# Evolution Analysis about Knowledge Transfer in the Open Innovation Process of Strategic Emerging Industrial

Yue Long*, QiHao Chen, Mei Wang, Pan Liu

***Abstract*-Knowledge transfer is essential for fostering open innovation in strategic emerging industries (SEI), where ecological and economic dynamics shape the innovation ecosystem. This study combines the Lotka-Volterra model and evolutionary game theory to build an ecological framework for knowledge transfer, tackling challenges like incentive compatibility and resource allocation. Through quantitative analysis and numerical simulations, we reveals how factors like knowledge stock, marginal utility, and tailored incentives drive symbiotic relationships and high-quality knowledge ecosystems. The findings offer theoretical insights and actionable strategies to optimize knowledge flows, boost innovation efficiency, and drive sustainable growth in SEIs.**

***Index Terms*-Knowledge transfer, Lotka-Volterra model, SEI, Open innovation**

## I. Introduction

Strategic emerging industries (SEI) emphasize knowledge and technology and are driven by open innovation. They rely on significant technological advancements and growing demands for innovation. Achieving innovation-driven growth, requires integrating knowledge, technology, market opportunities, and other critical elements across domestic and international contexts. For example, Chang'an New Energy Automobile, Tsinghua University of China, and Liszt Internal Combustion Engine of Austria have engaged in open innovation in the new energy automobile industry and mastered core technologies [1]. SEI derives from colliding technological innovation and market opportunities [2]. To address uncertainties in technology and market dynamics, developing an industrial interconnection network founded on resource sharing and technological complementarity is essential [3]. Innovation is a systematic process of exploring and integrating various elements of knowledge. This process generates novel knowledge or its amalgamation [4]. Innovation entities leverage knowledge inflows and outflows to integrate internal and external resources, driving R&D and commercialization [5]. In the knowledge economy era, knowledge has increasingly become a strategic resource [6]. In SEI innovation, knowledge is increasingly interactive and essential. Consequently, technological progress driven by complex systems has created an innovation ecosystem with symbiotic mechanisms [7]. Thus, open innovation in SEI reflects a knowledge transfer relationship between innovation entities. The relationships and levels of knowledge transfer between these entities play a crucial role in promoting open innovation. Knowledge transfer refers to transferring knowledge from one social entity to another, which is then absorbed, digested, integrated, and applied by the latter [8].

Current researches on intersubjective knowledge transfer behavior have primarily focused on narrow comparisons, such as motivations [9-12], contradictions [13], mechanisms [14-17], and influencing factors [18][19].

With the deepening of China's innovation-driven development strategy and the formation of dual circulation markets at home and abroad, knowledge transfer within the open innovation process of China's SEI has exhibited the following characteristics: (1) The open innovation process of China's SEI aims to promote industrial-technological progress and acquire high-quality knowledge, which includes both quantity and authenticity.[10]. As a vital strategic resource, high-quality knowledge plays a fundamental role in promoting industrial and technological innovation, and it is essential to transfer high-quality knowledge resources among different subjects. (2) With the establishment of long-term cooperative relationships and the deepening of interactions in the open innovation process of SEI, knowledge transfer among the subjects has evolved from a one-way flow to a multi-directional and multi-stage process. Reflecting ecological characteristics akin to symbiosis and competition in biological systems, innovation entities construct mutually beneficial and

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competitive relationships. To realize knowledge economization, we need a specialized division of labor and collaboration to promote allocating knowledge resources across organizations. Consequently, knowledge transfer exhibits overlapping attributes of ecological, economic, and organizational dynamics. (3) Industrial innovation entities construct high-quality knowledge chains through diverse organizational forms, including supply chains, strategic alliances, and industry-university-research collaborations. They further drive open innovation by facilitating knowledge transfer. However, disparities in knowledge stock and the marginal utility of knowledge utilization among entities result in varying levels of willingness to engage in knowledge transfer. Such disparities create obstacles in the interaction of knowledge and interests, destabilizing the knowledge chain and, in severe cases, causing distortions or interruptions. The low ecological level of knowledge transfer causes inefficiency in the open innovation process.

