Modeling and Analysis of Interorganizational Knowledge Transfer Considering Reputation Mechanisms

Xiaoxia Huang *, Peng Guo, Xiaonan Wang and Ding Wang

School of Management, Northwestern Polytechnical University, Xi’an 710072, China; guopeng@nwpu.edu.cn (P.G.); xiaonan_wang@mail.nwpu.edu.cn (X.W.); wangdingxibeigongda@mail.nwpu.edu.cn (D.W.)
* Correspondence: huangxiaoxia@mail.nwpu.edu.cn; Tel.: +86-029-8843-1784

Abstract: Transferring a quantity of credible knowledge is a key sustainable competitive advantage for multi-agent cooperation in an interorganizational network (ION). This study presents simulation research to identify the impacts of reputation mechanisms in interorganizational knowledge transfer through systematic evolutionary game theory, addressing the sustainability of knowledge transfer behaviors in innovation, R&D, and low green carbon. The simulation results showed that an agent’s reputation provides information about having valuable knowledge, which can reduce some of the opportunistic behaviors of knowledge transfer faced by knowledge agents. Regardless of its form, we found that reputation distribution significantly promotes interorganizational knowledge transfer behaviors. In addition, higher reputation thresholds and more significant differences in the impact of high and low reputations prominently contribute to knowledge transfer efficiency and effectiveness. The relationship between reputation mechanisms and the efficiency and effectiveness of knowledge transfer is examined. This study sheds light on the sustainable management of interorganizational projects from reputation mechanisms.

Keywords: knowledge transfer; reputation mechanisms; interorganizational network; coevolutionary rule; evolutionary game theory

1. Introduction

In recent years, interorganizational knowledge transfer has gathered much academic attention [1]. This could be owed to the fact that interorganizational knowledge transfer through cooperative approaches (e.g., interorganizational projects [2]) has emerged as a proper organizational strategy [3] for value creation or sustainable competitive advantage in a complex and dynamic environment [4,5]. However, interorganizational knowledge transfer is difficult and complicated and has a high failure rate [6]. Consequently, whether and how a mechanism exists to facilitate interorganizational knowledge transfer is an exciting area for further theoretical research.

Among the growing number of knowledge transfer studies that use a network perspective, the study of knowledge transfer of the IONs is the most powerful [7,8]. Evolutionary game theory is an analytical framework of multi-agent interaction for modeling knowledge transfer or non-transfer behavior among knowledge agents [9]. However, interorganizational knowledge transfer is not easy because it requires mobilizing, coordinating, and integrating knowledge agents’ behaviors at different times, statuses, and geographical distances [10–12]. Under such circumstances, it becomes difficult to consider knowledge transfer across heterogeneous agents in interorganizational terms purely in terms of network structure. In the absence of governance mechanisms, agents in IONs often seek technical and managerial knowledge through direct relationships with other agents. Many of these efforts have been devoted to investigating traditional mechanisms related to knowledge transfer performance [11,13]; however, governance mechanisms based on the characteristics of heterogeneous agents in the context of interorganizational knowledge transfer...
transfer have been less studied [11,14]. Concerning repeated interactions between the multi-agent, reputation has been recognized as an essential determinant of cooperative behavior, in theoretical [15,16] and experimental settings [17,18].

Above all, this study makes two key contributions to the literature. First, trust has been considered extensively studied on informal governance mechanisms [19], while reputation as a signal of external behaviors has received little attention [20]. By introducing reputation mechanisms to the interorganizational knowledge transfer model, this study finds that reputation mechanisms effectively promote interorganizational knowledge transfer. Second, efficiency and effectiveness are often considered two essential indicators of knowledge transfer behavior. They are rarely explored regarding the knowledge transfer behavior of heterogeneous agents in interorganizational relationships. This study addresses knowledge transfer in the context of IONs. It investigates how the knowledge transfer behaviors of different agents are differentiated by three dimensions of reputation mechanisms, including reputation distribution, reputation threshold and multiplicative factor, and decaying rate, leading to ways to promote the efficiency and effectiveness of knowledge transfer.

The remainder of this article is organized as follows: The following section reviews the literature on interorganizational knowledge transfer and role of reputation mechanisms, and briefly introduces evolutionary game theory in ION. After that, we abstract the ION as a scale-free network, propose a mathematical model of interorganizational knowledge transfer, and construct an evolutionary model on the complex network. Then, we introduce the reputation mechanism into the proposed model to assess the efficiency and effectiveness of knowledge transfer between the multi-agent in the ION. Further, we discuss the impact of the three dimensions of reputation mechanisms on interorganizational knowledge transfer based on the simulation results. Before summarizing the research conclusions in the final section, we provide insights on the managerial implications, existing limitations, and possible future work.

2. Literature Review

For a systematic introduction to the research topic and the methodology to be used in this study, three main research areas were explored: existing interorganizational knowledge transfer studies, the role of reputation mechanisms in knowledge transfer, and a brief introduction to evolutionary game theory to explain how multi-agent interaction analysis framework has been applied to ION.

2.1. Interorganizational Knowledge Transfer

As the complexity of projects increases, it is difficult for a single agent to complete megaprojects [21,22], which results interorganizational R&D projects with specific goals in a limited period [23]. Multiple agents cooperate on R&D projects, to overcome innovation impediments, reduce R&D costs, obtain complementary resources, exchange technologies, benefit from synergy effects, short R&D cycle, or share risks [24]. To gain a first-mover advantage in dynamic industries where new knowledge is constantly emerging, agents must continually generate new knowledge flows to accumulate and update their portfolio of knowledge stock [6,25]. Interorganizational relationships can be represented as networks, where the nodes are agents and the links are cooperative relationships between multi-agents. ION has become the primary means agents acquire knowledge in interorganizational R&D projects [23].

Knowledge transfer is defined as the process by which one agent is influenced by the experience and can be measured by changes in the knowledge of the recipient agent [26]. Extant studies on knowledge transfer report the composition of factors affecting knowledge transfer and the process mechanisms of knowledge transfer. The factors affecting knowledge transfer mainly include knowledge absorptive capacity, innovation ability, transfer costs, and reward and punishment mechanisms [8,27,28]. A knowledge transfer process model is usually constructed by introducing explicit and tacit knowledge transformation effect mechanisms. However, there are still three important research gaps in this field. First,
although previous studies suggested that the context-dependence, monopoly, anonymity of knowledge, and the lack of integrity of knowledge agents hinder knowledge transfer [29], transfer dilemmas caused by knowledge complementarity [22], trust [30], and coordination level [31] among interorganizational knowledge agents have not been considered along with the present challenges. Second, in current knowledge transfer literature, knowledge transfer efficiency is an important indicator to evaluate the innovation performance of IONs [12], whereas how to stimulate and improve the efficiency and effectiveness of knowledge transfer as two research findings have not received sufficient attention [11]. To this end, this study considers efficiency and effectiveness as the two leading indicators of knowledge transfer. When two knowledge agents cooperate, they pool their knowledge as input for new knowledge production [32].

