

Retraction

Retracted: Evolutionary Game Analysis of Knowledge Sharing in Low-Carbon Innovation Network

Complexity

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] C. Zheng, "Evolutionary Game Analysis of Knowledge Sharing in Low-Carbon Innovation Network," *Complexity*, vol. 2021, Article ID 9995344, 11 pages, 2021.

Research Article

Evolutionary Game Analysis of Knowledge Sharing in Low-Carbon Innovation Network

Cuicui Zheng ^{1,2}

¹School of Economics and Management, Yanshan University, Qinhuangdao 066004, China

²School of Economics and Management, Tonghua Normal University, Tonghua 134000, China

Correspondence should be addressed to Cuicui Zheng; zhengcc1988@stumail.yzu.edu.cn

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Low-carbon technological innovation is the main means to develop a low-carbon economy, and network knowledge sharing and collaborative innovation is an effective model for the development of low-carbon technologies. First of all, this article adopts a decision-making experiment and evaluation laboratory method and interpretation structure model, combines the two methods, extracts the advantages of the two, and discards the shortcomings of the two, thus constructing a new optimized and upgraded interpretation structure model. We give methods to explore the main influencing factors of collaborative innovation of low-carbon technologies for online knowledge sharing. Based on the industrial network knowledge sharing and cooperation network environment, the network evolution game model of network knowledge sharing knowledge collaboration is constructed to study the rewards and punishments, the profit distribution rate, the knowledge potential difference, and the parameter pairing of the network knowledge sharing cooperation network structure in the process of network knowledge sharing and collaborative knowledge innovation. The influence of the network knowledge sharing cooperation strategy is obtained through simulation to change the size of the relevant parameters so that the network knowledge sharing cooperation agent chooses the network evolution game of the sharing strategy to realize the optimal evolutionary stable strategy. According to the simulation results, this article proposes suggestions from the following aspects, aiming to improve the overall knowledge synergy effect of the network knowledge sharing and cooperation network.

1. Introduction

With the rapid development of the knowledge economy, network knowledge sharing has entered a critical period of innovation-driven development strategy. As the core force of technological innovation, the network often faces the problem of limited knowledge resources of its own, lack of independent innovation capabilities, and difficulty in breaking through the core technical difficulties [1]. At the same time, as the number of patent applications for universities and scientific research institutions is increasing year by year, the conversion rate of patent achievements is low, and the patent achievements do not match the market demand [2]. In order to solve the above dilemma, collaborative innovation of network knowledge sharing came into being. Network knowledge sharing and cooperation is a

complex process. Due to the scarcity of resources and the asymmetry of the status of the network and academic research institutions, collaborative innovation entities will reduce the efficiency of network knowledge sharing and cooperation due to conflicts in the distribution of interests, which will affect the cooperation stability and sustainability [3]. Network knowledge sharing and cooperation may put actively collaborative members in a disadvantageous position, making the partners face prisoners' dilemma and adverse selection in the process of network knowledge sharing collaborative innovation [4].

Game theory has been widely used in the research of network knowledge sharing cooperation, such as constructing a game model in which the main body chooses whether to participate in network knowledge sharing collaborative innovation from the perspective of macro income

and so on [5]. The core of network knowledge sharing and cooperation is to realize the recreation of knowledge through knowledge sharing, transfer, absorption, utilization, and integration between the subjects, thereby completing the overall collaborative innovation process [6]. Reasonable use of knowledge resources can promote the efficiency of network operations, and cross-organizational knowledge and experience exchanges have gradually become the key to network seeking and maintaining core competitiveness [7]. At present, the main reason for the low efficiency of network knowledge sharing and collaboration is the low efficiency of knowledge collaboration and transformation. Therefore, from the perspective of knowledge resources, it is of profound significance to explore the existing issues of knowledge collaboration strategies between subjects of network knowledge sharing and cooperation. It can be regarded as a two-player game. It is obvious that the saddle point is stable in the X direction, which means that the policy theory made by X at this time has achieved the optimal benefit. The Y direction is unstable at this time, which means that the profit of Y decision-making at this time is at least not the largest.

In the context of network knowledge sharing and cooperation network, this article will analyze the problem of knowledge sharing in the innovation network by constructing the evolutionary game model of the innovation network and analyze the probability and benefit value of collaborative innovation of each participant in the innovation network from the perspective of bounded rationality, and then through the simulation experiment to analyze the impact of related factors on the degree of knowledge collaboration in the network knowledge sharing network. The knowledge sharing strategies of network members are divided into three categories: "sharing," "non-sharing," and "returning." Based on the evolutionary game theory, the knowledge sharing game model between members is established, the knowledge sharing platform is used to build a simulation model, and the different return values are analyzed. At the beginning of the game, the type of a certain participant is naturally selected. The choice is not observed by another participant. In order to show his type, the former chooses the observable actions after choosing. Under the circumstances, the evolutionary equilibrium reached by the knowledge sharing game provides an analysis basis for the strategic choice and behavior governance of knowledge sharing among members of the innovation network.

2. Related Work

In the era of the knowledge economy, knowledge has increasingly become the main resource for economic development. The only way for the network to maintain a sustainable competitive advantage in the ever-changing market is to continuously use knowledge to innovate. However, as knowledge and technological innovation become more and more complex, cooperative innovation in the form of network organization between networks has become a magic weapon to gain a competitive advantage. Collaborative innovation is a dynamic process of continuous evolution among the cooperative entities of network

knowledge sharing. Taking into account of the incomplete rational factors of the cooperative entities, evolutionary game theory has been widely used in the analysis and research of network knowledge sharing cooperation strategies in recent years. Wang and Zheng [8] established an evolutionary game model of cooperative innovation between universities and networks to explore the relevant factors that influence the choice of online knowledge sharing and cooperation strategies under open innovation. Zhao et al. [9] pointed out that the ultimate orientation of the R&D alliance is knowledge sharing, constructing a game matrix of whether the two networks choose to share or not, and derives that the excess income distribution rate is a prerequisite for the choice of knowledge sharing strategy, and further analyzes the sharing strategy by copying dynamic equations of evolutionary stability. When discussing the collaborative innovation of knowledge in the network value chain, Sun and Zhang [10] constructed an evolutionary game model for analysis.