Overall, the open innovation of SEI facilitates significant and high-quality knowledge transfer. Leveraging the ecological and economic characteristics of knowledge transfer among entities to build a robust knowledge transfer ecosystem is critical to ensuring the sustainable and stable operation. Consequently, exploring the evolutionary principles governing knowledge transfer within the open innovation process of SEI has garnered considerable attention due to its high theoretical and practical significance. In this context, this paper aims to address the following research questions:

(1) How can an eco-evolutionary model that incorporates the new features of knowledge transfer in the open innovation process of SEI be designed?

(2) How can a knowledge transfer evolutionary model based on the Lotka-Volterra model and evolutionary game theory be constructed?

(3) What are the most effective strategies for allocating knowledge resources across organizations in the context of open innovation for SEI?

To address these issues, this paper proposes a knowledge transfer evolution model for SEI within the open innovation process. The model incorporates new features, including the ecological and economic characteristics of knowledge transfer in the open innovation process of SEI. Thus, this paper enhances the comprehension of knowledge transfer and offers new directions for further research in this field. This paper begins with a comprehensive literature review on open innovation and knowledge transfer. Additionally, it presents a theoretical analysis focusing on knowledge transfer within the context of open innovation, particularly in strategic emerging industries. Furthermore, previous studies examine various disciplines within the context of open innovation and propose an evolutionary framework for facilitating knowledge transfer in this process. The knowledge transfer evolution model integrates the Lotka-Volterra framework to investigate the patterns and prerequisites for creating a high-level knowledge transfer ecosystem. In addition, this study validates the evolutionary trajectory of knowledge transfer in strategic emerging industries through case simulations. In conclusion, this study proposes directions for future research and managerial insights to advance the theoretical understanding of knowledge transfer in the context of open innovation within strategic emerging industries.

## II. Literature Review

Open innovation in SEI extends the concept of technological innovation found in traditional industries. This paper primarily focuses on the knowledge transfer ecology and evolution mechanism of SEI within the open innovation process.

### *A. Open innovation*

In the open innovation process, Laursen and Salter (2010) [9] define it as the engagement of diverse and resources to achieve and sustain innovation. Industrial innovation involves collaboration among participants with complementary resources, enabling the flow of knowledge, technology, and resources through formal or informal innovation networks [10]. Within this process, knowledge transfer between entities reduces innovation costs and shortens the innovation cycle [11]. By coordinating the "competition and cooperation relationship" among the entities, organizations can acquire heterogeneous, diverse, and unique knowledge, resources, and technologies, ultimately achieving high innovation output [12].

### *B. Knowledge transfer*

In knowledge transfer, Nonaka categorized knowledge into explicit knowledge and tacit knowledge. Explicit knowledge is structured to form a knowledge system, whereas tacit knowledge is embedded in the process of learning and creation [18]. Knowledge is exclusive, heterogeneous, and dynamic in nature. It enables the acquisition of valuable knowledge resources, supports development, and facilitates the integration of external experience with internal knowledge [19]. However, knowledge transfer is often hindered by behaviors such as evasive hiding, playing dumb, and rationalized hiding [13]. Industry actors must balance the openness to acquire knowledge while avoiding knowledge leakage [16]. Factors such as asymmetric interdependence, technological monopolies, and differences in learning abilities contribute to opportunistic behaviors like "free-riding" and "rip-offs" in innovation. Thus, governance through effective design mechanisms is necessary [17]. Contract negotiation, signing, and execution, as key governance mechanisms, enhance the likelihood of successful knowledge transfer [15]. Research highlights a competitive and cooperative relationship among entities in knowledge transfer, emphasizing the dynamic evolution of the process and the importance of its ecological attributes [14]. Knowledge transfer involves complex decision-making. . Game theory has been widely used as an essential analysis tool and common research language for the inter-subject relationship study in the knowledge transfer process [20]. With the advancement of research, the analysis method of neoclassical economics has evolved from the Nash equilibrium of game theory to the trend equilibrium analysis in evolutionary game [21]. From the perspective of the knowledge transfer process, an organization's knowledge system is dynamic because of its evolutionary characteristics, environmental changes, and the influences of various incentives [22]. Research must adopt multiple perspectives to address these complexities. For instance, Yi and Wu integrate knowledge management and ecological theory to examine the ecological evolution law of multi-agent knowledge interaction in the community [23]. He emphasizes that the openness of enterprise knowledge is a crucial factor in fostering collective wisdom within the open innovation community [14] .