Third, knowledge transfer contributes to the performance and innovation of R&D projects and has become an essential motivation for developing IONs [1]. Interorganizational knowledge transfer has been widely discussed in the literature on technology sourcing, supply chains, and alliances [33,34]. However, agents on interorganizational R&D projects face significant challenges acquiring the required knowledge through IONs. The extent to which agents differ in knowledge transfer is related to their social influence [9,35]. Differences in knowledge transfer, both in terms of efficiency and effectiveness, can be considered resources, and agents should be able to evaluate and activate these resources based on the ability of their partners to use appropriate mechanisms to transfer knowledge [29]. The literature on knowledge transfer has suggested options for successful knowledge transfer strategies, such as managerial oversight, incentives and training programs [36], and formal and informal governance mechanisms [14] based on knowledge characteristics and barriers to knowledge transfer. Still, governance mechanisms due to differences in the reputation information of knowledge agents that address transfer barriers are inadequate and unclear.

2.2. Role of Reputation Mechanisms

Reputation is the overall perception and possible expectation of what a person or agent represents and associated with it [37]. Reputation is crucial for the survival of knowledge agents in networked interorganizational alliances as it reflects the past’s economic strength and social influence [38,39]. Regarding governance mechanisms, reputation mechanisms are becoming a much-discussed issue as an aspect of informal mechanisms [37,38,40–42]. Scholars have studied reputation from the knowledge management perspective and linked it to agents’ reputation [41,42]. The reputation of knowledge agents is closely related to the social behavior of knowledge agents, and it can be used to obtain information about the knowledge transfer behavior of knowledge agents [9,43]. Knowledge agents should have a good reputation if it repeatedly and successfully fulfills their promise to engage in knowledge transfer practices [40]. Conversely, multi-agents that do not act on their expressed intentions, such as failing to transfer knowledge, can negatively affect it.

Reputation mechanisms are a powerful tool [20] to reduce the potential risk of interacting with wholly or nearly unknown agents in open and large-scale systems in environments with no incentive to engage in trustworthy behavior [21]. Agents face a great deal of uncertainty in identifying valuable knowledge and assessing knowledge transfer capabilities, and they often turn to signals from reputation [44]. From an economic and institutional perspective, reputation plays a vital role in reducing partners’ uncertainty in assessing a firm’s knowledge transfer behavior since a positive reputation is based on superior performance over a certain period. The ability of past knowledge transfer behavior indicates the likelihood of becoming a source of valuable knowledge in the future. Thus, agent reputation is regarded as the “credibility” of their stated intentions and is intuitively expected [16]. Knowledge agents tend to cooperate with agents with good reputations for knowledge transfer activities and are pretty loyal to those they perceive as having good reputations. The social influence of potential partners becomes significant in dealing with this uncertainty. Reputation as a signal that the agent is more likely to have valuable
knowledge to share. Agents facing strong demand for new knowledge and high levels of uncertainty may seek external connections with these types of high-influence partners. This allows agents to identify external sources that offer valuable knowledge prospects and establish ongoing relationships.

The critical question is whether this reputation-based mapping of knowledge resources is accurate and effective. If reputation mechanisms performed this function, it would imply an interaction between the effect of reputation on knowledge transfer and the impact of that reputation mechanism on the efficiency and effectiveness of knowledge transfer. Often, information about potential partners is incomplete. Multi-agent opportunistic behavior, risk-averse behavior, etc., further increase the uncertainty of knowledge acquisition and are of growing concern [21]. A good reputation can reduce the perceived risk of knowledge agents in their strategic choices. The benefits of knowledge transfer and standing are widely recognized, but the potential link between reputation and knowledge transfer efficiency and effectiveness dilemmas has not been explored. To address these issues, we construct a model based on interorganizational multi-agent knowledge transfer behavior and investigate the role of reputation mechanisms in the model.

2.3. Evolutionary Game Theory in ION

Evolutionary game theory is an analytical framework of multi-agent interaction for modeling knowledge transfer or non-transfer behavior among knowledge agents [9]. Nowak and May describe the interaction between the multi-agent using the prisoner’s dilemma game behavior on a spatial square grid, in which selfish agents on the grid can form compact clusters to keep them from invading by defective individuals. Motivated by their findings, various game mechanisms such as social diversity, utility weight, reward and punishment, heterogeneity of payoffs, voluntary participation, and individual mobility are incorporated into the spatial lattices, showing convincingly that they can promote the evolution of cooperation to be a higher level [45–47]. An interorganizational R&D project is a complex system with multiple tasks, agents, and goals. In an interorganizational R&D project, there are cooperative relationships between each agent and several other agents, forming an ION. Previous studies on knowledge transfer are mainly based on complex network analysis [35,48,49]. As a game model applied to spatial structure, evolutionary game theory provides a robust framework for studying cooperation issues. The earlier research work about evolutionary games of complex network in structured populations has always been studied by many researchers. In addition to the above, reputation as an effective solution to overcome temptation and enhance cooperation to describe the structure of the population has also attracted widespread attention. Unlike other biological systems, reputation is significant for the survival of an innovative agent in a networked interorganizational R&D alliance, as the information reflects the agent’s economic strength and social influence in the past. Therefore, reputation has become the core of indirect reciprocity and the focus of evolutionary game theory research in recent years. This study considers the coevolution of the importance of the multi-agent and strategy in the knowledge transfer model through systematic evolutionary game theory.

3. Materials and Methods

3.1. Mathematical Model

In this section, a mathematical model of interorganizational knowledge transfer is formulated that includes interorganizational characteristics, knowledge transfer agents, and knowledge absorption processes. The benefits generated by the accumulation of knowledge agents in the ION are regarded as the process of knowledge transfer. Moreover, the following assumptions, which are widely adopted in the literature and validated by scholars [8,31,50], form the basis of our study:

1) Definition of accumulated knowledge stock

We assume that each knowledge agent initially invests equal amounts of knowledge. Although the effectiveness of knowledge transfer has not been discussed by Zhou et al. [50]
and Xu et al. [8], studies have shown that time scales of knowledge transfer should be systematically understood [51,52]. Thus, we assume

\[ k_i(t) = \frac{1}{\tau} \sum_{s=t-\tau}^{t-1} \rho^{t-s} k_j \]  

(1)

where \( k_i(t) \) is the accumulated knowledge stock transferred from agent \( j \) to agent \( i \) at time \( t \); \( \rho \in (0, 1] \) describes the time depreciation coefficient; and \( \tau \in (0, 1] \) is the time window that can produce the effect of knowledge transfer.

(2) Direct benefits and costs from knowledge transfer

\( a_i k_i(t) \) indicates the amount of knowledge acquired by agent \( i \) from agent \( j \); \( a_i \) is the knowledge transfer efficiency, which depends on the absorptive ability of agent \( i \) and the context in which it occurs. \( c_i k_i(t) \) describes the cost of knowledge transfer from agent \( i \) to agent \( j \); and \( c_i \) is the knowledge transfer cost coefficient.

(3) Reorganization benefits from knowledge transfer

\( \beta_j v_{i,0} k_j(t) \) represents benefits by understanding the original knowledge, which is the synergy and digestion of own knowledge and input knowledge obtained by agent \( i \) from agent \( j \) at time \( t \). \( \beta_j \) is the knowledge reorganization coefficient, which reflects the understanding, comprehension, and application ability of the knowledge of agent \( i \); \( v_{i,0} \) is the initial stock of knowledge of agent \( i \).