In the actual network knowledge sharing and cooperation system, the contacts between subjects are not completely coupled or completely random, but are connected in a complex network structure. Therefore, considering the network environment of network knowledge sharing and cooperation, the use of the evolutionary game model to explore the knowledge cooperation strategy of network knowledge sharing appears to be closer to reality. At present, scholars have used the network evolution game method when studying the diffusion of low-carbon innovation technology. Liu and Yang [11] regarded the technology diffusion carrier as a scale-free network, constructed a game matrix for innovation adoption under the regulation of market mechanism and evolutionary game model, and then constructed a complex network evolutionary game model for analysis. Yuan et al. [12] regarded traditional network clusters as small-world networks and established the main low-carbon strategy update rules on the basis of exploring the learning model of the main clusters. By constructing the evolutionary game model of industrial clusters based on complex networks, it analyzed the influences on the promotion of new low-carbon strategies and the key factor. The essence of knowledge sharing behavior is a game process in which both parties on the network choose between "sharing" and "not sharing." Introducing the game into the discussion process can quantify the problem and make the research process clearer. Xu and Xu [13] used evolutionary game theory to study the problem of knowledge sharing between transnational networks and proposed a "cockfighting game" to verify the impact of low-carbon innovation network knowledge sharing on the tacit knowledge sharing behavior of cross-administrative cluster innovation network networks. When making a decision, the network always adopts a different strategy from that of the other party. A hybrid strategy is a strategy formed by allocating a probability to each pure strategy. The hybrid strategy allows players to choose a pure strategy randomly. Some researchers have used game theory to explore the equilibrium solution of knowledge sharing between supply chain node networks, used evolutionary game theory to study the problem of

knowledge sharing in collaborative knowledge innovation [14], added the “return” strategy to the traditional knowledge sharing strategy, and used the evolutionary game model to analyze the conditions for the knowledge sharing game to reach equilibrium in the innovation network under different benefits [15]. With the continuous economic development, industrial clusters have gradually developed to be located in geographical spaces belonging to different administrative regions, and the innovation network is divided into different administrative regions. Scholars have begun to subdivide knowledge into explicit knowledge and tacit knowledge [16]; they also believe that explicit knowledge is just a small island where knowledge emerges, and the sharing of network skills, technical know-how, core capabilities, experience, and other tacit knowledge elements that are difficult to transfer in a short period of time is the network to acquire core capabilities and reduce innovation costs [17]. To this end, some scholars used evolutionary game theory to analyze the evolutionary stability strategy of knowledge-based employees’ tacit knowledge sharing within the organization, considered reciprocity, reputation, altruism, and other factors, and used evolutionary game theory to analyze network tacit knowledge sharing decision-making problems [18]. The evolutionary game theory is used to study the evolutionary stable strategy of tacit knowledge sharing between organizations [19]. Although these literature studies are based on bounded rationality, in general, they only considered the internal factors such as knowledge sources, knowledge characteristics, technical means, networks, and how external incentive policies affect the choice of network tacit knowledge sharing behaviors but they lack discussion [20–23].

3. Construction of an Evolutionary Game Model for Knowledge Sharing in Low-Carbon Innovation Networks

3.1. The Hierarchy of Evolutionary Game Theory. The network evolution game model is mainly composed of three parts: network structure, game model, and update rules [24, 25]. Based on the background of the network environment of knowledge sharing and cooperation in a specific industry network, this article establishes a cooperative attitude game model and evolutionary rules between the network and academic research institutions. Construct a network $G = (V, E)$ according to graph theory, where V represents the set of nodes in the cooperative network and E represents the set of all connections. They analyzed the results of the proposed method compared with other traditional methods and the running performance on the Spark platform [26, 27]. Through a comprehensive analysis of the factors that affect innovation performance, it can be concluded that organizing joint invention patents is the most direct and effective way to study the knowledge sharing and collaborative innovation behavior between cooperating subjects. Therefore, this article builds an industrial network knowledge sharing knowledge collaborative innovation network based on the joint invention patent situation

between the network and academic research institutions from Figure 1.

In the cluster innovation network across administrative boundaries, the explicit knowledge sharing of the network is generally carried out under completely rational conditions, and the sharing effect is immediate, and the network can be adjusted accordingly in a short time according to their respective target benefits. Through repeated imitation and learning, revision, and adjustment of strategies, a dynamic equilibrium of shared strategies is formed. The selection and dynamic adjustment process of this tacit knowledge sharing behavior show the regularity of the evolution process of tacit knowledge sharing in the cluster network and have the characteristics of an evolutionary game. Therefore, this article can learn from the evolutionary game theory and, based on the actual situation of tacit knowledge sharing of the cross-administrative boundary cluster innovation network, propose the following hypotheses:

- (1) Hypothesis 1: the cluster innovation network is formed by two networks that produce homogeneous products across the administrative boundary. The definition of Nash equilibrium is that when everyone else’s strategy is given, everyone has no incentive to change the strategy. Strong homogeneity, strong administrative boundaries, and low-carbon innovation network knowledge sharing play a leading role in the development of subclusters. The tacit knowledge sharing strategy set of the two is {share, not share}.

$$D_1 = aA \cdot (k_1 + k_2) + b_1 \cdot k_1 - c_1 \cdot k_1. \quad (1)$$

- (2) Hypothesis 2: the two networks are network 1 and network 2. The inverse demand function of innovative products is $p = a - b(q_1 + q_2)$, where p is the price of the product, and q_1 and q_2 are the innovation output of network 1 and network 2. A and b are both constants greater than 0. The unit production cost of the network is M_1 and M_2 , respectively, and $a > M_i$ ($i = 1, 2$).

$$D_2 = (1 - a)A \cdot (k_1 + k_2) + b_2 \cdot k_1 - c \cdot k_2. \quad (2)$$

- (3) Hypothesis 3: H_1 and H_2 are the tacit knowledge level of network 1 and network 2, α_1 and α_2 are the degrees of sharing, D_1 and D_2 are the public input level of knowledge sharing in the low-carbon innovation network, and the discount value of the public input level is T_1 , T_2 , and $T_i = t_1 - D - i$ ($i = 1, 2$, t is the discount rate, and $0 < t < 1$). In order to promote the development of innovation activities of its subgroups, low-carbon innovation network knowledge sharing invests in the construction of public facilities and strengthens funding for public services such as education and health, so as to reduce the cost of network innovation. Thus, the actual unit production cost of network 1 is $M_1 - H_1 - 2H_2 - D_1$, and the actual unit production cost of network 2 is $M_2 - H_2 - H_1 - D_2$.