By analyzing the existing achievements, two key research gaps can be identified:

(1) Most studies on inter-subject knowledge transfer focuses on its dynamic nature but rarely examines the intersection of its ecological and economic dimensions.

(2) Existing research methods for knowledge transfer in industrial innovation mainly use game theory and limited integration of ecological perspectives to analyze the ecological and evolutionary behavior of knowledge transfer.

Building on the the characteristics of knowledge transfer in the open innovation process of SEI, it can be found that with increasing openness and need for industrial innovation, as well as increasing urgency and importance of high-quality knowledge transfer, the primary knowledge transfer behavior of SEI is not only dynamic but also ecological and economic which is different from traditional knowledge transfer relationships. The relationship and level formed by knowledge transfer behavior exist in significant differences, so the knowledge transfer ecology gradually evolves to a multi-level. However, current research has not fully integrated these characteristics to reveal the knowledge transfer mechanism of open innovation entities in SEI. Therefore, the potential advantages of a high-quality knowledge chain formed by knowledge transfer among industry entities remain underutilized. To address these gaps, this paper integrates knowledge management, game theory, ecology, and other theories to explore and reveal the ecological and evolutionary mechanism of knowledge transfer in SEI's open innovation process. This paper aims to provide new insights into the theory and methodology of knowledge chain management in the open innovation process of SEI, ensuring the stable operation of knowledge transfer and offering a theoretical reference for open innovation in SEI.

## III. Model Design

For clarity, this paper categorizes the open innovation entities of SEI into core organizations (such as enterprises) and node organizations (such as scientific research institutes, universities, etc.). According to the knowledge-based view [24][25], knowledge transfer in SEI differs from traditional subject-based knowledge transfer. From the perspective of ecological theory, it is different from the traditional subject knowledge transfer. Knowledge transfer between entities in the open innovation process of SEI emphasizes the high-quality, multi-level and long-term nature of knowledge transfer among entities. Consequently, various ecological relationships, such as mutual influence, interdependence, and constraint, are formed. Moreover, persistent disparities in knowledge stock, the marginal utility of knowledge utilization, incentives, and constraints exist among interacting entities. These interactions will coexist or evolve into different ecological relationships and levels of knowledge transfer, as shown in Figure.1

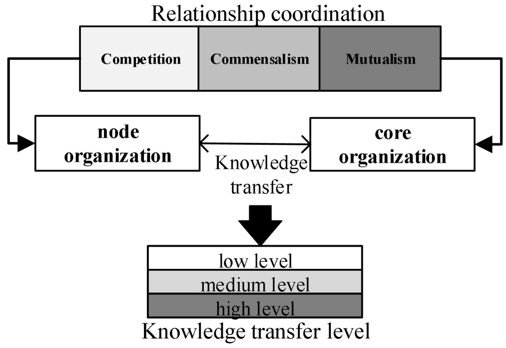


Figure.1 Ecological Evolution of Knowledge Transfer in the open innovation process of SEI.

