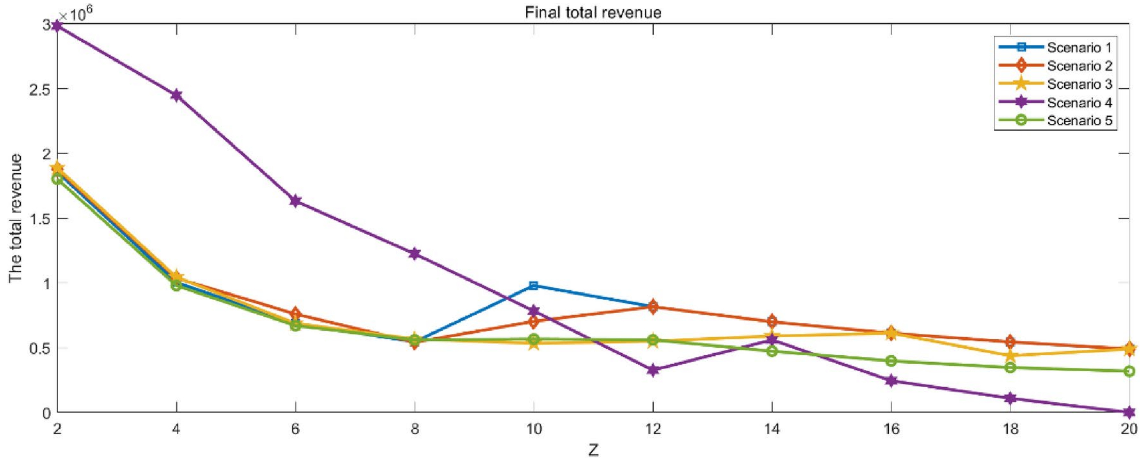

Fig. 3. Total revenue for five different initial scenarios under varying reputation thresholds, with $Temp = 40, B = 25, S = 20, X = 10$, and reputation thresholds $Z \in [0, 20]$.

optimal reputation threshold for real-world scenarios. For instance, when the initial proportions of the four strategies are evenly balanced, a moderate reputation threshold is our preferred choice. In situations where the initial proportions of trustworthy and untrustworthy strategies are equal, if consumers outnumber providers significantly, a moderate reputation threshold is deemed optimal. On the contrary, if providers constitute a larger proportion, a higher reputation threshold should be selected as the most suitable option. This is due to the fact that providers possess the goods being traded and hold the upper hand in transactions. Therefore, we need to elevate the reputation threshold to encourage providers to adopt honest trading practices. When the initial proportion of untrustworthy strategies far exceeds that of trustworthy strategies, a lower reputation threshold, achieved through the use of rewards, can facilitate the establishment of trust. Conversely, in other cases, a moderate reputation threshold should be chosen as the optimal approach.

Heatmap of individual strategy evolution under different reputation threshold

In this section, we will analyze the impact of different reputation thresholds on the evolution of individual strategies among participants under various initial scenarios. Figures 4, 5, and 6 present heatmaps of strategy evolution for Scenarios 1, 2, and 5, respectively. Each figure consists of three rows, representing the evolution processes when the reputation threshold is set to 2, 6, and 12, respectively.

It is evident from Figs. 4, 5, and 6 that regardless of whether Z is small, large, or medium, and whether the initial strategy distribution is uniform or not, untrustworthy players of the same type gradually form clusters over time. That is, even if untrustworthy participants still exist in the end, they will be unable to conduct transactions because they share the same identity as their neig- hbors. And, in the same scenario, by comparing the heatmaps under different reputation thresholds, it can be found that a higher reputation threshold accelerates the formation of such clusters.

Conversely, the two trustworthy strategies will appear more evenly distributed in the network, facilitating healthy transactions.These indicate our model can effectively promote the formation and development of a trust-based market.

Evolution of strategy proportion and total revenue under different reputation thresholds

In this section, we will analyze the evolution process of the proportions of different strategies and the system's total revenue over time steps for Scenarios 1, 2, and 5,with Z covering three trust scenarios ranging from lower, moderate to higher threshold values.The following Figs. 7, 8, and 9 present the evolution processes of the proportions of each strategy and the total revenue in Scen- arios 1, 2, and 5, respectively, as the reputation threshold Z is set to 2, 6, and 10.

Firstly, from Figs. 7, 8, and 9, it can be observed higher reputation threshold accelerates the speed of trust evolution.And, the initial proportions of different strategies have a significant impact on the stability of the evolution state. The more balanced the proportions, the faster the evolution state reaches stability. For example, when the reputation threshold Z is set to 12, the proportions of strategies in Figs. 7 and 8 stabilize around the 110th step, whereas in Fig. 9, even after the given 10,000 steps, the evolution state still has not stabilized. When the initial proportions are consistent, a higher reputation threshold leads to a faster stabilization of the evolution state, which is evident from Figs. 7 and 8.

Secondly, by comparing the fluctuation of the proportions of strategies TP and TC in Figs. 7, 8, and 9, We find that as evolution progresses, the higher the reputation threshold, the smaller the gap between the proportions of TP and TC, as well as the gap between the proportions of UP and UC. Furthermore, in all three scenarios, the total proportion of untrustworthy players exhibits a decreasing trend. Especially in Figs. 7 and 8, the final proportions of UP and UC reach zero. Especially, in scenario 2, even though the gap between the proportions of strategies TC and TP is 40% in the initial state, it eventually evolves to zero.