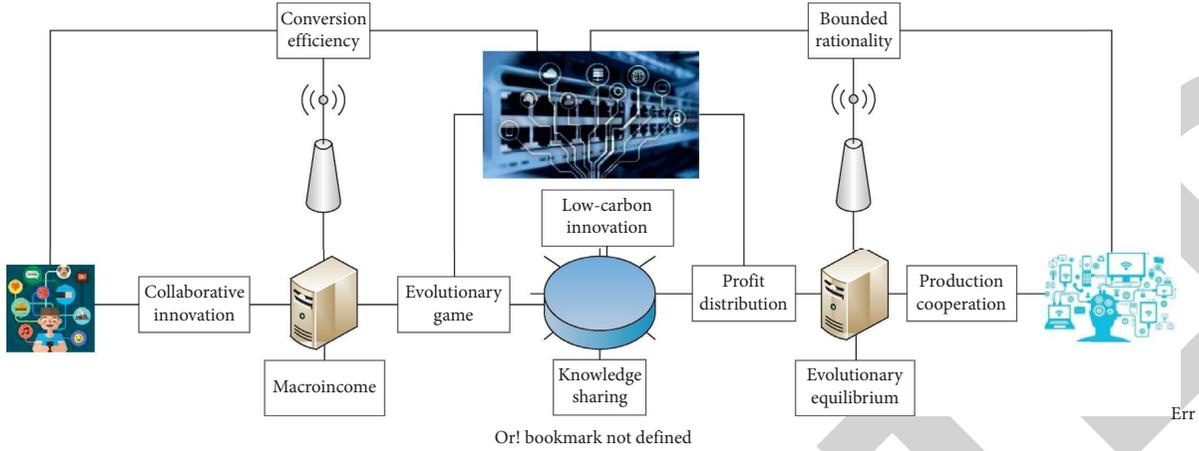


FIGURE 1: Hierarchical distribution of evolutionary games.

$$P_1 = aA \cdot (k_1 + b \cdot k_2) + b \cdot b_1 \cdot k_2 - c \cdot k_1. \quad (3)$$

- (4) Hypothesis 4: C_1 and C_2 are the shared costs of network 1 and network 2. Knowledge transfer and acceptance capabilities are affected by the level of public input for knowledge sharing in low-carbon innovation networks, and there are certain risks. Let the risk coefficients be e_1 and e_2 , respectively, and the actual sharing cost of network 1 can be obtained as $C_1(1-D_1+e_1)$, the actual shared cost of enterprise 2 is $C_2(1-D_2+e_2)$.

$$Q_2 = (1-a)A \cdot (k_1 + b \cdot k_2) + b_2 \cdot k_1 - cb \cdot k_2, \quad (4)$$

$$Q_1 = aA \cdot (b \cdot k_1 + k_2) + b_1 \cdot k_2 - bc \cdot k_1. \quad (5)$$

- (5) Hypothesis 5: when the network is shared, low-carbon innovation network knowledge sharing encourages the amount of tacit knowledge spilled; when the network is not shared, low-carbon innovation network knowledge sharing obtains the tacit knowledge spillover of another network based on the network due to opportunistic behavior punishment based on the amount. Suppose λ_1 and λ_2 are the incentive coefficients of knowledge sharing in the low-carbon innovation network where network 1 and network 2 are located, and γ_1 and γ_2 are the penalty coefficients. Probability calculations are used in the equilibrium of mixed strategy games because each strategy is random, and when a certain probability is reached, the optimal payment can be achieved. Then, when network 1 is shared, the spillover compensation for knowledge sharing in the low-carbon innovation network is $\lambda_1\alpha_1H_1$, no sharing is obtained when the local government is punished by γ_2 ; the compensation for low-carbon innovation network knowledge is shared when network 2 is λ_2 , and the penalty for low-carbon innovation network knowledge is shared when network 2 is not γ_2 .

3.2. Low-Carbon Innovative Algorithm Design. In order to further explore the collaborative innovation mechanism of network knowledge sharing, analyze the knowledge collaboration behavior between academic research institutions and the network, and improve the degree of collaboration of cooperative entities, the following algorithm is proposed:

Step 1: the network knowledge sharing partner completes the agreed network knowledge sharing cooperation through collaborative knowledge innovation. If the former takes action before the two parties reach a contract, it is a signal transmission; if they act after the contract is reached, it is information screening. In this type of game, the information is incomplete. When $\beta-i=1$, it is determined that the cooperating subject is actively participating in the network knowledge sharing and knowledge collaboration; when $\beta-i < 1$, then the subject is considered to be passive collaboration, $\beta-i$ is the total amount of knowledge that the subject participates in the knowledge collaboration; third, the efficiency of innovation transformation A is used to represent the cooperation in the process of network knowledge sharing collaborative innovation. The main body has the ability to jointly transform knowledge input into organizational profit; then, the common benefits obtained by both parties through network knowledge sharing knowledge collaboration is expressed as A ; then, the income distribution ratio is expressed as α ($0 < \alpha < 1$), which indicates the proportion of common benefit secondary school research institutions and $1-\alpha$ indicates the proportion of network gains.

$$P_2 = (1-a)A \cdot (b \cdot k_1 + k_2) + b \cdot b_2 \cdot k_1 - c_2 \cdot k_2. \quad (6)$$