As shown in Figure 1, knowledge transfer in the open innovation process of SEI is driven by the ecological adaptation and market regulation of different subjects, and the simultaneous interaction of knowledge and interests should be considered. This paper categorizes the evolution of knowledge transfer into two modes: without incentive compatibility and with incentive compatibility. (1) Based on knowledge management and ecological theories, knowledge transfer ecology can be divided into two dimensions: the knowledge transfer relationship and the knowledge transfer level. In the process of knowledge transfer, disparities in knowledge stock, scope, depth, and absorptive capacity lead entities to adopt diverse transfer strategies. These knowledge transfer strategies manifest in knowledge transfer, absorption, digestion, integration, and application among subjects and form the relationship of competition, commensalism, and the evolution of knowledge transfer (as shown in Figure.1). Mutualism, the highest level of knowledge transfer relationships, occurs when two organizations mutually promote and develop each other. To analyze the relationships between knowledge transfer and development level further, this paper divides the development level into different levels, such as the low level, the medium level, and the high level, which represent the levels of knowledge transfer from low to high, thus representing the high-quality knowledge transfer. (2) Consider the knowledge transfer ecology in terms of incentive compatibility. The open innovation knowledge transfer process integrates ecological and economic perspectives. Marginal utility differences exist among entities in utilizing external knowledge. Therefore, we should design a knowledge-benefit transfer mechanism based on incentives and constraints, guiding the subjects with the low marginal utility of knowledge resources to transfer into high marginal utility. Entities acquiring knowledge resources compensate those transferring resources, thereby promoting knowledge transfer from lower to higher levels. Accordingly, it can achieve specialized division of labor and cooperation and cross-organizational resource allocation, forming a high-level knowledge transfer ecosystem.

## IV. Ecological Modeling and Evolutionary Analysis of Knowledge Transfer

### A. Theoretical basis, model variables, and assumptions

Building on the previous description of the characteristics and evolution of agent knowledge transfer in the open innovation process of SEI, this paper integrates ecology, knowledge management, and related fields to analyze the evolution of agent knowledge transfer in industry. The Lotka-Volterra model in biology [26][27] illustrates the interactions between different biotic populations. Given the excellent description of inter-subjectivity, the model is gradually used to study the relationship evolution among multi-agent [28]. The knowledge transfer discussed in this paper refers to the interaction and evolution of knowledge and interests among relevant entities in the open innovation process. Drawing from previous research [29], the Lotka-Volterra model extends the traditional game theory framework. The knowledge transfer behavior and its evolution process in the open innovation process mirror the interaction and evolutionary dynamics observed among biological populations, As such, the Lotka-Volterra model is well-suited to describe the knowledge transfer behaviors and evolutionary processes of industrial open innovation entities. The variables and assumptions related to knowledge transfer behavior and evolution are detailed as follows:

For clarity, this paper uses $x_i$ to represent the innovation entities in SEI $i=(1,2)$ (Figure 1). $x_1$ represents subject 1 (e.g., a firm involved in an innovation). $x_2$ represents subject 2 (such as universities and research institutes involved in innovation), and the variables of the model are as follows:

$n_i$ represents the initial state of knowledge stock $x_i$ at the time $t$ (reflecting the subject's level of knowledge cognition and storage, which comprehensively represents its knowledge repository).

$\Delta n_i$ represents the change of knowledge stock $x_i$ at the time $t$, whose value represents the changes in knowledge reserves $x_i$.

$N_i$ represents the maximum stock of knowledge (including the amount of knowledge owned, the depth and span of knowledge owned) $x_i$ without the influences of other subjects (in the condition of independent existence), representing the maximum knowledge stock formed by the cognitive levels of the subject in the original environment).

$\alpha_i$ represents the proportion of stock knowledge transfer $x_i$ determined by observing the benefits of knowledge transfer, reflecting the decision-making willingness of knowledge transfer.

$n_{ij}$ represents the coefficient of subject knowledge transfer in industrial innovation $x_i$, whose value and plus-minus reflect the knowledge transfer relationships between entities.

$r_i$ represents the pure growth rate of knowledge stock $x_i$ that is not affected by external conditions.

$\gamma_i$ represents other entities' impacts on the growth of knowledge stock $x_i$ in the process of innovation.

$\Delta\pi$ represents the total benefits all entities obtained by knowledge transfer.

$\Delta\pi'_{x_i}$ represents the benefits $x_i$ obtained after acquiring the knowledge of other entities to carry out the innovation.