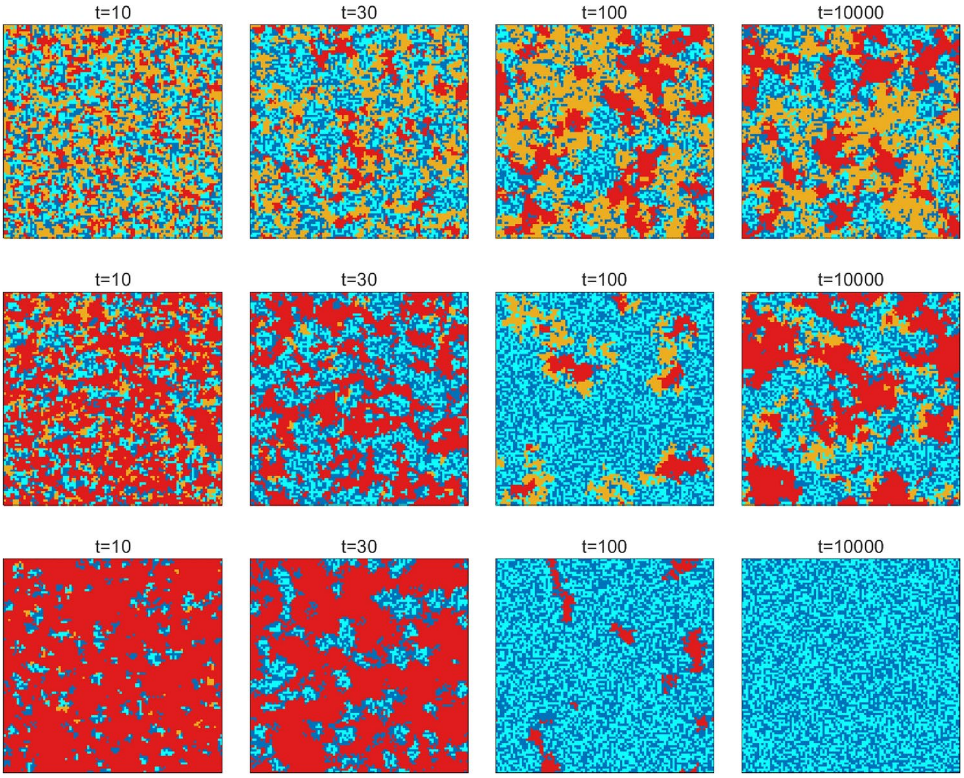

Fig. 4. Heatmaps showing the individual strategy evolution under different Z values in Scenario 1 ($k_{TP} \approx k_{UP} \approx k_{TC} \approx k_{UC} \approx 0.25N$). Note: Dark blue represents trustworthy providers, light blue represents trustworthy consumers, red represents untrustworthy providers, and yellow represents untrustworthy consumers.The first, second, and third rows represent the evolution process of different strategies over time steps t = 10, 30, 100, and 10,000, respectively, when the reputation threshold Z is set to 2, 6, and 12.

Combined with the even distribution of trustworthy strategies and the clustering phenomenon of similar untrustworthy strategies observed in Figs. 4, 5, and 6,the reduction of the gap betwe- en the proportions of strategies TP and TC to zero plays a crucial role in the sharing economy. It can help the market achieve supply–demand balance, reduce resource waste.

Thirdly, by comparing the graphs in Figs. 7d, 8d, and 9d, we can still clearly observe that the higher the reputation threshold, the lower the revenue, which is consistent with revenue lines shown in Fig. 3.

Heatmaps of the evolution of individual reputation values with different reputation thresholds

In this section, we analyze the impact of different reputation thresholds on the evolution of individual reputation values of participants in various scenarios. Figures 10, 11, and 12 present heatmaps of the evolution of individual reputation values for Scenarios 1, 2, and 5, respectively. Each figure contains three rows, representing the results when the reputation threshold is set to 2, 6, and 12, respectively. It is evident from these three figures that, under the given parameter, a higher reputation threshold leads to higher individual reputation values in the final state. Even in Fig. 12, where, the reputation threshold is set to 12, although there are still some participants with low reputation (which may be related to the overall model parameter settings), the individual reputation of most participants has improved.

Sensitivity analysis of the model

Considering that population size has a significant impact on evolutionary outcomes, in this section, we expand the population size by setting L to 500 to explore whether the aforementioned findings are applicable to larger populations.

Figure 13 presents line graph showing the proportion of the four strategies varying with the reputation threshold under Scenario 5, when L is set to 500. Compared with Fig. 1e where L is 100, the trends of the lines are basically consistent, indicating that the findings of this paper are also applicable to larger population sizes, thus verifying the robustness of the model presented in this paper.