(4) Synergistic benefits and costs from knowledge transfer

The synergistic benefits of the knowledge stock are a concave function of the collaboration level \( \theta \), which is the resultant of the knowledge agent own investment into knowledge and the knowledge shared or spilled over by other knowledge agents [31,53], and is defined for agent \( i \) as

\[ \theta \xi_i(k_i(t), \gamma_i) k_j^\gamma = \theta |\gamma_i k_i(t) + (1 - \gamma_i)| k_j^\gamma \]  

(2)

where \( \theta \) is the coefficient of knowledge synergy; \( k_j^\gamma \) shows that trust has a positive effect on knowledge sharing. \( \xi_i \) represents the agent’s learning capability or absorptive capacity and \( \xi_i \) depends on the complementarity of its knowledge with that of other agents, denoted as \( \gamma_i \). Referred to the form of the cost function in the studies of Joseph et al. [54], \( \theta \mu_i k_i(t) k_j(t)/2 \) represents the synergistic costs of interorganizational knowledge transfer for collaborative processes; \( \mu_i \) is the collaboration cost coefficient.

(5) The reward and punishment for knowledge transfer

\( \lambda k_i(t) \) indicates the reward by the interorganizational alliance; \( \lambda \) is the reward coefficient; and \( \psi \) means the punishment for defection.

The model includes the knowledge reorganization effect, knowledge transfer cost, reward and punishment mechanisms, and other factors described by Zhou et al. [50], and Xu et al. [8], as well as the synergistic benefits and costs generated by the collaborative process of interorganizational knowledge transfer agents described by Arsenyan et al. [31].

\[ e_i(t) = a_i k_i(t) - c_i k_i(t) + \beta_j v_{i,0} k_j(t) + \theta \xi_i(k_i(t), \gamma_i) k_j(t)^\gamma - \theta \mu_i k_i(t) k_j(t)/2 + \lambda k_i(t) - \psi_i \]  

(3)

For the convenience of analysis, we modify Equation (3) by Equations (1) and (2) as follows:

\[ e_i(t) = a_i \frac{1}{\tau} \sum_{s=t-\tau}^{t-1} \rho^{t-s} k_j + \beta_j v_{i,0} \frac{1}{\tau} \sum_{s=t-\tau}^{t-1} \rho^{t-s} k_j + \theta \left[ \gamma_i \frac{1}{\tau} \sum_{s=t-\tau}^{t-1} \rho^{t-s} k_j + (1 - \gamma_i) \right] \left( \frac{1}{\tau} \sum_{s=t-\tau}^{t-1} \rho^{t-s} k_j^\gamma \right) \\
- c_i \frac{1}{\tau} \sum_{s=t-\tau}^{t-1} \rho^{t-s} k_i + \lambda \frac{1}{\tau} \sum_{s=t-\tau}^{t-1} \rho^{t-s} k_i - \psi_i - \theta \mu_i \frac{1}{\tau} \sum_{s=t-\tau}^{t-1} \rho^{t-s} k_j(1 + 1) \frac{1}{\tau} \sum_{s=t-\tau}^{t-1} \rho^{t-s} k_j)/2 \]  

(4)

\[ \psi_i = \begin{cases} 0, & k_i(t) > 0 \\ \psi, & k_i(t) = 0 \end{cases} \]  

(5)
where $e_i(t)$ is the benefits function of knowledge transfer agent $i$ at time $t$.

### 3.2. Evolutionary Model

We analyze the evolutionary model of interorganizational knowledge transfer. Each agent can adopt two pure strategies: transfer as cooperation (C) and non-transfer as defection (D).

In the game between knowledge agent $i$ and knowledge agent $j$ in the ION, the benefits of each knowledge agent vary under different strategy combinations. According to the references, this study establishes the game benefit matrix of knowledge transfer between knowledge agents in the ION (as shown in Table 1).

Strategy 1: If both agents select to transfer strategy, the payoff of agent $i$ is expressed in Equation (6) as

$$
o(i, t) = \alpha_i \frac{1}{T} \sum_{s=t-T}^{t-1} \rho^{t-s}k_j + \beta_{ij}v_{ij} \frac{1}{T} \sum_{s=t-T}^{t-1} \rho^{t-s}k_j + \theta \left[ \gamma_i \frac{1}{T} \sum_{s=t-T}^{t-1} \rho^{t-s}k_i + (1 - \gamma_i) \right] \left( \frac{1}{T} \sum_{s=t-T}^{t-1} \rho^{t-s}k_j \right)
- c_i \frac{1}{T} \sum_{s=t-T}^{t-1} \rho^{t-s}k_i + \lambda \frac{1}{T} \sum_{s=t-T}^{t-1} \rho^{t-s}k_i - \theta \mu_i (\frac{1}{T} \sum_{s=t-T}^{t-1} \rho^{t-s}k_i) (\frac{1}{T} \sum_{s=t-T}^{t-1} \rho^{t-s}k_j) / 2
$$

Strategy 2: If agent $i$ and agent $j$ select the (transfer, non-transfer) strategy, the payoff of agent $i$ is expressed in Equation (7) as

$$p(i, t) = -c_i \frac{1}{T} \sum_{s=t-T}^{t-1} \rho^{t-s}k_i + \lambda \frac{1}{T} \sum_{s=t-T}^{t-1} \rho^{t-s}k_i$$

Strategy 3: If agent $i$ and agent $j$ select the (non-transfer, transfer) strategy, the payoff of agent $i$ is expressed in Equation (8) as

$$q(i, t) = \alpha_i \frac{1}{T} \sum_{s=t-T}^{t-1} \rho^{t-s}k_j + \beta_{ij}v_{ij} \frac{1}{T} \sum_{s=t-T}^{t-1} \rho^{t-s}k_j - \psi$$

Strategy 4: If both agents select the non-transfer strategy, the payoff of agent $i$ is expressed in Equation (9) as

$$r(i, t) = -\psi$$

Table 1. 2 × 2 game matrix form based on Equations (6)–(9).

<table>
<thead>
<tr>
<th>Knowledge Transfer $j$</th>
<th>C</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>knowledge transfer $i$</td>
<td>C</td>
<td>D</td>
</tr>
<tr>
<td>C</td>
<td>$o(i, t)$, $p(i, t)$</td>
<td>$p(i, t)$, $q(j, t)$</td>
</tr>
<tr>
<td>D</td>
<td>$q(i, t)$, $p(j, t)$</td>
<td>$r(i, t)$, $r(j, t)$</td>
</tr>
</tbody>
</table>

Note: transfer strategy as cooperation (C), and non-transfer strategy as defection (D).

Later, we analyze the game payoff matrix of interorganizational knowledge transfer. The agents will obtain their payoff by playing the game in pairs, where they will obtain the reward (R) and punishment (P) payoff if they take the same action; while a defecting agent will be tempted to acquire a higher payoff (T) and the cooperating one can only receive the sucker’s payoff (S) provided that they select the distinct strategies. Hence, the payoff of agent $i$ can be described by the following payoff matrix:

$$M = \begin{pmatrix}
R & S \\
T & P
\end{pmatrix} = \begin{pmatrix}
o(i, t) & p(i, t) \\
q(i, t) & r(i, t)
\end{pmatrix}$$
After presenting the game payoff matrix of the multi-agent, we use $U_i(t)$ to denote the accumulated payoffs of knowledge agent $i$ in the ION at time $t$, which can be illustrated in Equation (11) as

$$U_i(t) = \sum_{j \in \Omega_i} s_i(t)M_{ij}(t)$$

where $s_i(t)$ and $s_j(t)$ denote the strategy of agent $i$ and agent $j$. $\Omega_i$ is all neighbors of agent $i$ where $s_i(t) = (1, 0)$ if agent $i$ is a cooperator in the knowledge transfer and $s_i(t) = (0, 1)$ if agent $i$ is a defector.