Step 2: while the organization is carrying out collaborative innovation and completing network knowledge sharing cooperation projects, there are knowledge sharing behaviors between organizations, and the cooperating entities can absorb each other's shared knowledge and internalize it and then form their own knowledge capital. $B-i$ ($i=1, 2; 0 \leq b-i \leq 1$) is used to

express the organization's knowledge learning absorptive capacity. Therefore, the knowledge capital that the organization increases in the process of network knowledge sharing and knowledge collaboration can be expressed as $b_i \beta_j$ ($i, j=1, 2$). Under normal circumstances, it is believed that the knowledge absorptive capacity of academic research institutions is greater than the absorptive capacity of the network, that is, $b_1 > b_2$.

$$H_1 = aA \cdot (b \cdot k_1 + b \cdot k_2) + b \cdot b_1 \cdot k_2 - c \cdot b_1 \cdot k_2 - e. \quad (7)$$

Step 3: due to the inherent attributes of knowledge, such as exclusiveness, complexity, and usefulness, the cooperative entity shares its own knowledge in the collaborative innovation process of network knowledge sharing and then is absorbed by other cooperative organizations, resulting in a decrease in core competitiveness. Therefore, the cost of knowledge sharing still exists when the organization conducts network knowledge sharing and cooperation. Use c ($0 \leq c \leq 1$) to represent the knowledge sharing cost coefficient of the cooperative entities, and the knowledge collaboration cost of the organization in the collaborative innovation process is $c-i$ ($i=1, 2$).

$$H_2 = (1-a)A \cdot (b \cdot k_1 + b \cdot k_2) + b \cdot b_2 \cdot k_1 - c \cdot b_2 \cdot k_2 - e, \quad (8)$$

$$p(i, t+1) = p(i, t)(1 - p(si, sj)) + p(j, t)(1 - p(si, sj)). \quad (9)$$

If there is a negative synergy in violation of the agreement, the partner or the evolutionary game model, third-party supervisory agency, etc., will punish the negative cooperating party. The penalty intensity is represented by E .

Based on the above algorithm in Figure 2, if the academic and research party and the network party choose active collaboration strategies at the same time, the income of the academic research party is $D1$, and the income of the network party is $D2$. If decision-makers are bounded rationally, then their strategic behavior and game results are usually far from the predictions based on complete ideal assumptions of the players, and game analysis based on complete rationality may fail. If the academic and research party chooses to collaborate actively, and the network party passively collaborates, the network party will pay compensation E to the academic research party. At this time, the income of the academic research party is $P1$ and the network party's income is $Q2$. Correspondingly, if the learning and research side is negative and the network side adopts an active strategy, the income of the learning and research side is $Q1$, and the income of the network side is $P2$. If both parties cooperate negatively, although the cost of coordination is reduced,

both will be punished. At this time, the benefits of both parties are $H1$.

3.3. Optimization of Network Knowledge Sharing Parameters. (1) $S-i$ represents the strategy adopted by node i , and $U(t)$ $d-i$ is the average expected return of node i to all adjacent nodes at time $p(s-i \leftarrow s-j)$ represents the degree to which the cooperation strategy adopted by node i is affected by the strategy of node j . (2) Parameter κ ($\kappa > 0$) which represents the possibility of an individual's rational behavior. When $\kappa \rightarrow 1$, it means that all information is submerged by noise, and the individual update strategy is completely random; when $\kappa \rightarrow 0$, it means a definite imitation rule; that is, when the average return of neighboring node j is greater than i itself, node i takes j . (3) Nash equilibrium is obtained through two peers, which helps us quickly determine the optimal strategy in an asymmetric game. That is, at time t , node i will randomly select a neighboring node for profit comparison, and at the next time, it will change to the other party's strategy with a certain probability.

Specifically, it can be seen from Table 1 that when the average expected return of node i at time t is greater than the average expected return of adjacent node j , node i is likely to stick to its own strategy at time $t+1$; on the contrary, if the average expected return of node i at time t is less than the average expected return of neighboring node j , node i is more likely to change its cooperation strategy according to the strategy of neighboring node j at the next moment. In an asymmetric 2 by 2, the degree of freedom is just unity, so that cooperation fraction (say, x) and defection fraction (say, y) are mutually dependent; i.e., $x + y = 1$ with $x \in [0, 1]$ & $y \in [0, 1]$.

Based on the above analysis, in order to further improve the collaborative innovation effect of the participants in the knowledge sharing of the innovation network, the degree of collaboration and the probability of participation in the knowledge sharing of each participant are enhanced. Therefore, this paper sets the probability and average benefit values of active knowledge sharing by all participants in the innovation network as P and $U-O$, as shown in Figure 3.

4. Application and Analysis of Evolutionary Game Model for Knowledge Sharing in Low-Carbon Innovation Networks

4.1. Conditional Simulation of Evolutionary Game Model. In order to better describe the equilibrium state that can be achieved by the dynamic evolutionary game between the subjects based on these three types of strategies, the article uses the simulation method to simulate the knowledge sharing strategy of the network members under the condition of changing the values of different variables. The different conditions that reach the equilibrium state of evolution are analyzed. The simulation software used is NetLogo, which is a multiagent modeling and simulation software, which is particularly suitable for modeling complex systems that evolve over time.