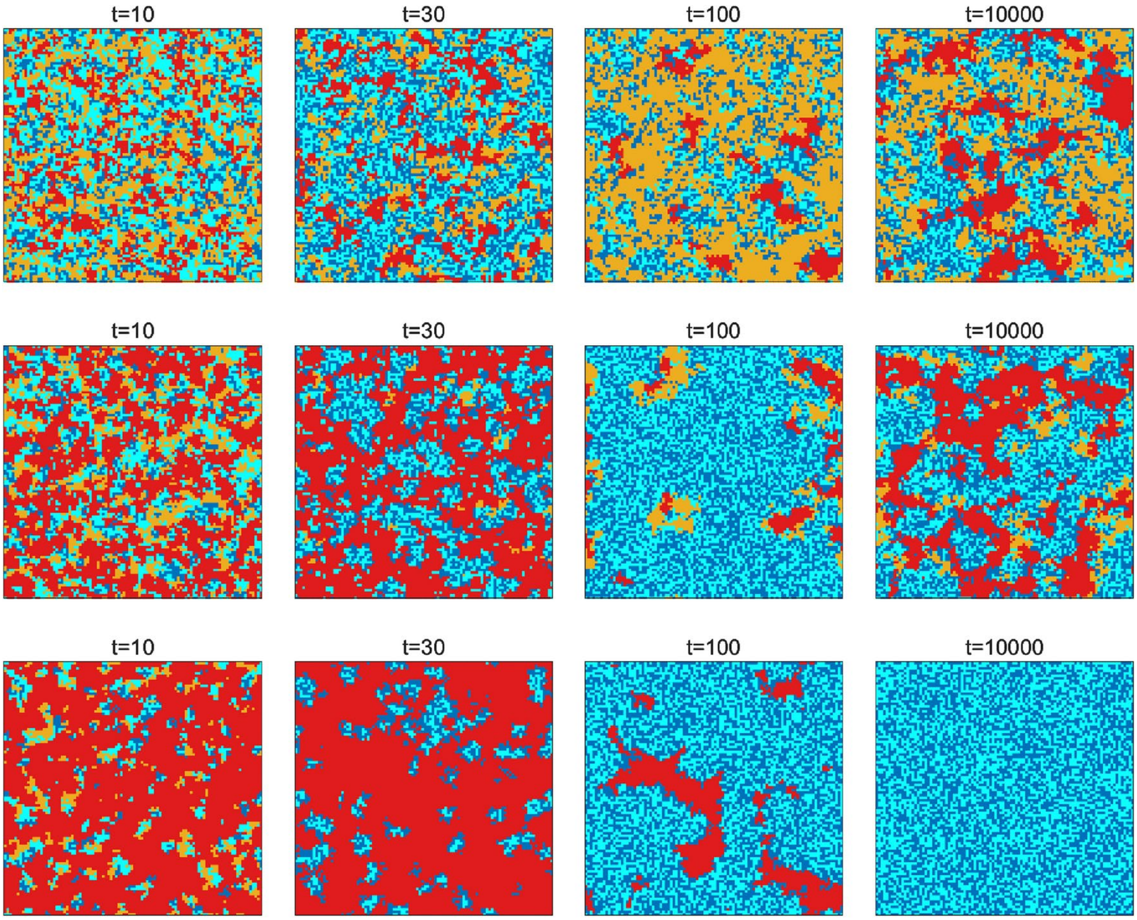

Fig. 5. Heatmaps of individual strategy evolution under different Z values in Scenario 2. ($k_{TP} \approx k_{UP} \approx 0.05N, k_{TC} \approx k_{UC} \approx 0.45N$). Note: Dark blue represents trustworthy providers, light blue represents trustworthy consumers, red represents untrustworthy providers, and yellow represents untrustworthy consumers.The first, second, and third rows represent the evolution process of different strategies over time steps t = 10, 30, 100, and 10,000, respectively, when the reputation threshold Z is set to 2, 6, and 12.

Comparison with traditional model without reward and punishment

In this section, we will compare the results of our model with those of a traditional model that does not incorporate a reward mechanism. Based on the payoff matrix presented in Table 1, net wealth π_i of agent i in the traditional model is as follows:

$$\pi_\mathrm{i} = \begin{cases} \mathrm{k_{TC}B - k_{UC}S} & \text{if } \mathrm{S_i == TP} \\ \mathrm{{}_{TC}Xk_{UC}X} & \text{if } \mathrm{S_i == UP} \\ \mathrm{k_{TP}B - k_{UP}X} & \text{if } \mathrm{S_i == TC} \\ \mathrm{k_{TP}Temp - k_{UP}X} & \text{if } \mathrm{S_i == UC} \end{cases} \tag{5}$$

Assuming that the strategy update rules and simulation experiments for the traditional model are consistent with those of our model, the final proportions of different strategies across five scenarios are presented in Table 3 as follows:

It is evident from the data in Table 3 that, with an appropriate reputation threshold, our model is more effective than the traditional model in facilitating the establishment of trust. Additionally, it promotes the ultimate balance between production and sales in the market, creating favorable conditions for the healthy development of the market.

Conclusion

In this study, we introduce an evolutionary game model that integrates reputation thresholds with the reputation scores of participants to explore the development of trust relationships within the sharing economy. We examine the progression of trust evolution in a square lattice network, where participants receive rewards if their individual reputation surpasses the set threshold, and otherwise, they incur penalties. The reputation scores of individuals are updated according to the strategies adopted during the evolutionary process, and each participant has the