$C$ indicates the liquidated damages $x_i$ paid for not carrying out knowledge transfer in the knowledge transfer process (such as intentional knowledge hiding halfway when breaching the contract).

$\beta$ represents the distribution coefficient of the total income in knowledge transfer.

Based on the process and characteristics of subject knowledge transfer behavior in the open innovation process of SEI, the following assumptions are made:

(1) In the process of knowledge transfer of industrial innovation, the knowledge stock of $x_i$ (such as enterprises) may be affected by other stakeholders (such as universities, governments, etc.), and using $\gamma_i$ to indicate separately, let $\gamma_{1=\pm\eta_{12}}\dfrac{n_2}{a_{1N_1}}(\gamma_1>0)$, here, + indicates a promoting effect and indicates inhibition. $x_i$ is the vital knowledge transfer capability (the more extensive the coefficient of $\eta_{12}$ is, the greater the knowledge transferability is), which indicates that other subjects have a more significant promotion effect on $x_1$ knowledge stock growth.

(2) Assuming $n_i/a_iN_i$ is the growth density of the knowledge stock $x_i$, and $a_i\in[0,1]$ is a threshold that represents the proportion of the subject's willingness to interact with its knowledge. $a_iN_i$ represents the amount of knowledge stock that is willing to transfer out. Because the maximum of knowledge stock is limited, it can be seen that with the density becoming more extensive, the growth will encounter more resistance, and the speed will gradually slow down. When $n_i$ equals to $a_iN_i$, the growth rate tends to zero.

(3) For clarity, it is assumed that the growth rate is linearly related to the resistance. $r_i$ represents the pure growth rate of the knowledge stock at an instantaneous moment $t$. At this time, knowledge stock is expressed as $\Delta n_i = r_i \times n_i$. Based on the above assumptions, the knowledge stock growth model of $x_1$ a time $t$ can be expressed as:

$$\frac{\Delta n_i}{n_i}=r_i-r_i\bullet\frac{n_i}{\alpha_i n_i}=r_i(1-\frac{n_i}{\alpha_i n_i}) \quad (1)$$

Considering the influence of other subjects on knowledge growth in the open innovation process of SEI, and based on the findings of a previous study [28], knowledge transfer does not reduce actual knowledge. The Lotka-Volterra model is therefore adjusted as follows:

$$\frac{\Delta n_i}{n_i}=r_i(1-\frac{n_i}{\alpha_i n_i}+\gamma_j) \quad (2)$$

Without loss of generality, when $i(i=1...n)$ industrial innovation carries out knowledge transfer under the influences of other agents, the agent's knowledge growth model can be modified as follows:

$$\frac{\Delta n_i}{n_i}=r_i(1-\frac{n_i}{\alpha_i n_i}+\sum_{j=2}^{n}\eta_{ij}\frac{n_j}{\alpha_i N_i}) \quad (3)$$

In open industrial innovation, the subjects of knowledge transfer utilize their stock knowledge and transferred knowledge to drive innovation and achieve commercialization. Following previous research [31], in this paper, we use the Cobb-Douglas function to represent the benefit the subject gained after obtaining the transfer of knowledge from other subjects in innovation:

$$\Delta\pi_i=\sum_{i=1}^{n}\varepsilon_i X_i^{Aai}(n_i^*+\Delta m_i^*)^{Bb_i}-\sum_{i=1}^{n}\varepsilon_i X_i^{Aai}(n_i^*)^{Bb_i} \quad (4)$$

The formula (4), $\varepsilon_i$ is a constant, and $\varepsilon_i>0$ . The coefficient of elasticity $A_{ai}$ affects the actual knowledge's attributes. The elasticity coefficient $B_{bi}$ reflects the attributes of the transferred knowledge, which are all constants. $0<A_{ai}<B_{bi}<1$ and $0<A_{ai}+B_{bi}<1$ , and $\Delta m_i^*$ refers to the amount of knowledge increased due to the interaction of the subject in the interaction process (such as the transfer of tacit knowledge to knowledge).