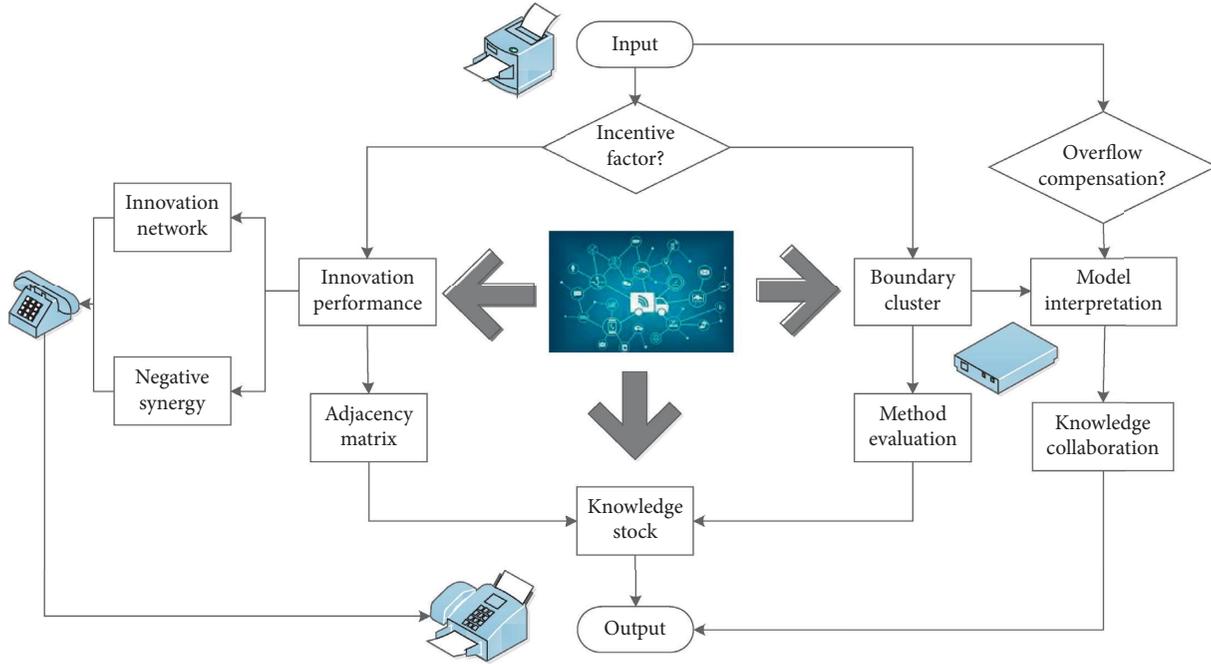


FIGURE 2: Low-carbon innovation algorithm process.

TABLE 1: Attribute distribution of network knowledge sharing nodes.

Node number	Update weight	Expected income	Significance level	Synergy factor
1	0.36	0.34	0.46	0.41
2	0.32	0.27	0.31	0.21
3	0.25	0.36	0.38	0.33

With the rapid development of the information industry, the mobile communication industry, as an important knowledge-intensive industry, has made rapid progress and rapid improvement in recent years. All these achievements cannot be separated from the in-depth innovation and development, continuous improvement, and progress of knowledge sharing in the innovation network. Therefore, this paper further analyzes the knowledge sharing mechanism in the network by constructing the knowledge sharing network in the communication industry and refers to the literature [28]. In Figure 4, a cooperative network based on the knowledge sharing of the mobile communication industry network is built.

From the above equilibrium point stability analysis and dynamic evolution phase diagram, it can be seen that the final result of system evolution may be knowledge sharing or knowledge nonsharing. It is mainly affected by the initial state of the game, and the difference in the initial values of the parameters will promote the evolution of the system to converge to different equilibrium points. (1) The impact of low-carbon innovation network knowledge sharing incentives on evolution: the upgrade factor of sample points in Figure 5 determines the probability of the system evolving to different results, and the position of the critical line is determined by the saddle point $E(\theta^*, \delta^*)$. Then, find the first

order of λ_2 and λ_1 for θ^* and δ^* , respectively. It can be seen that there is a negative correlation between the change of θ and the change of λ_2 ; that is, when λ_2 increases, θ decreases accordingly. Therefore, the saddle point is not a Nash equilibrium but only an optimal in a certain direction. At this time, Y still needs to continue to adjust its strategy to achieve the optimal when the strategy of X is given. At this time, the area of N increases, and the probability of the system evolving to $D(1, 1)$ increases. That is, network 2 will choose knowledge sharing. The same analysis shows that when λ_1 increases, network 1 will choose knowledge sharing. (2) The impact of low-carbon innovation network knowledge sharing penalty on evolution: find the first derivative of γ_2 and γ_1 for θ^* and δ^* , respectively, and get $\theta^* < 0$. Therefore, when γ_2 increases, θ decreases accordingly. At this time, the area of N increases, and the probability of the system evolving to $D(1, 1)$ increases; that is, network 2 will choose knowledge sharing. The same analysis shows that when γ_1 increases, network 1 will choose knowledge sharing. (3) The impact of low-carbon innovation network knowledge sharing public input level on evolution: calculate the first derivative of D_2 and D_1 for θ^* and δ^* , respectively, and get $(D_2) < 0$. That is, when D_2 increases, θ decreases accordingly. At this time, the area of N increases, and the probability of the system evolving to $D(1, 1)$ increases; that is, network 2 will choose knowledge

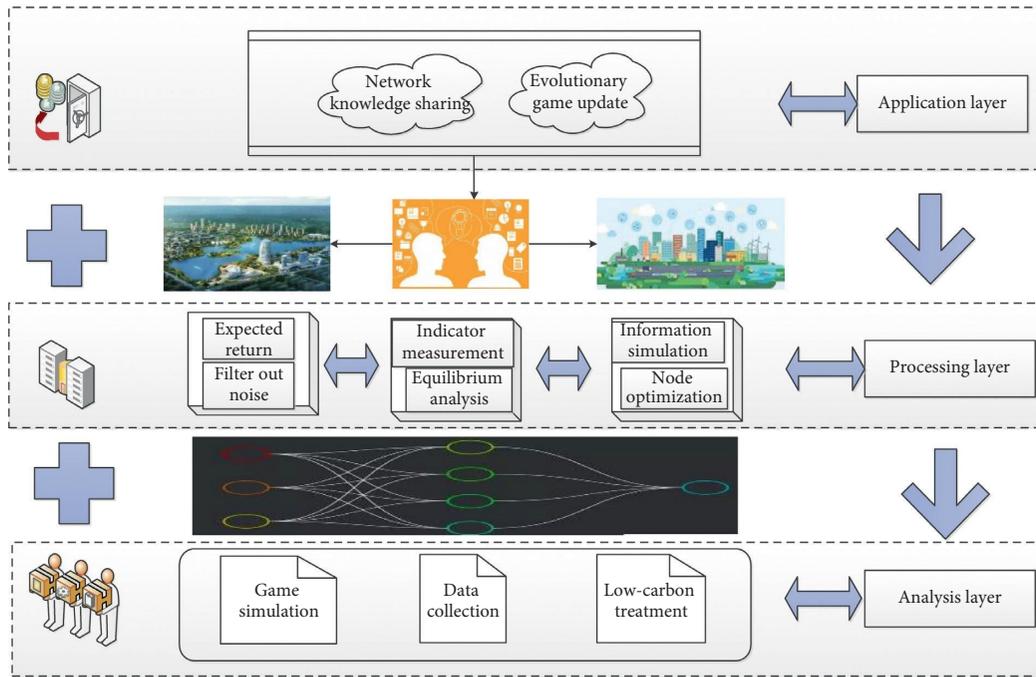


FIGURE 3: Framework structure of network knowledge sharing model.