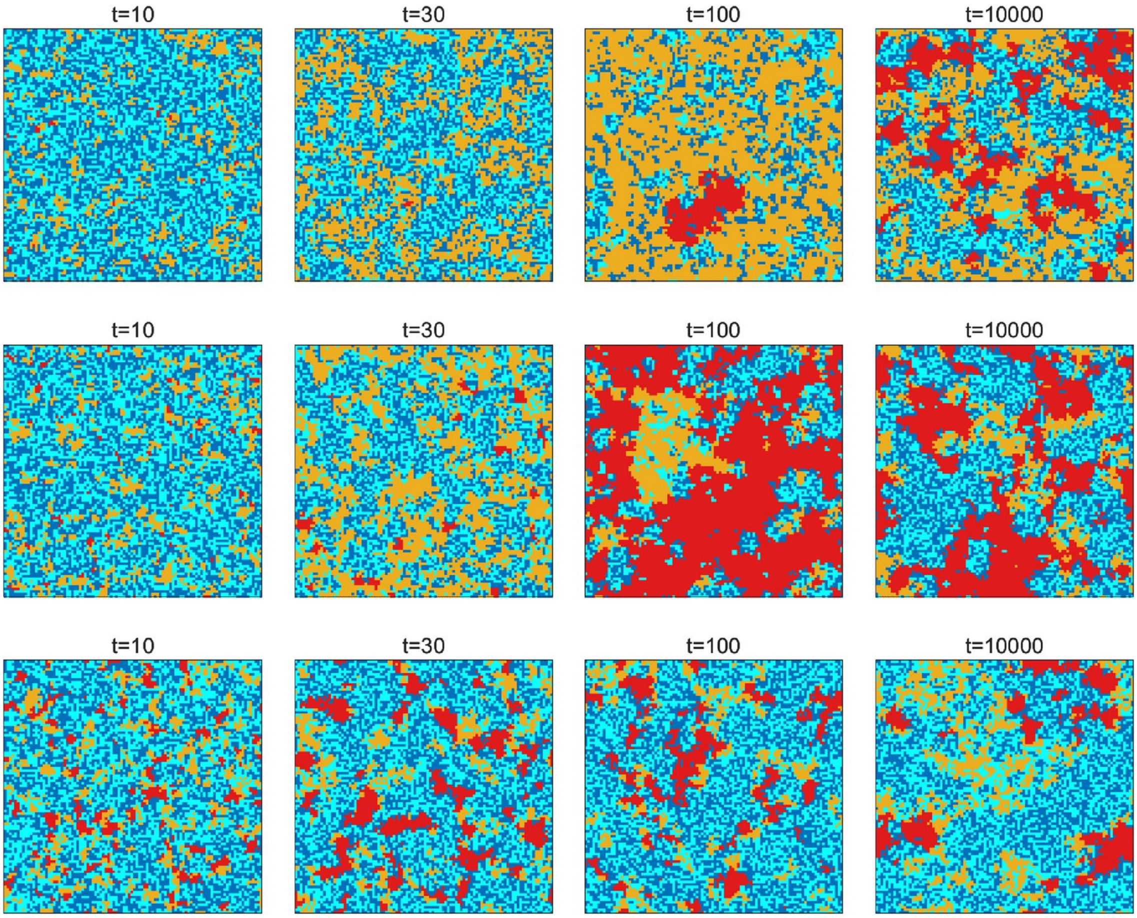

Fig. 6. Heatmaps of individual strategy evolution under different Z values in Scenario 5 ($k_{TP} \approx k_{TC} \approx 0.45N, k_{UP} \approx k_{UC} \approx 0.05N$). Note: Dark blue represents trustworthy providers, light blue represents trustworthy consumers, red represents untrustworthy providers, and yellow represents untrustworthy consumers.The first, second, and third rows represent the evolution process of different strategies over time steps t = 10, 30, 100, and 10,000, respectively, when the reputation threshold Z is set to 2, 6, and 12.

option to adopt the role of a trustworthy provider, an untrustworthy provider, a trustworthy consumer, or an untrustworthy consumer.

We conducted simulation experiments to model the evolution of four strategies in different initial scenarios. The results show that within the specified number of evolution steps, when the initial proportion of trustworthy participants is equal to that of untrustworthy participants, a higher reputation threshold makes it easier to establish trust, ultimately leading to a situation where the proportion of untrustworthy participants is zero. When the initial total proportion of trustworthy participants is higher than that of untrustworthy participants, as the reputation threshold increases, even if untrustworthy participants still exist in the end, trustworthy participants still dominate the market. Conversely, when the total proportion of untrustworthy participants is higher than that of trustworthy participants, a larger reputation threshold cannot guarantee the emergence of trust and may even lead to a situation where the total proportion of trustworthy participants becomes zero. However, there always exist some smaller reputation thresholds that ensure the model ultimately evolves into a state where the total proportion of trustworthy participants reaches 100%.

The simulation experiments further demonstrate that as the reputation threshold increases, the gap between the proportions of trustworthy providers and trustworthy consumers becomes smaller over time, even reaching zero. This helps to balance market supply and demand.For untrustworthy providers and untrustworthy consumers, a higher reputation threshold is more likely to lead to the formation of clusters by a single strategy, This prevents untrustworthy participants from engaging in transactions due to having the same identity as their neighbors and ultimately, ensures that the untrustworthy trading behavior does not occur again.

Recently, reputation mechanisms have been widely applied in various fields[37–42].Our future work will continue to leverage the reputation mechanism, we will align more closely with real-world shared economy platforms and consider incorporating more real-world factors (such as external evaluations or social connections) to continue exploring the evolution of trust in other network structures (such as small-world networks or scale-free networks). Additionally, we plan to combine existing machine learning techniques to construct time series for individual reputation scores, reputation thresholds, personal gains, external evaluations, social connections,