3.3. Network Model

ION can be defined as a group of organizations linked by a cooperation agreement, conducting projects together [23]. Therefore, we consider ION as a complex network with nodes (i.e., multi-agent), and edges between nodes (i.e., relationships between multi-agents). Based on this, we use an undirected graph $G(t) = (V, E(t))$ to describe ION in period $t$, where $V = \{1, 2, \ldots, N\}$ is the set of nodes, and $E(t) = \{e_{ij}(t) | i, j \in V\}$ is the set of edges in period $t$. We define the adjacency matrix of ION with $A = [a_{ij}]_{N \times N}$, where $a_{ij} = 1$ if agent $i$ and $j$ is directly connected, that is, they are involved in knowledge transfer in the ION; and $a_{ij} = 0$ if agent $i$ and agent $j$ are not directly connected, that is, they mutinied against each other and the path of knowledge transfer was interrupted. Many recent studies have shown that IONs exhibit the characteristics of heterogeneous networks, manifesting themselves as scale-free networks [55]. Therefore, we adopt the BA scale-free model proposed by Barabási and Albert [45] to generate an ION, which can be calculated by the following:

1. Growth: starting from a network with $m_0$ nodes, each time a new node is introduced and connected to $m$ existing nodes, where $m \leq m_0$.

2. Preferential attachment: the probability $\Pi_i$ that a new node is connected to an existing node $i$ satisfies the following relationship with the degree $d_i$ of node $i$ and the degree $d_j$ of node $j$:

$$\Pi_i = \frac{d_i}{\sum_{j} d_j}$$

The typical characteristic of this network is that while most nodes are only connected with a few nodes, a few of them are connected to a large number of nodes, so the ION has heterogeneity. We study the knowledge transfer behavior of heterogeneous agents in the ION.

4. Methodology

4.1. Reputation Mechanisms

Improving one’s reputation and rewarding others were critical predictors of knowledge transfer and diffusion [33,41,42]. We introduce the concept of reputation to record the historical knowledge transfer behavior of knowledge agents in IONs. Specifically, knowledge agents decide whether or not to engage in knowledge transfer by considering the reputation of their neighbors. To explain the influence of reputation mechanisms on interorganizational knowledge transfer, we analyze reputation distribution [42,56], reputation multiplicative factor [39], and reputation decaying rate [57].

The reputation distribution of knowledge agents in IONs will affect the knowledge transfer strategy [47]. We analyze three initial distributions of $R_i(0)$. (a). Constant initial R (CIR): $R_i(0) = 50$; (b). Uniform initial R (UIR): $R_i(0) \sim U[1, 100]$; (c). Gaussian initial R (GIR): $R_i(0) \sim N(50, 16.67^2)$, according to ‘3σ principle’, we let $\sigma = 16.67$, it also be forced to $R_i(t) = 1$ if $R_i(t) < 1$; $R_i(t) = 100$ if $R_i(t) > 100$.

Next, we introduce reputation in the model, and all agents are assigned a dynamic reputation value based on their past behavior. To illustrate the reputation mechanisms in knowledge agent selection, we define the reputation $R_i(t)$ of agent $i$ at time $t$ as they transfer
knowledge to their neighbors in past games, where $R_i(t) \in [1, 100]$, agent’s reputation at time $t$ depends on their historical memory and present strategy selection:

$$R_i(t) = \phi R_i(t-1) + \Delta_i(t)$$  \hspace{1cm} (13)

where $\Delta_i(t)$ is 1 if $s_i(t) = (1, 0)$ when agent $i$ transfers knowledge at time $t$, and $\Delta_i(t)$ is $-1$ if $s_i(t) = (0, 1)$ when agent $i$ defects at time $t$. $\phi$ denotes the decaying rate. Thus an agent’s reputation value is the weighted sum of the times they have chosen knowledge transfer in the past games [58]. For $\phi \to 0$, the memory effect vanishes and the reputation mainly depends on the choice of current knowledge transfer strategy; for $\phi \to 1$, reputation value is accumulated since the beginning of the evolution.

Then, we set a reputation threshold $R_c$, which will divide the interorganizational alliances into two types of multi-agent: when reputation accumulates to a certain extent $R_c$, it leads to prestige and brings many hidden benefits to the agent; when reputation is reduced to a certain level $R_c$, it leads to disgrace and indicates that the collaboration with this agent will have a bad influence on their returns. Accordingly, based on the reputation value of agent $i$ at time $t$, $\eta_j$ in Equation (14) can be set as follows

$$\eta_j = \begin{cases} 1, & \text{if } R_j(t) \geq R_c \\ \eta_j, & \text{if } R_j(t) < R_c \end{cases}$$  \hspace{1cm} (14)

where $\eta_j$ is a multiplicative factor that depends on the reputation of agent $j$.

### 4.2. Learning Dynamics Based on Reputation Mechanisms

Unlike the traditional process based on the Fermi rule, an agent is randomly selected (denote as $i$) and allowed to update his strategy at each stage. Then, one of their neighbors is casually picked (indicate as $j$), and then agent $i$ imitate the strategy of agent $j$ with a probability that is proportional to the neighbors’ reputation multiplicative factor $w_j$. This rule ensures that agents with good reputations have a higher probability of being noticed and imitated. By comparing the payoff difference of agent $i$ and agent $j$, whether agent $i$ imitates the strategy of agent $j$ depends on the probability $P(s_j \rightarrow s_i)$, which can be summarized in Equation (15) as

$$P(s_j \rightarrow s_i) = \eta_j \frac{1}{1 + \exp[(U_i(t) - U_j(t))/K]}$$  \hspace{1cm} (15)

where $U_i(t)$ and $U_j(t)$ represents the accumulated payoff of agent $i$ and $j$ at time $t$ respectively. $K(K > 0)$ is the noise effect that describes uncertainty in the strategy updating. Based on experience and other literature, we set $K = 0.1$ in this study.

Therefore, to measure the consequences of knowledge transfer in the ION, we use $p_c(t)$ to define the fixed frequency of cooperators in the ION at the end of time $t$, which is expressed in Equation (16) as

$$p_c(t) = \lim_{N \to \infty} \frac{\sum_{i=1}^{N} s_i(t)}{N}$$  \hspace{1cm} (16)

where $p_c(t) \to 0$ signifies that there is almost no knowledge transfer between knowledge agents, and the ION has virtually been broken down, while $p_c(t) \to 1$ signifies that the ION functions well.

To measure the knowledge growth of the ION, we employ the average knowledge stock $\bar{k}(t)$. The average knowledge version of knowledge agents is affected more by the final payoffs of agents $U(t)$ and the number of knowledge agents. Let $\bar{k}(t)$ be the average knowledge of the process of interorganizational knowledge transfer at time $t$, and it can be written as
The cooperation rate and the average knowledge transfer volume of knowledge agents are key information to evaluate the efficiency and effectiveness of knowledge transfer activities, respectively. Therefore, this study compares the evolutionary differences of reputation mechanisms in terms of knowledge transfer efficiency and effectiveness to understand how reputation mechanisms affect interorganizational knowledge transfer behavior fully.