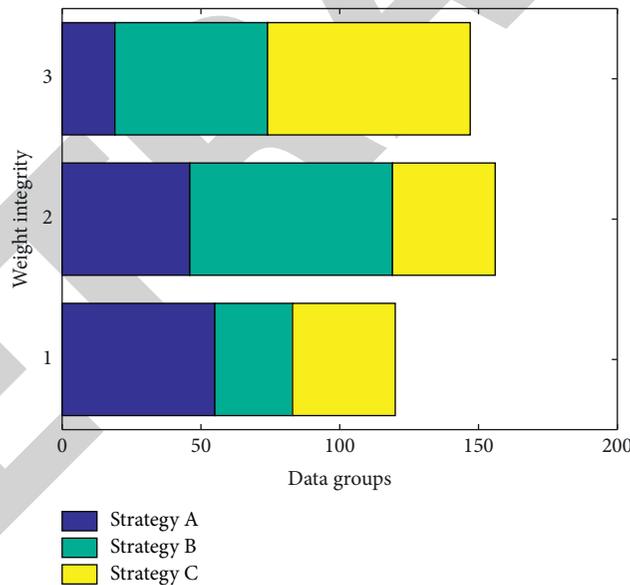


FIGURE 4: Histogram of model node weights.

sharing. The same analysis shows that when $D1$ increases, network 1 will choose knowledge sharing.

4.2. Discussion on System Integration Stability. The rewards and punishments of the main body in the process of network knowledge sharing and knowledge collaboration should be clear when signing the cooperation agreement. If either party in the network breaches the contract, the other party needs to be compensated. In order to analyze the influence of rewards and penalties on knowledge sharing behavior in the

innovation network, the stability of system integration was discussed by changing rewards and penalties without changing other parameters. Because of both variables, x and y , can enjoy freely flexible dynamics, making x and y slip away from an internal equilibrium ($E5$ in the author's model), leading to one of the other trivial equilibria ($E1-E4$). By setting the value of each parameter in the innovation network, the influences of different rewards and punishments on the synergistic effect and revenue of each participant in the innovation network are analyzed, as shown in Figure 6. In the innovation network, the values of each

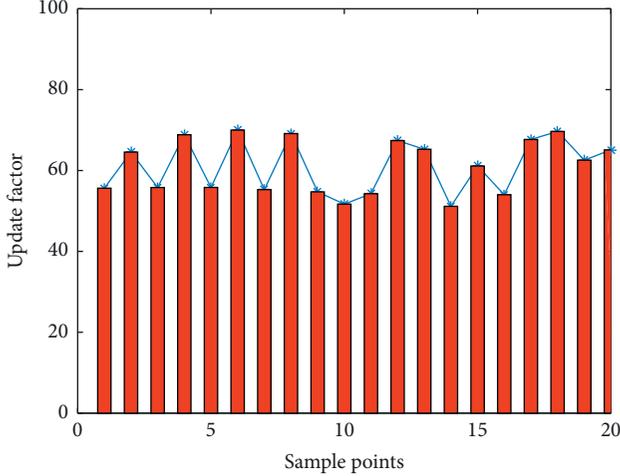


FIGURE 5: Stability analysis of network knowledge sharing.

parameter are set as $A = 1$, $\beta = C = \alpha = 0.5$, $K1 = 2$, $K2 = 1$, $B1 = 0.8$, $B2 = 0.2$, and Figure 6 is obtained. According to the analysis of Figure 6, when the participants in the innovation network are not punished, the degree of synergy among the participants is low. In this case, a punishment mechanism should be set to improve the enthusiasm and synergy of the participants in the innovation network. With the increase of the reward and punishment mechanism of each participant in the innovation network, the initiative and synergy of each participant in innovation are strengthened, and it is shown that when the punishment mechanism is 3, the innovation and synergy of each participant is the strongest. When the punishment mechanism is less than 1, the profit value of each participant in the innovation network is the smallest. With the gradual increase of the punishment mechanism, the utility value of each participant in the innovation network is also gradually increasing. When the punishment mechanism reaches 2, the utility value of each participant in the network reaches the maximum..

When knowledge sharing is carried out among all participants in the innovation network, the benefit value gained when either party chooses to carry out negative cooperation is smaller than the benefit value when choosing to carry out positive cooperation. In innovation networks, with the increase of penalties, negative cooperation on choice of one party will suffer big loss, and at the same time, the incentives for active cooperation will increase. After the evolutionary game, organizations in the innovation network have an increased probability of selecting active cooperation. At the same time, the overall network utility has also been improved. For an asymmetric game, if (X, Y) is an ESS, then it must be a strict Nash equilibrium; that is, a Nash equilibrium in which each player's strategy is the only optimal response to the other player's strategy. When the punishment intensity reaches a certain value, all participants in the innovation network will tend to be stable and choose to actively participate in knowledge sharing. Similarly, setting reasonable profit distribution coefficient has a very important influence on promoting the stability of all participants in the innovation network. The unreasonable profit