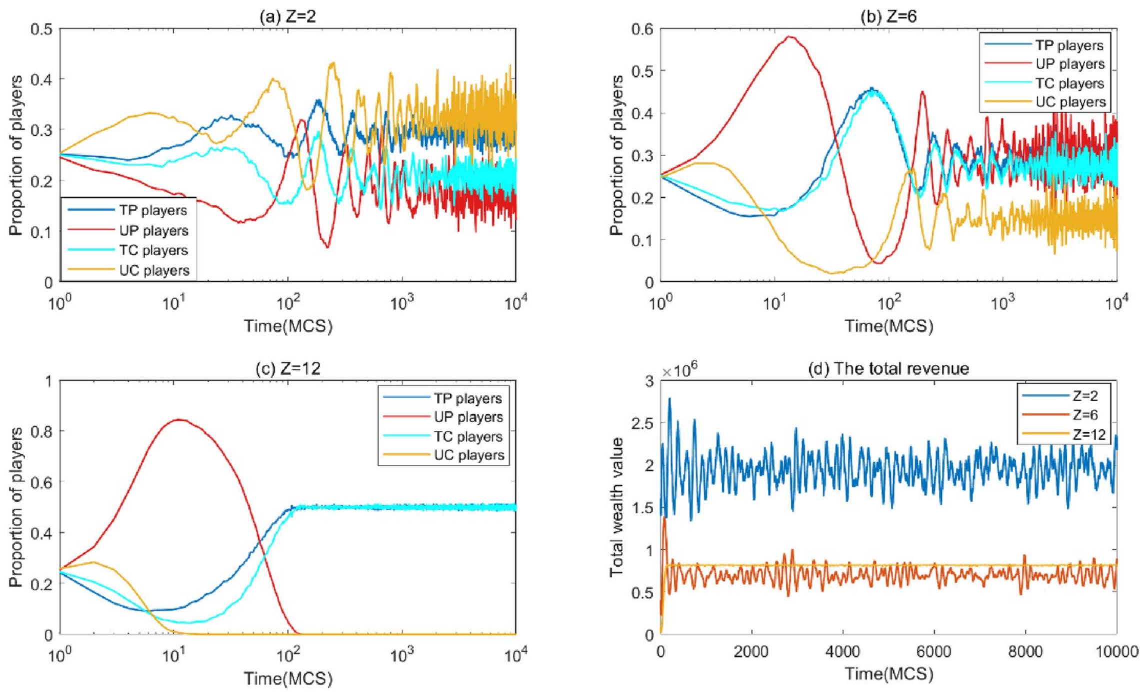

Fig. 7. The evolution of the player proportion and total payoffs over tome steps in Scenario 1 ($k_{TP} \approx k_{UP} \approx k_{TC} \approx k_{UC} \approx 0.25N$).

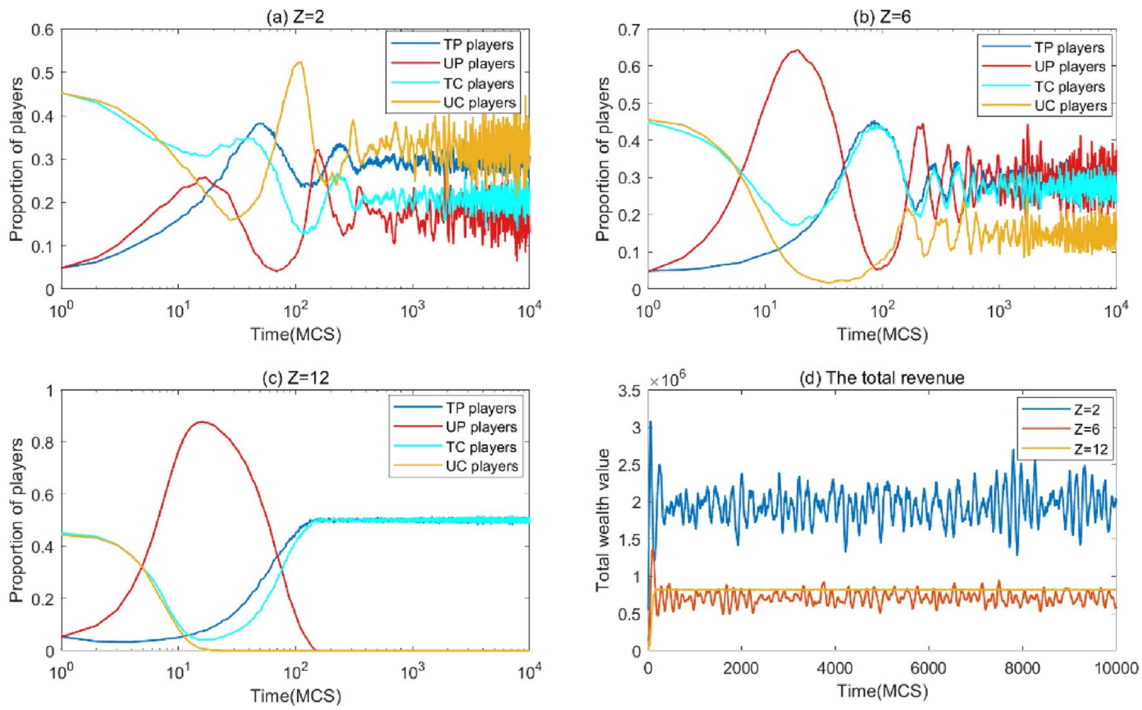

Fig. 8. The evolution of the player proportion and total payoffs in Scenario 2($k_{TP} \approx k_{UP} \approx 0.05N, k_{TC} \approx k_{UC} \approx 0.45N$).

and trust proportions. By using methods such as factor analysis or random forests, we will compare the extent to which various factors influence the formation of trust. We will employ multivariate variational mode decomposition models to decompose the multidimensional time series and ultimately integrate statistical and machine learning methods for prediction.