5. Results and Discussion

This section simulates a series of experiments to reflect the above-described cases. The evolution of interorganizational knowledge transfer behavior under reputation mechanisms has been discussed for \( N = 300, \alpha = 0.5, \tau = 1, \rho = 0.1, \beta = 0.1, v = 10, \mu = 0.1, \lambda = 0.5, \psi = 6, K = 0.1 \). However, these parameters are not the focus of this study. The initial stock knowledge of each agent is standardized and set to 10. Therefore, at the beginning of the evolution of knowledge transfer in IONs, the stock knowledge of agents is homogeneous, whereas the egocentric network of each agent is heterogeneous (scale-free network). Each simulation is carried out here. Initially, an equal proportion of strategies C (transfer) and D (non-transfer) are randomly assigned at different network vertices. Then 10,000 Monte Carlo steps (MCS) are run, and in each step, for example, the neighbors of each knowledge agent are determined by the initial scale-free network structure. After playing the game, knowledge agents obtain a fixed payoff and change their reputation according to their actions. In each simulation, we use the reputation mechanisms explained in Section 3 and repeat the ION evolution 50 times to test the robustness of the evolution of ION knowledge transfer results.

For all experiments, we first observe how initial reputation distribution influences the evolution of ION knowledge transfer behavior. Different reputation distributions lead to similar outcomes. The presence of an initial reputation distribution significantly facilitates the evolution of knowledge transfer than non-reputation distribution. Secondly, we learn the relationship between reputation thresholds \( R_c \), multiplicative factors \( \eta \) and knowledge transfer behavior in details, and we evaluate the knowledge transfer effects of reputation mechanisms according to some key points of \( R_c, \eta \). Then we choose three representative factors influencing the knowledge transfer process to understand the influence based on multiplicative factors of reputation mechanisms. Last but not least, we compare the evolution differences between several decaying rates of reputation.

5.1. The Influence of Initial Reputation Distribution on Knowledge Transfer

In Figure 1, the cyan symbol represents the results of the traditional model without any reputation effect, while the other symbols describe the CIR, UIR, and GIR in our model, respectively. Figure 1a shows the time evolution of the fraction of cooperators at each MCS step under the influence of non-reputation and different initial reputation distributions. For the evolutionary curve of non-reputation, the proportion of cooperators, \( p_c \), rapidly declines and stabilizes at around 0.22. The reason is that in an environment without reputation, multi-agents are more likely to select defective strategies when faced with external temptations. However, the UIR and GIR systems with reputational distributions undergo a process of decline, rise, and eventually stabilize after a few limited-time steps (UIR reaches 0.96 and GIR reaches 0.98). The difference is that the CIR does not undergo a decreasing process but increases directly and rapidly to a stable value of 0.96. Hence, in the context of repeated interactions between knowledge agents and in terms of the positive impact of reputation on cooperation, our results are consistent with those of the theoretical and experimental settings in [18,42].
Figure 1. Reputation of all agents in the networked populations are constant reputation distribution, uniform reputation distribution and Gaussian reputation distribution when $R_i(0) = 50, R_i(0) \sim U[1,100], R_i(0) \sim N(50,16.67^2)$, respectively. (a) Time evolution of fraction of cooperators when the distribution of reputation is different. (b) Temporal evolution of the average knowledge stock of knowledge agents when reputation distribution is different. The other simulation parameters are set to be: $c = 1.5, \eta = 0, \theta = 0.6, \gamma = 0.5, \sigma = 0.4$.

Figure 1b illustrates the knowledge transfer effect of interorganizational agents, from which we can conclude that the cyclical evolutionary process of the average knowledge transfer of repeated ION is relatively consistent with the specific evolutionary process of the corresponding Figure 1a. Therefore, the single evolutionary results are not a result of extreme cases but of generality. Thus, they have the value of analysis. In particular, in the non-reputation model, if the benefits of agent’s knowledge transfer are lower than the average benefits without knowledge transfer between neighbors, agents will abandon the knowledge transfer strategy, resulting in the average amount of knowledge transferred at around ~10. In this case, the non-reputation curve means that the role of reputation is not considered in the evolution of knowledge transfer, and the system depicts a typical phased process of change. However, under an ION structure with the initial reputation distributions, the average stock knowledge initially decreases slowly from 0 to a certain value and then grows to a maximum value of 30. Reputational ION knowledge agents can obtain higher returns from interactions than non-reputational ION knowledge agents.

As shown in Figure 1, this process indicates that initial differences rapidly induce the formation of local clusters and eliminate the tendency for the game to evolve randomly, thereby facilitating cooperation [47]. More precisely, the presence of reputation promotes cooperation compared to non-reputation networks, whether they are homogeneous reputation distributions (i.e., CIR) or heterogeneous reputation distributions (i.e., UIR, GIR). During the evolutionary process, different types of initial reputation distributions have less impact on the proportion of collaborators and the average amount of knowledge transfer, which eventually converge. The evolution patterns of the three curves with reputation distributions are almost identical, indicating that they were distinct from each other [47]. Compared to regular lattice networks, the power-law distribution of scale-free networks eliminates individual heterogeneity differences, i.e., a cluster will be formed with a core of fewer nodes having more neighbors, which then occupies the entire network. This suggests that in scale-free networks, the form of reputation distribution plays a weak role in the network topology.

Figure 2 shows the evolution results for different initial reputation distributions under different ION scales. Fundamentally, any form of reputation distribution can help to
promote better knowledge transfer behavior. That is to say, knowledge agents choose to collaborate in good reputational interorganizational projects, which can facilitate knowledge transfer. For example, when reputation is not considered, knowledge agents do not have access to their neighbors’ historical knowledge transfer behavior, and their choices can only refer to neighbors’ gains. Knowledge agents need repeated trial and error to determine whether their neighbors are free-riders, which leads to less efficiency and effectiveness of knowledge transfer. This is consistent with the intuition that working with good reputation knowledge agents is a low-risk behavior to increase the return. Another finding is that the contribution of reputation distributions to knowledge transfer behavior is less influenced by network scale. The curve evolution results are almost identical (i.e., \( N = 300 \) and \( N = 500 \)). Compared with ION of reputation distributions, ION without reputation is more vulnerable to network scale’s topology due to the absence of information on historical knowledge transfer behavior. Especially for scale-free networks, the degree distribution follows a power law, at least asymptotically. In other words, having a reputation contains a large more groups who select knowledge transfer behavior than not having a reputation when IONs are the same scale. In the non-reputation evolution curve, especially when the network scale is small (\( N = 100 \)), the whole ION knowledge transfer performs less efficiently and effectively. The UIR model is used in the following discussion to show the stochastic nature of organizational reputation.

![Figure 2](image.png)

**Figure 2.** Reputation of all agents in the networked populations are constant reputation distribution, uniform reputation distribution and Gaussian reputation distribution when \( R_i(0) = 50, R_i(0) \sim U[1, 100], R_i(0) \sim N(50, 16.67^2) \), respectively. (a) Evolution of fraction of cooperators with network scale when the distribution of reputation is different. (b) Evolution of the average knowledge stock of knowledge agents with network scale when different reputation distribution. The other simulation parameters are set to be: \( c = 1.5, \eta = 0, \theta = 0.6, \gamma = 0.5, \sigma = 0.4 \).