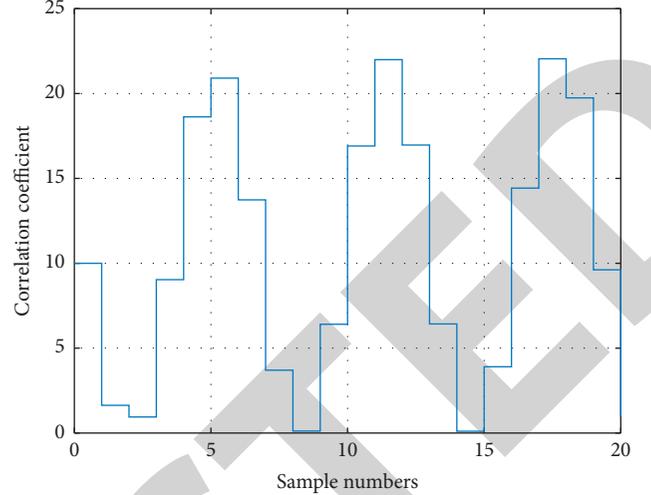


FIGURE 6: Ladder diagram of the correlation coefficient of the evolutionary game.

distribution coefficient will seriously affect the enthusiasm and stability of the party with the benefit loss to participate in the knowledge sharing in the innovation network. Therefore, the relationship between knowledge sharing effect and benefit distribution of each participant in the innovation network is discussed by setting different benefit distribution coefficient α values of network knowledge sharing benefits is the key to determining whether the cooperation between subjects can be stable and sustainable. Unreasonable income distribution rate can easily cause one party to choose negative knowledge collaborative innovation and may even lead to the breakdown of network knowledge sharing cooperation. Control other parameter values to be constant, take 5 typical α values, and analyze the relationship between the network knowledge sharing network knowledge synergy effect and the income distribution rate.

It can be seen that points $(0, 0)$ and points $(1, 1)$ are evolutionary stable points, indicating that the difference between the sharing cost of network 1 and network 2 and the incentive of the evolutionary game model is less than the penalty for knowledge sharing in low-carbon innovation networks. At this time, the two networks may choose to share knowledge at the same time or choose not to share knowledge at the same time. The specific choice of evolutionary stability strategy is related to the initial state of the two networks. The evolutionary dynamic path of the system is shown in Figure 7. It can be seen that the broken line connected by two unstable points B and C and saddle point E constitutes the boundary of the system's convergence state, and the saddle point is the threshold of system evolution. Because the probability is continuous, even if the set of strategies is limited, there will be an infinite number of mixed strategies. Conversely, the asymmetric game is used to determine the equilibrium of symmetric peers. When the initial state of the system is near these two values, small changes in the initial state will affect the final result of the system evolution; when the initial state falls within M region, the evolution system will converge to point $A(0, 0)$.

4.3. Example Results and Analysis. It can be seen from Figure 8 that by changing the value of the benefit distribution coefficient, it is found that when the benefit distribution coefficient is 0.5, the probability and benefit value of each participant in the innovation network to actively carry out knowledge sharing reach the maximum and gradually form a straight line. So this article through the analysis of each participation main body in the innovation network probability of knowledge innovation and the efficiency value, it is concluded that the unreasonable interest distribution coefficient will directly affect the innovation network in low interests, the probability that the party with less profit will choose to cooperate will decrease. It will eventually destroy the stability of the innovation network and reduce the efficiency of knowledge sharing.

Generally speaking, the breadth and depth of knowledge reserve of different participants in the innovation network are also different, that is to say, the knowledge potential difference is formed by different participants in the innovation network in order to promote the diffusion and transfer of knowledge. Therefore, this paper analyzes the knowledge sharing effect of the participants in the innovation network by changing the knowledge potential difference.

The network structure formed by the interconnection among the nodes in the innovation network is not accidentally formed, and the knowledge sharing effect of the innovation network is closely related to the degree of knowledge sharing nodes, which is different from the traditional evolutionary game. The results as shown in Figure 9. Among them, the 5 groups of blue curves represent the loops whose starting points are 0.1, 0.3, 0.5, 0.7, and 0.9, and each group can be divided into 5 iterations. In the innovation network, the node degree represents the sum of the number of edges connected to the node, and the greater the node degree, the more obvious the role of nodes in the innovation network. Therefore, by changing the size of the node degree of the innovation network, the influence of node degree on the knowledge sharing effect of the innovation network is analyzed, and the role of the core node in the innovation network on knowledge sharing is further clarified.

Figure 10 shows the influence of node degree on the collaborative efficiency of each agent in the innovation network under different penalty mechanisms when other parameters remain unchanged. Further analysis in Figure 10 shows that there is a positive relationship between the enthusiasm of each node in the innovation network to participate in knowledge sharing and the severity of punishment. It can be seen that the probability of the overall active collaboration of network knowledge sharing and cooperation network nodes increases with the increase of rewards and punishments. Among them, the 5 groups of red curves, respectively, represent the loop with the starting point of 0.1, 0.3, 0.5, 0.7, and 0.9, and each group can be divided into 5 iterative parts, representing different paths to the saturation point. When E is 0, the probability that most nodes actively collaborate is less than 0.5. With the increase in rewards and punishments, the probability of active collaboration of nodes with a degree greater than 2 has been

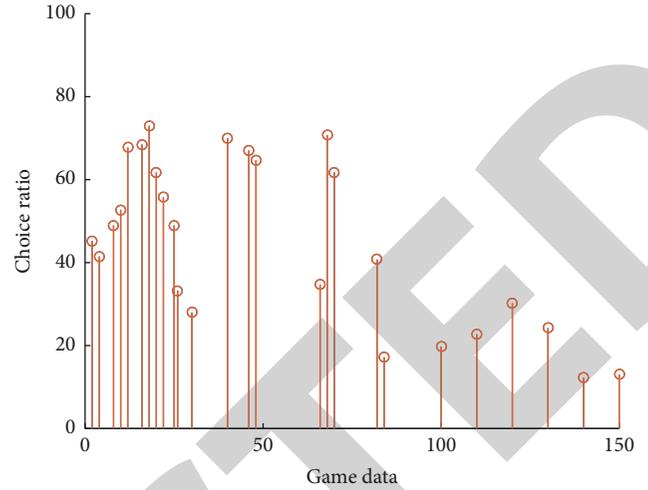


FIGURE 7: Analysis of the selection ratio of network knowledge sharing.