(4) Based on the previous research [29], assuming that the core and node organizations start knowledge transfer simultaneously, the payoffs are, respectively $\beta\Delta\pi$ $(1-\beta)$. If the core organization chooses to transfer knowledge and the node organization chooses not to transfer (such as hidden knowledge halfway to breach the contract), the final benefit of the core organization is the benefit after absorbing the transferred knowledge minus the liquidated damages $\Delta\pi_1^{'}-C$ . In the same way, the income of the node organization is $\Delta\pi_2^{'}-C$ . If neither of them carries out knowledge transfer, the income is 0. Combined with the previous research foundation [32], the agent's decision is divided into knowledge transfer decisions and knowledge non-transfer decisions (such as hidden knowledge) $(1-\alpha_1)(1-\alpha_2)$ . represents the proportion of willingness to choose not to transfer of the core organization $x_1$ and the node organization $x_1$ .

The evolution model of knowledge transfer, with or without incentive compatibility, is analyzed, and the formation principles and conditions of a high-level knowledge transfer ecosystem are explored.

### *B. Evolutionary model of knowledge transfer in the open innovation process of SEI without incentive compatibility*

Based on the previous analyses, the innovation entities in this model primarily include enterprises, research institutes, universities, etc. Innovation entities use formal or informal connections to transfer knowledge through ecological adaptation. As defined earlier, innovation entities are divided into the core organization $x_1$ (e.g., universities, research institutes) and the node organization $x_2$ (Such as universities, scientific research institutes, etc.). High-quality knowledge transfer behavior occurs in the basic research and application development stages. The industry expands its knowledge stock through open innovation in the knowledge transfer process, combined with the previous research basis [28]. At this point, the growth model of the knowledge stock of the two agents is expressed as:

$$\begin{cases}\dfrac{\Delta n_1}{n_1}=r_1(\dfrac{\alpha_1 N_1-n_1+\eta_{12}n_2}{a_1 N_1})\\[2ex]\dfrac{\Delta n_2}{n_2}=r_2(\dfrac{\alpha_2 N_2-n_2+\eta_{21}n_2}{a_2 N_2})\end{cases} \quad (5)$$

In Equation (5), when the knowledge transfer reaches equilibrium, there is $\begin{cases}r_1(\alpha_1 N_1-n_1+\eta_{12}n_2)/\alpha_1 N_1=0\\ r_2(\alpha_2 N_2-n_2+\eta_{21}n_1)/\alpha_2 N_2=0\end{cases}$. At this time, the knowledge transfer coefficients $\eta_{12}$ and $\eta_{21}$ can be expressed as:

$$\eta_{12}^{'}=\frac{n_1^{'}-\alpha_1 N_1}{n_2^{'}},\eta_{21}^{'}=\frac{n_2^{'}-\alpha_2 N_2}{n_1^{'}} \quad (6)$$

In the formula (6), $\eta_{12}^{'}$ and $\eta_{21}^{'}$ means when the knowledge transfer reaches equilibrium, the value of knowledge transfer coefficient when the knowledge transfer of two organizations is in equilibrium [28]. $\eta_{12}^{'}>0$ and $\eta_{21}^{'}>0$ . At the same time, the knowledge transfer between the two organizations forms mutualism. When $\eta_{12}^{'}$ and $\eta_{21}^{'}$ are large, $n_1^{'}=\alpha_1 N_1(1+\eta_{x_1x_2})/(1-\eta_{x_1x_2}\eta_{x_2x_1})$ , thus, $\alpha_1 N_1$ has a positive feedback effect on the final equilibrium $\eta_1^{'}$ . When $\eta_{12}^{'}>0$ , $\eta_{21}^{'}<0$ or $\eta_{12}^{'}<0$ , $\eta_{21}^{'}>0$ , the knowledge transfer between the two organizations forms a commensalism relationship. When $\eta_{12}^{'}<0,\eta_{21}^{'}<0$ , it forms a competitive relationship and has no practical significance.