### 5.2. The Influence of Reputation Threshold and Multiplicative Factor on Knowledge Transfer

To further analyze the reasons for differences in reputation effects and gather specific information on the origin of the observed phenomenon, we set \( R_i(t) \geq 70 \) for high reputation and \( R_i(t) < 70 \) for low reputation. The figure shows four types of agents: cooperators with high reputation (HC) and low reputation (LC), and defectors with high reputation (HD) and low reputation (LD). As shown in Figure 3, at the beginning of the game, four types of agents are randomly distributed in the ION, with about one-fourth of each agent, of which 50% are cooperators (transfer strategy) and 50% are defectors (non-transfer strategy).
Figure 3 shows that both LC and HC are disadvantaged groups compared to their neighbors LD and HD at the beginning of the network evolution. According to Equation (15), strategies are updated and converted to LD and HD respectively (this process may be reversible). We can observe that LD and HD form clusters by integrating with their neighbors, increasing the proportion of defectors. The evolutionary curves for the subsequent steps from 10 to 100 are different for the two subgraphs. The differences in reputation multiplicative factors ultimately lead to evolutionary curves toward full cooperation or full defection. Figure 3a displays that when $\eta = 0.01$, defectors form clusters, while agents holding strategy C also form clusters. At their intersection, a cooperator has greater payoffs than a defector since the former has more cooperative neighbors and the amount of knowledge transferred will be greater. However, in Figure 3b, when $\eta = 0.80$, the role of the reputation multiplicative factor is not sufficient to accumulate giant reputation partners in a short period. We found that there are fewer and fewer cooperative agents in the cluster, and the increase in defectors allows low-reputation defectors to occupy the entire network. Our findings are consistent with the study of Chen et al. [39], where the level of cooperation will be greatly enhanced as the strategy spreading factor $\eta$ varies from 0.80 to 0.01. The origin of facilitating knowledge transfer can be attributed to the fact that the difference of strategy spreading factor between two types of agents (i.e., high and low reputation agents) widens, and the influential agents can have a surprising ability to convince other knowledge agents to adapt their strategies.

Next, in Figure 4, we plot the time evolution of the fraction of cooperators $p_c$ at the stationary state for different reputation thresholds $R_c$ and multiplicative factors $\eta$. In Figure 4a, all agents are divided into two categories based on the reputation threshold for each MCS step: high reputation agents with $R \geq R_c$ who have the greater capacity for knowledge transfer ($\eta = 1$) and become influential and low reputation agents with $R < R_c$ who have the smaller knowledge transfer factor ($\eta = 0.04$). When we consider reputation classification, agents may still not resist the temptation to defect and defectors can invade the cluster of cooperators, causing the fall of the proportion of agents at the
initial steps. With the introduction of reputation classification, some agents may become influential (LC) and obtain a higher probability of convincing their nearest neighbors to adopt their strategy. Once the influential cooperators survive, they become the compact core clusters, attracting more agents to join the cooperators. For larger reputation thresholds (i.e., \( R \geq 95 \)), the shortest decline in the proportion of cooperators occurs. Then cooperators win a competitive advantage over defectors and the entire population quickly organizes into a large cooperative cluster, creating a higher level of cooperation of 0.84. Previous studies on reputation classification among partners [35] support that the introduction of reputation classification can greatly facilitate the development of knowledge transfer.

![Figure 4](image.png)

**Figure 4.** (a). Fraction of cooperators \( p_c \) as a function of MCS step under a fixed multiplicative factor \( \eta = 0.04 \) for different reputation thresholds \( R_c \). Here, they are set to be: \( c = 1.6, \theta = 0.6, \gamma = 0.5, \sigma = 0.4 \). (b). Fraction of cooperators \( p_c \) as a function of MCS step under a fixed reputation threshold \( R_c = 60 \) for different multiplicative factors \( \eta \). Here, they are set to be: \( c = 1.5, \theta = 0.5, \gamma = 0.5, \sigma = 0.4 \).

Figure 4b considers the effect of the reputation multiplicative factor (\( \eta \)) on knowledge transfer at a fixed reputation threshold \( (R_c = 60) \). It is seen that the cooperation level, similar to Figure 4a, increases as the reputation multiplicative factor \( \eta \) decreases. In addition, the evolution of the proportion of cooperators in the ION was analyzed for various multiplicative factors \( \eta \), with other parameters fixed. Once again, the results suggest that the level of cooperation will increase considerably as the multiplicative factor of reputation effect changes from 0.3 to 0.001. The origins of facilitating collaboration can be attributed to the fact that the difference in reputation multiplicative factors between the two types of agents (i.e., high and low reputation agents) expands and influential agents can occupy a surprisingly high capability and persuade other agents into adopting their strategies (i.e., actively participate in knowledge transfer activities). Most importantly, the multiplicative factor will help cooperators build a collaborative advantage, allowing for higher reputational value than their neighbors, which will further enable cooperators to become influential and thus have more increased knowledge transfer capabilities and easily create clusters of cooperators. Similar phenomena have also been observed in Ref. [35].

To delve deeper into the role of reputation classification, we show in Figure 5 the distribution of reputation thresholds in the ION at a steady state. Figure 5a reveals that reputation values are uniformly distributed in the interval \((1,100)\) at \( t = 0 \). In our introduction of reputation classification, collaborators can resist the invasion of defectors to avoid being completely defeated by defectors, thus achieving a higher level of knowledge transfer. For
example, when the reputation threshold is 60, we can observe that nearly 60% of knowledge agents are defectors with reputation values between 1 and 10. Still, about 40% of agents are cooperators with high reputation values and distributed within (91,100). When the reputation threshold increases from 80 (panel (c)) to 95 (panel (e)), the proportion of low-reputation knowledge agents decrease, and the proportion of high-reputation knowledge agents increases. Thus, as shown in Figure 5, ION usually evolves into a condition in which the whole system consists of two main types of knowledge agents: low-reputation defectors at one time and high-reputation collaborators at the other. In the evolutionary process of group interaction, the competition between collaborators and defectors drives collaborators to gain advantages over defectors. Under the effect of reputation mechanism, the group that conducts knowledge transfer will become larger and larger. Ideally, full cooperation across organizational networks can be achieved when the reputation threshold is high enough. Larger reputation thresholds are more favorable for the survival of high reputation individuals and the survival of cooperators. The phenomenon differs from that observed in Ref. [39], the difference being that the latter is a regular lattice.

As shown in Figure 6, the results for different $\eta$ and $R_c$ values for the ION setting illustrate the joint effect of reputation thresholds and multiplicative factors on the proportion of cooperators and the average amount of knowledge transferred. In particular, it can be observed that decreasing $\eta$ for a fixed value of $R_c$ will also raise $p_c$ levels, while increasing $R_c$ will elevate $p_c$ for any given value of $\eta$, but $\eta$ needs to be reduced to some value for reputation effects to be truly effective.