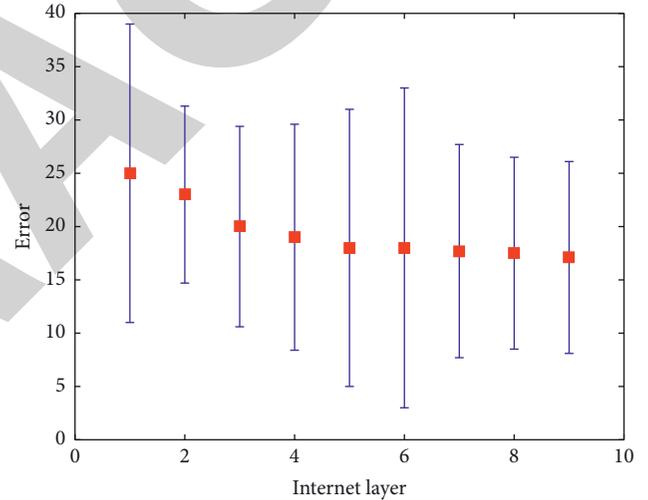


FIGURE 8: Synergy error analysis of different network layers.

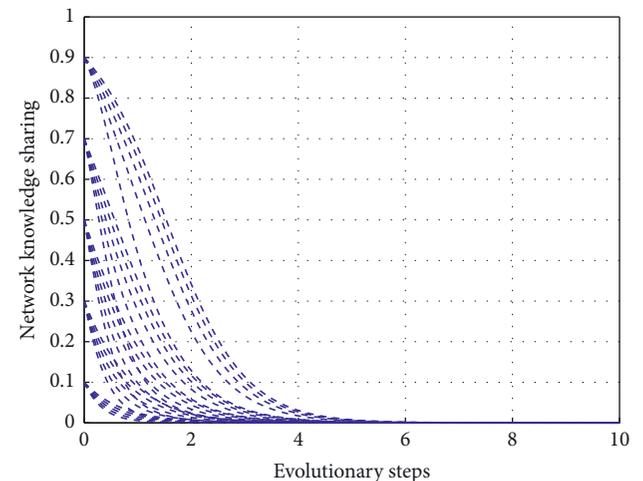


FIGURE 9: Evolutionary game path of network knowledge sharing.

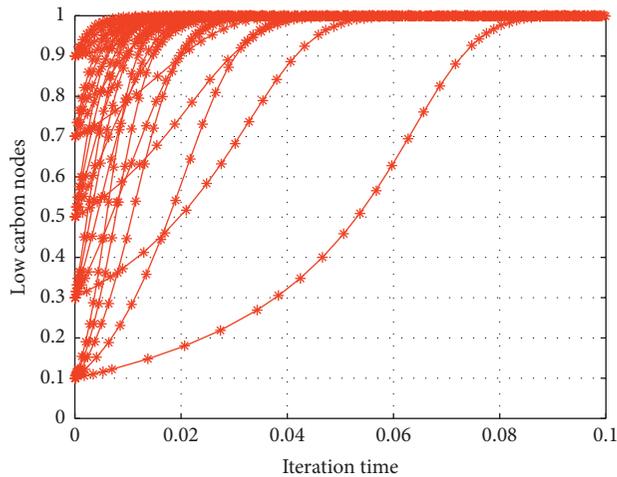


FIGURE 10: Iterative trend of model low-carbon innovation nodes.

greatly increased. When the penalty intensity is set to 0, the probability of each node in the innovation network to actively participate in the collaboration is also small. When the penalty intensity is increased, the synergy probability of each node will increase. When the penalty intensity is set to 2, the probability of each node participating in collaboration increases to 0.7. It can be found that setting a reasonable penalty intensity will help improve the efficiency of knowledge sharing in the innovation network and enhance the probability of collaboration among nodes. At this time, compared with the level of public investment, the penalty coefficient has a more significant impact on the choice of network knowledge sharing behavior. The evolutionary game model is more effective in maximizing social welfare by adjusting the penalty coefficient; when $0 < F(i, D-i) < 1$, the level of public investment has a more significant impact on the choice of online knowledge sharing behavior, and the evolutionary game model is more effective in maximizing knowledge sharing on low-carbon innovation networks by adjusting the level of public investment.

5. Conclusion

By adopting the method of expert scoring, the factors affecting the evolutionary game of knowledge sharing in low-carbon innovation networks are grasped and summarized. The design algorithm sorts all factors into 5 levels. The first level is the factor of contract breach penalty. It has the most direct impact on the success of collaborative innovation in network knowledge sharing; middle-level factors are the most core part, mainly including six factors: collaborative income distribution, risk-sharing mechanism, and knowledge sharing regulations, laws and regulations at the bottom of the interpretive structure model soundness, financial support from financial institutions, and related services of intermediaries at the 4th level are all global factors that affect the collaborative innovation of low-carbon technologies for online knowledge sharing. Next, an evolutionary game model is constructed, the payout matrix is listed, and the evolutionary game strategy of collaborative

innovation of network knowledge sharing low-carbon technology is analyzed. Five equilibrium points are calculated according to the dynamic results of the replicator, which are $E1(0,0)$, $E2(1,0)$, $E3(0,1)$, $E4(1,1)$, and $E5(x^*, y^*)$, among which $E5$ is the saddle point, which is not the focus of this article. The analysis of the evolution stability of VS divides it into 6 cases for analysis and simulation, analyzes its evolution direction under different initial values, and obtains its evolution path diagram. It is found that the evolution direction of Cases V and VI is uncertain, and the results of Case V do not belong to the research focus of this article, so we proceed to analyze the factors that affect the game result to converge to the equilibrium point $E3(1, 1)$ in Case VI. The results of the influence of each factor on the network knowledge sharing to achieve low-carbon technology collaborative innovation show that the liquidated damages, synergistic benefits, evolutionary game model subsidies, carbon emissions difference, and carbon emission tax have a positive effect on collaborative innovation, whereas R&D costs and knowledge spillover effects have a negative inhibitory effect on collaborative innovation of cost allocation ratio and revenue allocation ratio and the impact is nonunidirectional.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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