To mitigate innovation risks and enhance innovation efficiency, the entities within SEI adopt open innovation strategies to accelerate innovation efficiency and reduce the risk by absorbing high-quality external knowledge. The preceding analysis indicates the existence of various ecological relationships in the knowledge transfer processes of innovators. While the mutual relationships of knowledge transfer between core organizations and node organizations have been identified, the degree of coordination in knowledge transfer remains unexplored, and the ecology of knowledge transfer needs to be completely clear. Therefore, further discussion of knowledge transfer level coordination degree is necessary.

Drawing on the research foundation of predecessors [14], this study uses the coordinated stability relation index (for short RHS) to characterize the horizontal coordination degree of knowledge transfer between core organizations and node organizations:

$$RHS=\frac{\eta_{12}+\eta_{21}}{\sqrt{\eta_{12}^2+\eta_{21}^2}} \quad (7)$$

Previous studies have shown that [14] knowledge Transfer Coefficient. $\eta_{12},\eta_{21}\in[-1,1]$ , then the distribution of values of the coordinated stability relation index $RHS\in[-\sqrt{2},\sqrt{2}]$ is shown in Figure.2:

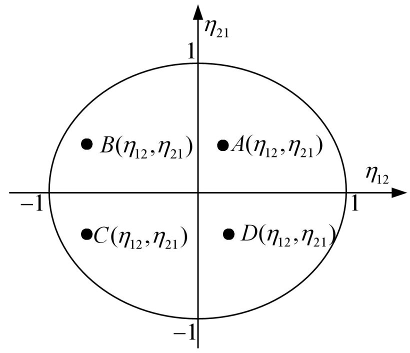


Figure.2 The degree of coordination of knowledge transfer level between subjects

The following is an analysis RHS of the value range, which reveals the stability of knowledge transfer between the core organization and the node organization:

(1) When $1 < RHS < \sqrt{2}$ , the value of the knowledge transfer coordination degree of the core organization and the node organization locates in the first quadrant of Figure.2. $\eta_{12}$ and $\eta_{21}$ are both bigger than 0, indicating that the knowledge transfer between the core organization and the node organization is more coordinated, the degree of knowledge absorption of both sides to the other side is in an appropriate range. Their knowledge transfer relationship is more stable and at a higher level.

(2) When $1 < RHS < 1$ , the value of the coordination degree of the knowledge transfer level of the core organization and the node organization is located in the second and third quadrants of Figure. 2. $\eta_{12}$ and $\eta_{21}$ are of different values, indicating that only one of them has been promoted by the other to absorb knowledge, and this kind of knowledge transfer relationship is not stable, and the level is not high.

(3) When $-1 < RHS < -\sqrt{2}$ the value of the knowledge transfer level coordination degree of the core organization and the node organization is located in the fourth quadrant of Figure. 2. $\eta_{12}$ and $\eta_{21}$ is both less than 0, indicating that both sides do not transfer their knowledge, there is no stable knowledge transfer relationship between them, and the level is not high.

To sum up, the larger the value RHS, the higher the coordination degree of knowledge transfer level between the core and node organizations. The actual knowledge transfer process represents $1 < RHS < \sqrt{2}$ the ideal knowledge transfer relationship between the core organization and the node organization, characterized by mutual benefits, commensalism, and a high level of coordination . As can be seen from equations (6) and (7), In the value of RHS, the compelling factor of $\eta_{12}$ and $\eta_{21}$ are closely related to the knowledge transfer decision-making willingness and the maximum knowledge stock $N_i$ . The following analysis focuses on how the above variables RHS value and impact knowledge transfer relationships and levels.

*C. Level coordination model of knowledge resource transfer considering incentive compatibility*

(1) Benefit matrix of inter-agent knowledge transfer

In the open innovation of SEI, there are differences in each subject's growth environment and knowledge stock, resulting in the different marginal utility of knowledge utilization. Consequently, efficient allocation of knowledge resources can be achieved by implementing knowledge transfer among innovative entities. Combined with the previous analyses, it is expected that knowledge transfer will form different levels of relationships, and the willingness $\alpha_i$ to transfer knowledge has become a key factor affecting the subjects' ability to transfer knowledge . To achieve a high-level knowledge transfer ecosystem, it is essential to coordinate and adjust the relationships and levels of knowledge transfer through mechanisms such as the transfer of knowledge usufruct, value compensation, and liquidated damages. This section further discusses the marginal utility of knowledge utilization $\Delta\pi_i'$ , utilization and distribution of income $\beta\Delta\pi$ , and the impact of changing liquidated damages $C$ on knowledge transfer.