To roughly assess the role of heterogeneity in reputation effects on knowledge transfer, we observed the evolution of the proportion of cooperators and the average knowledge transfer with the cost coefficient in the ION game, as shown in Figure 7. Three significant results can be identified: First, at lower cost parameters, cooperative behavior can survive and even reach a value of 1.0 for the level of cooperation. However, the average knowledge transfer still decreases with increasing costs. Second, there is a relatively short period...
of expansion during the evolutionary process. During the expansion period, the level of cooperation falls sharply from an initial value of 1.0. It appears to have a different downward trend due to the heterogeneous influences of the reputation effect. The impacts on average knowledge transfer, on the contrary, seem to be slower. Third, the level of cooperation for $\eta = 0.001$ is higher than for $\eta = 0.1$; the magnitude of the oscillation for $\eta = 0.001$ is smaller than for $\eta = 0.1$. In summary, reputation multiplicative factor and reputation threshold, as the two leading indicators of reputation classification, are favorable for the urgency of cooperation \[39\] and the average knowledge transfer.

Figure 6. (a) Evolution of fraction of cooperators $p_c$ for the specified $\eta - R_c$ parameter space. (b) Evolution of the average knowledge stock of knowledge agents for the specified $\eta - R_c$ parameter space. The other simulation parameters are set to be: $c = 1.6, \theta = 0.5, \gamma = 0.5, \sigma = 0.5$.

Figure 7. The effects of heterogeneity of reputation factors for different impact results (a) Fraction of cooperators $p_c$, (b) Average knowledge stock of knowledge agents. The other simulation parameters are set to be: $\theta = 0.4, \gamma = 0.5, \sigma = 0.4$. 
Furthermore, in the model we have constructed, trust, knowledge complementarity, and coordination coefficients were analyzed in terms of changes in the proportion of collaborators under the influence of the reputation multiplicative factor, as shown in Figure 8. More specifically, knowledge transfer behavior cannot be sustained if trust, complementarity, and coordination among knowledge agents are relatively low. However, as these parameters increase, knowledge transfer behaviors begin to emerge and flourish. When the knowledge transfer behavior exceeds a particular value, it implies that all knowledge agents are involved. This phenomenon can be explained intuitively. For an ION that lacks trustworthiness, even if the behavior of knowledge agents is recorded through reputational mechanisms, the knowledge transfer is minimal. For an ION with a high degree of trust, one will still occasionally believe in the rationality of their behavior in the face of a neighbor defecting them and not engaging in knowledge transfer.

Consequently, the entire cluster would present a knowledge transfer situation that improves the innovation capability of the entire ION. When the trust level is in a certain parameter region, it necessitates the influence of reputation mechanisms. Reputation mechanisms provide information on knowledge transfer behavior in IONs. Therefore, the greater the difference in the effect with and without reputation (i.e., the smaller the reputation multiplicative factor), the more significant the facilitation effect on interorganizational knowledge transfer behavior. The degree of complementarity and coordination level remain the same.

5.3. The Influence of Decaying Rate of Reputation on Knowledge Transfer

By comparing different values of $\phi$, we obtain the effect of memory-decaying rate $\phi$ on the evolution of an agent’s reputation. When $\phi$ tends to 0, agents who update their learning strategies are just relying on their present game, while $\phi$ tends to 1, the game returns to our initial model [59]. Then, based on the results in Figure 9, we select several typical decaying rate values for a more intuitive comparison and plot the variation tendency of cooperation rate $p_c$ at the steady state. In Figure 9, the blue curve ($\phi = 1$) corresponds to our original model, which vividly shows that the fraction of cooperators continues to increase and with the increase in time steps, only cooperators will exist [57]. The greater the decaying memory coefficient of reputation, the more critical the past performance of the multi-agent as the composition of reputation. The more important is the level of reputation as the criterion for selecting interorganizational alliances. Therefore, the promotion of cooperation is apparent. However, when the decaying memory rate is lower ($\phi = 0.98$), the proportion of historical information is lower, and the fraction of cooperators $p_c$ rises first, then decreases rapidly, and finally approaches the stationary state ($p_c = 0.48$). Multi-agents perform knowledge transfer using only part of the information of past neighbors as a basis for strategy update. The role of reputation effects in interorganizational cooperation is weakened and replaced by the randomness of heterogeneous agents. It is evident from the
figure that it is necessary to ensure the completeness of reputation information acquisition to bring in the promoting role of reputation effect. The historical cooperation of enterprises is the basis of the value of corporate reputation. When $\phi$ becomes smaller, it is equivalent to weakening the reputation effect, which implies that the long-term past reputation degree of the agent is not considered.

![Graph](image)

**Figure 9.** Influences of decaying rate of reputation mechanisms on the evolution of knowledge transfer. (a) Evolution results of fraction of cooperators for different values of $\phi = 0.9, 0.98, 0.99, 1$. (b) Evolution results of average knowledge for different values of $\phi = 0.9, 0.98, 0.99, 1$. The other simulation parameters are set to be: $c = 1.4, R_e = 60, \theta = 0.6, \gamma = 0.5, \sigma = 0.4$.

Figure 10 shows the reputation frequencies of the knowledge agents of the ION at simulated births of 0, 50, 100, and 5000. The results are shown in the scale-free network. At the beginning of the simulation, the knowledge agent acquires reputation randomly. It can be seen that the reputation of the knowledge agent in the first case gradually increases and eventually reaches the reputation value of (91,100). In addition, the reputation of the knowledge agent in the second case slowly decreases after MCS = 50, this is slower than the case of the regular network and the random network in Ref. [60]. The agent still has part of the reputation of the knowledge agent at (41,60) at MCS = 500, when the collaborators or defectors can coexist. Another point is that a decrease in the reputation decaying coefficient leads to a decrease in the efficiency of knowledge transfer, suggesting that lower levels of prior knowledge seeking and sharing mean that less information is helpful for these mechanisms.
Figure 10 shows the reputation frequencies of the knowledge agents of the ION at different parameter settings. The panels (a–d) correspond to the distribution of reputation values for different MCS steps under a fixed decaying memory coefficient $\phi = 1.00$. The panels (e–h) correspond to the distribution of reputation values for different MCS steps under a fixed decaying memory coefficient $\phi = 0.98$. The other simulation parameters are set to be: $c = 1.4$, $R_c = 60$, $\theta = 0.6$, $\gamma = 0.5$, $\sigma = 0.4$.

6. Conclusions and Implications

6.1. Conclusions

Evolutionary game theory was employed to investigate the evolutionary impact of reputation mechanisms on interorganizational knowledge transfer behaviors in this study. The knowledge flow within the context of knowledge transfer was investigated, and how three aspects of reputation mechanisms affect the efficiency and effectiveness of knowledge transfer activities were examined. Numerical simulations were conducted to verify the assumptions. The following conclusions have arrived:

(1) First, when the reputation of a knowledgeable agent is high, they will be more likely to choose the knowledge transfer strategy. Furthermore, the low or high reputation can be divided into three dimensions: reputation distribution, reputation multiplicative coefficients and reputation threshold, and reputation decaying coefficients. Meanwhile, we have explored the joint effects of complementarity, trust and coordination levels of knowledge agents, and reputation influencing factors on knowledge transfer behavior. The results show that the level of complementarity, trust, and coordination of knowledge agents directly affects the contribution of reputation effects to knowledge transfer behavior.