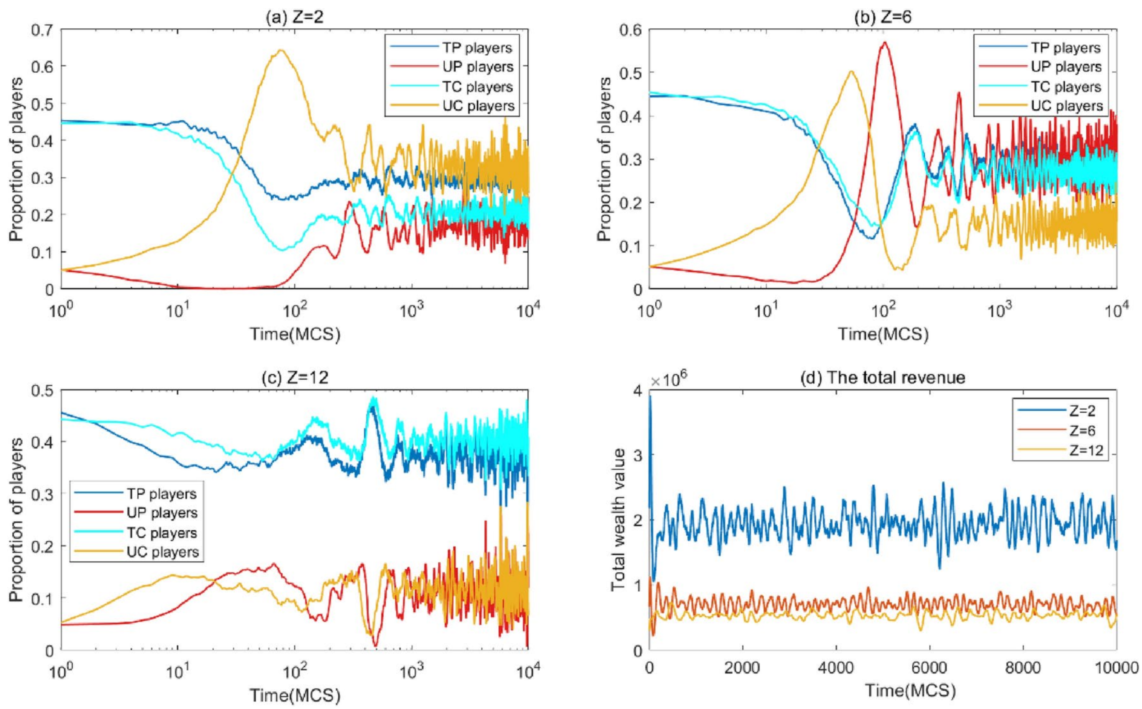

Fig. 9. The evolution of the player proportion and total payoffs in Scenario 5($k_{TP} \approx k_{TC} \approx 0.45N, k_{UP} \approx k_{UC} \approx 0.05N$).

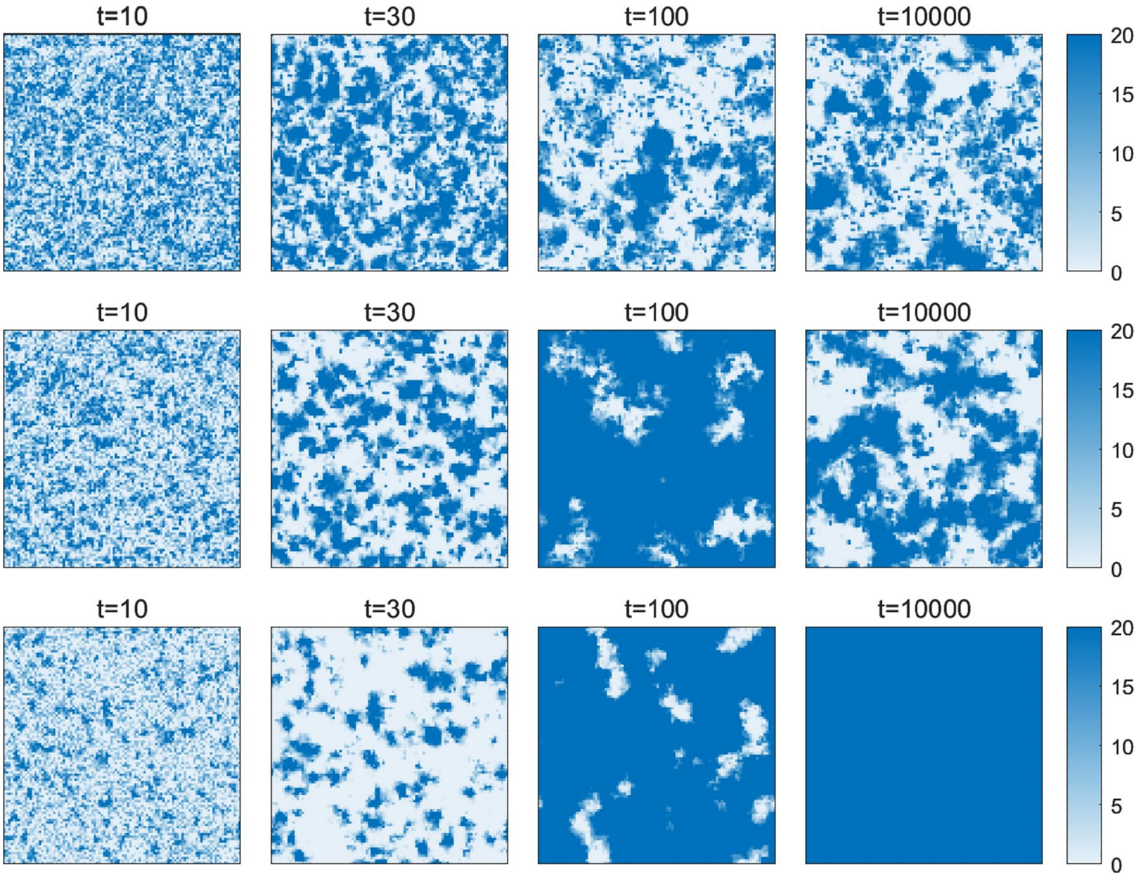

Fig. 10. Heatmaps showing the reputation values evolution under different Z values in Scenario 1($k_{TP} \approx k_{UP} \approx k_{TC} \approx k_{UC} \approx 0.25N$).Note:The first, second, and third rows represent the evolution process of different strategies over time steps t = 10, 30, 100, and 10,000, respectively, when the reputation threshold Z is set to 2, 6, and 12.

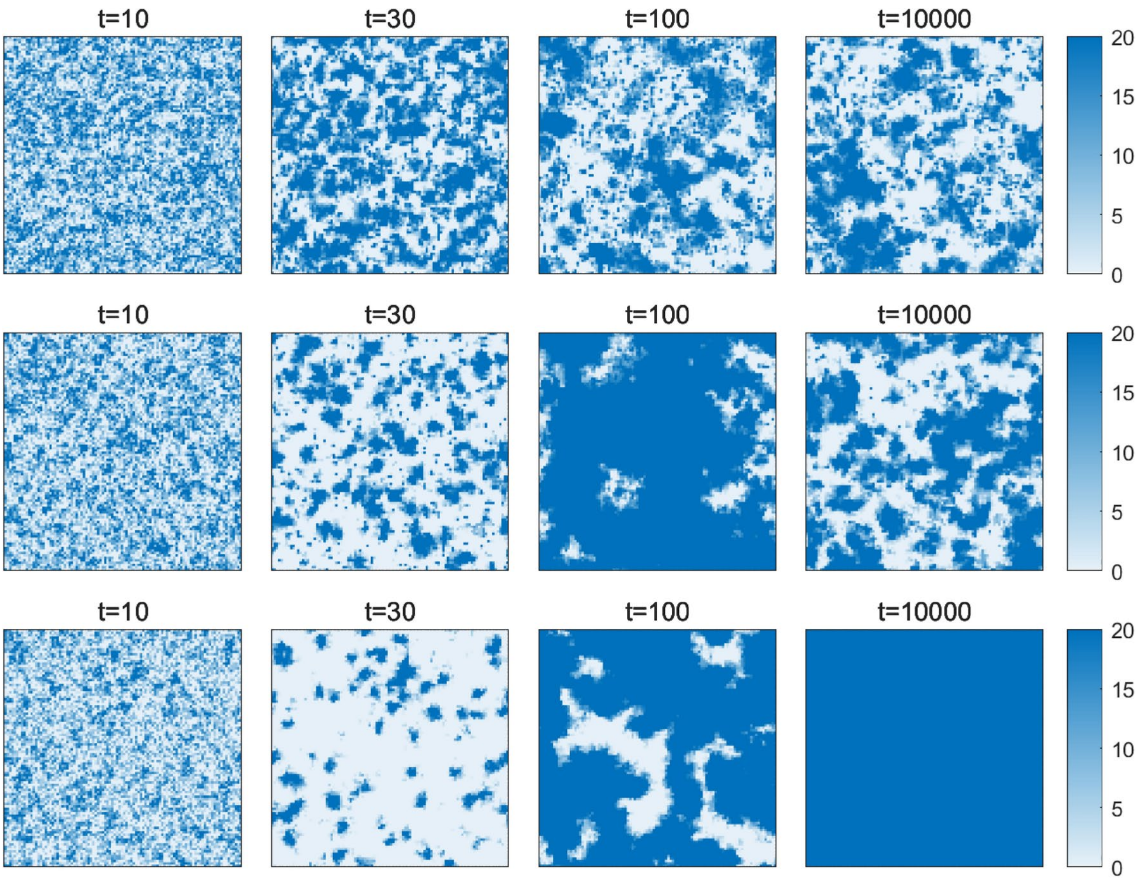

Fig. 11. Heatmaps showing the reputation values evolution under different Z values in Scenario 2($k_{TP} \approx k_{UP} \approx 0.05N, k_{TC} \approx k_{UC} \approx 0.45N$). Note: The first, second, and third rows represent the evolution process of different strategies over time steps t = 10, 30, 100, and 10,000, respectively, when the reputation threshold Z is set to 2, 6, and 12.