(2) Second, we find that a favorable reputation mechanism can effectively increase the proportion of knowledge agents’ willingness to engage in knowledge transferring in IONs. Moreover, the system convergence rate and steady-state are different under different parameter settings. We have performed extensive numerical simulations to demonstrate the evolutionary behavior of interorganizational knowledge transfer under the influence of reputation mechanisms from three dimensions. Regardless of the different conditions presented by the initial reputation distribution of knowledge agents in the ION (CIR, UIR, and GIR), the final effect on knowledge transfer behavior remains the same. Meanwhile, about the reputation multiplicative factor and reputation threshold, the smaller the reputation multiplicative factor ($=0.001, 0.08$), and the higher the reputation threshold, the more pronounced the contribution to knowledge transfer behavior. Finally, the effects of reputation decaying coefficients on knowledge transfer behaviors were revealed. The more available information on past historical knowledge transfer behavior, the better the reputation promotion effect. If there is no reference to past behavior (down to 0.98), the impact of the reputation mechanisms is significantly reduced (cooperation rate of 0.48).
In summary, by exploring the long-term evolution law of knowledge transfer behavior of knowledge agents in IONs, introducing reputation mechanisms, and studying the influence of reputation mechanisms on the efficiency and effectiveness of knowledge transfer, agents can be encouraged to adopt knowledge transfer strategies. With time, the whole network will form a virtuous knowledge transfer cycle, and the knowledge transfer efficiency and transfer effectiveness are enhanced. This will be conducive to the sustainable knowledge innovation of the agent, thus promoting the maintenance of core competitiveness and the improvement of sustainable innovation capability [61]. This study presents simulation research to identify the impacts of reputation mechanisms in interorganizational knowledge transfer through systematic evolutionary game theory. It can also answer the sustainable management of knowledge transfer behavior in innovation, R&D, and a low carbon environment.

6.2. Implications

We present several managerial implications. We offer several managerial implications to facilitate effective knowledge transfer in IONs and thereby improve the sustainability of interorganizational projects.

(1) First, with the implementation of green and low-carbon policies, interorganizational innovation network management with environmental performance at its core has received increasing attention. This study presents simulation research to identify the impacts of reputation mechanisms in interorganizational knowledge transfer through systematic evolutionary game theory, addressing the sustainability of knowledge transfer behaviors in innovation, R&D, and low green carbon. Through knowledge transfer between multi-agents, the utilization of green knowledge in IONs can be improved to provide knowledge support for enterprises to deal with environmental issues. Consequently, enterprises committed to innovative knowledge should focus on reputational information (historical emission exceedances, etc.) to increase their willingness to transfer green knowledge and take advantage of the improved organizational performance resulting from knowledge transfer, thereby realizing environmental value and improving the sustainability of IONs.

(2) The ION reputation evaluation system is established based on a long-term perspective, and the knowledge transfer mechanism is adjusted according to the results of the cooperative behavior of the multi-agent. The decaying effect indicates that the temporal persistence of reputation effect breeds opportunistic behaviors of knowledge agents once past information is ignored. In addition, the more significant the difference is between the cumulative effect of high and low reputations, the more knowledge agents are inclined to knowledge transfer in IONs, and that reputation mechanism is highly valued.

Author Contributions: X.H.: Formal analysis, Software, Validation, Data curation, Visualization, Writing—original draft, Writing—review and editing. P.G.: Formal analysis, Conceptualization, Methodology, Supervision. X.W.: Conceptualization, Methodology, Software, Validation. D.W.: Methodology, Resources, Writing—review and editing. All authors have read and agreed to the published version of the manuscript.

Funding: This paper was supported by the National Natural Science Foundation of China (Grant Nos. 71672145, 72171195), and the Provincial Natural Sciences Basic Research Plan in Shaanxi, China (Grant No. 2021JM-078).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data is contained within the article.

Acknowledgments: The authors gratefully acknowledge the financial support from the National Natural Science Foundation of China (Grant Nos. 71672145, 72171195), the Provincial Natural Sciences Basic Research Plan in Shaanxi, China (Grant No. 2021JM-078). The authors would like to thank the anonymous reviewers for their insightful comments.
Conflicts of Interest: The authors declare no conflict of interest.

Nomenclature

\[ m \] number of existing nodes connected to a new node at each time step
\[ m_0 \] number of nodes in an original ION
\[ G(V,E) \] ultimately ION with \( V = \{1,2,\ldots,N\} \) and \( E = \{e_{ij} | i,j \in V\} \)
\[ \alpha_i \] knowledge transfer absorption efficiency of knowledge agent \( i \)
\[ \beta_i \] comprehension and application ability of knowledge agent \( i \)
\[ \tau_i \] length of the stock knowledge time window of knowledge agent \( i \)
\[ \rho_i \] the depreciation rate of stock knowledge of knowledge agent \( i \)
\[ v_{i,0} \] own stock knowledge of agent \( i \) in an ION
\[ k_i \] amount of knowledge transferred from agent \( i \) to agent \( j \)
\[ k_j \] amount of knowledge transferred from agent \( j \) to agent \( i \)
\[ \theta \] collaboration level between agents
\[ \gamma_i \] knowledge complementarity of agent \( i \)
\[ \sigma_i \] the trust level of agent \( i \) to agent \( j \)
\[ c_i \] knowledge transfer cost coefficient of agent \( i \)
\[ \mu_i \] collaboration cost coefficient of agent \( i \)
\[ \lambda_i \] reward coefficient obtained when agent \( i \) selects knowledge transfer
\[ \psi \] penalties for opportunism, or free-riding, or non-transfer
\[ e_i(t) \] revenue function of knowledge transfer of agent \( i \) in ION
\[ M \] payoff matrix of evolutionary game
\[ o(i,t) \] the payoff if agent \( i \) and agent \( j \) both select the transfer strategy at time \( t \)
\[ p(i,t) \] the payoff if agent \( i \) and agent \( j \) select the (transfer, non-transfer) strategy at time \( t \)
\[ q(i,t) \] the payoff if agent \( i \) and agent \( j \) select the (non-transfer, transfer) strategy at time \( t \)
\[ r(i,t) \] the payoff if agent \( i \) and agent \( j \) both select the non-transfer strategy at time \( t \)
\[ \zeta_i \] knowledge absorption capacity function of agent \( i \)
\[ s_i(t) \] the strategy of agent \( i \)
\[ \Delta_i(t) \] 1 if agent \( i \) transfers knowledge at time \( t \), otherwise being 0
\[ U_i(t) \] accumulated payoffs of agent \( i \) at time \( t \) in ION
\[ \phi \] decaying rate of a reputation effect
\[ R_i(t) \] reputation value of agent \( i \) at time \( t \)
\[ R_c \] high reputation standard value
\[ \eta_i \] the multiplicative factor of high reputation
\[ P_i(s_{-i}) \] improved coevolutionary rule
\[ \nu_i(t) \] the proportion of agents choosing knowledge transfer at time \( t \) in ION
\[ \bar{n}(t) \] average knowledge transfer of agents at time \( t \) in ION

References
6. Fang, S.-C.; Yang, C.-W.; Hsu, W.-Y. Inter-organizational knowledge transfer: The perspective of knowledge governance. J. Knowl. Manag. 2013, 17, 943–957. [CrossRef]