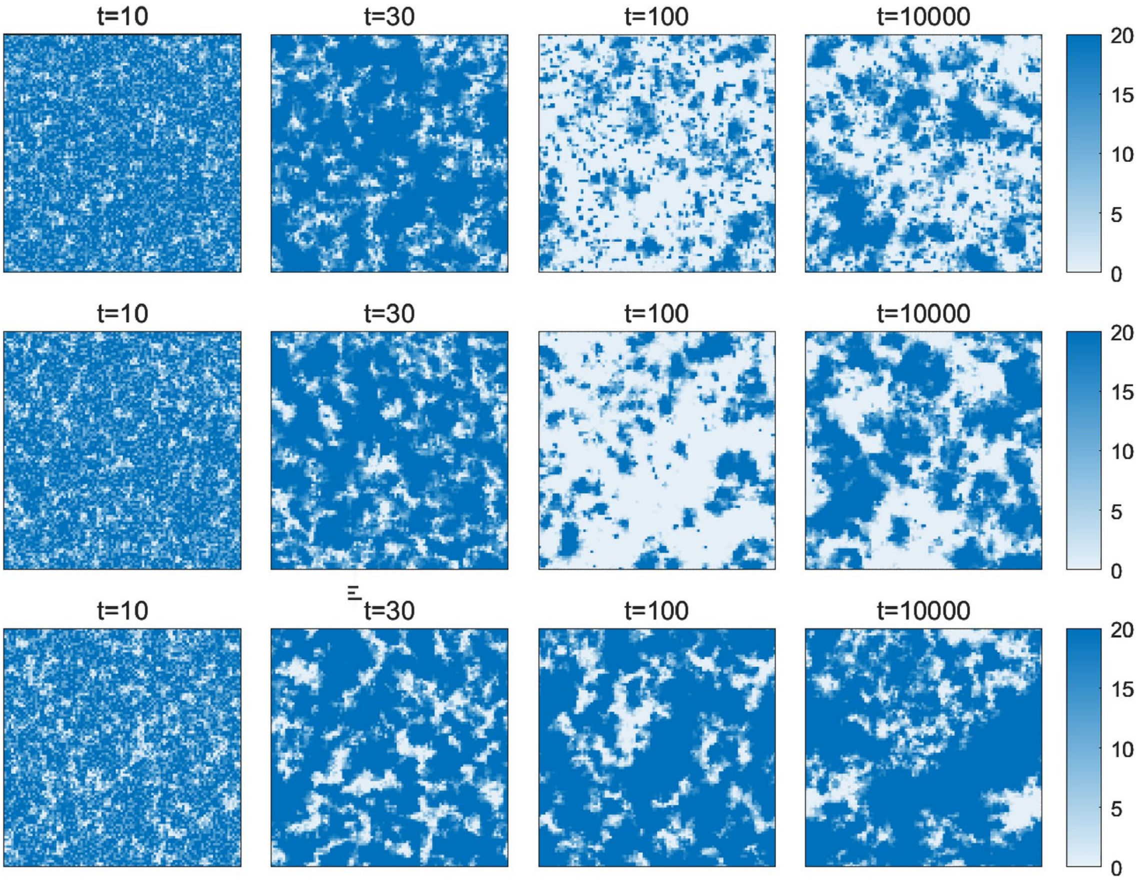

Fig. 12. Heatmaps showing the reputation values evolution under different Z values in Scenario 5($k_{TP} \approx k_{TC} \approx 0.45N, k_{UP} \approx k_{UC} \approx 0.05N$). Note: The first, second, and third rows represent the evolution process of different strategies over time steps t = 10, 30, 100, and 10,000, respectively, when the reputation threshold Z is set to 2, 6, and 12.

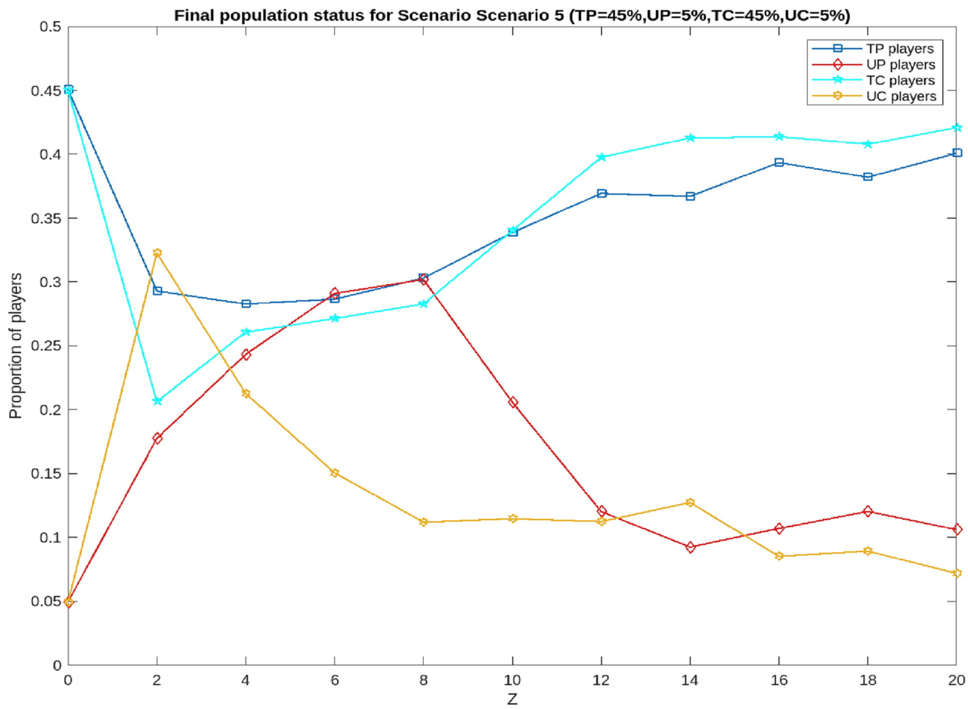

Fig. 13. Line graph showing the evolution process of the final proportion of different strategies with respect to the reputation thresholds in five different scenarios(the number of players having strsteries *TP*, *UP*, *TC*, and *UC*,$\in [0, 250000]$), with $L = 500$, and reputation thresholds $Z \in [0, 20]$.

	Traditional model				Our model				
	TP	TC	UP	UC	TP	TC	UP	UC	Z
Scenario 1	0.5	0.5	0	0	**0.5**	**0.5**	**0**	**0**	$Z \geq 10$
Scenario 2	0.5	0.5	0	0	**0.5**	**0.5**	**0**	**0**	$Z \geq 12$
Scenario 3	0.18	0.48	0.06	0.28	**0.5**	**0.5**	**0**	**0**	$Z = 20$
Scenario 4	0.1	0.1	0.8	0	**0.5**	**0.5**	**0**	**0**	$4 \leq Z \leq 8$
Scenario 5	0.4	0.4	0.15	0.05	**0.4**	**0.4**	**0.1**	**0.1**	$Z = 20$

Table 3. Final proportions of the four different strategies in the traditional model versus our model with appropriate reputation threshold in different scenarios.

Data availability

The dataset generated and analyzed in this study has been de-identified to protect the privacy of the participants. These data are now publicly available and stored in this published article and its supplementary material. For further details about the data, please contact the corresponding author.

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Author contributions
S.J. wrote the main manuscript text and Z.W. prepared all figures. All authors reviewed the manuscript.

Declarations

Competing interests
The authors declare no competing interests.

Additional information
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