In the process of open innovation, the flow of knowledge among different subjects, each subject converts knowledge resources into benefits, such as the benefit of $x_1\Delta\pi_1' = \varepsilon_1 X_1^{A_{a1}}(n_1^* + \Delta m_1^*)^{Bb_1} - \varepsilon_1 X_1^{A_{a1}}(n_1^*)^{Bb_1}$ is, and $\Delta\pi_2'$ can be same inferred, Overall earnings $\Delta\pi = \sum_{i=1}^{2} \Delta\pi_i$ . According to the previous assumptions, the revenue ratios determined by the core organization and the node organization through knowledge transfer are, respectively, $\beta$ and $1-\beta$ . The benefit value of the core organization and the node organization brought by cooperation is expressed as: $\beta\Delta\pi$ and $(1-\beta)\Delta\pi$ .

Based on the above assumptions and inferences, the benefits matrix under two different decision-making modes of the core organization and the node organization is presented (as shown in Table I)

TABLE I
PROFIT MATRIX OF KNOWLEDGE RESOURCE TRANSFER BETWEEN CORE ORGANIZATION AND NODE ORGANIZATION

| Core( $x_1$ )<br>Node( $x_2$ ) | Transfer<br>( $\alpha_1$ ) | No transfer<br>( $1-\alpha_2$ ) |
|---|---|---|
| Transfer( $\alpha_1$ ) | $\beta\Delta\pi, (1-\beta)\Delta\pi$ | $C, \Delta\pi_2' - C$ |
| No transfer( $1-\alpha_2$ ) | $\Delta\pi_1' - C, C$ | 0,0 |

(1) Establishment of Evolutionary Game Model among Entities and Analysis of Decision-making Evolution

In the knowledge transfer process within open innovation, the knowledge transfer subject acts as an independent entity with incomplete common interests. The subject's decisions may vary based on the design of the knowledge transfer mechanism. ( $\Delta\pi_i'$ , $\beta\Delta\pi$ And $C$ ). This section will analyze the evolution processes of the core organization and the node organization under different decisions and further discuss the evolution mechanism of knowledge transfer decisions of innovation agents.

Based on the previous assumptions and payoff matrix, the repeated dynamic equations of the knowledge transfer game between the core and node organization are obtained:

$$\begin{cases} d\alpha_1/dt=\alpha_1(1-\alpha_1)[\beta\Delta\pi-\Delta\pi_1^{'}+C)\alpha_2+C(1-\alpha_2)] \\ d\alpha_2/dt=\alpha_2(1-\alpha_2)[(1-\beta)\Delta\pi-\Delta\pi_2^{'}+C)\alpha_1+C(1-\alpha_1)] \end{cases} \quad (9)$$

Let $F(a_1)=0$ , $\alpha_1=1$ , $\alpha_2=C/(\Delta\pi_1^{'}-\beta\Delta\pi)$ .Let, therefor $F(a_2)=0$ $\alpha_2=0$ , $\alpha_1=C/[\Delta\pi_2^{'}-(1-\beta)\Delta\pi]$ , $F^{'}(\alpha_2)=(1-2\alpha_2)[(C-((1-\beta)\Delta\pi)\alpha_1]$.

Based on study[33], when $F(\alpha_1)=0$ and $F^{'}(\alpha_1)>0$ or $F(\alpha_2)=0$ and $F^{'}(\alpha_1)<0$ , if the state formed by the evolution of the core organization game is an evolutionarily stable strategy, then:

(1) When $\alpha_2>C/(\Delta\pi_{X1}^{'}-\beta\Delta\pi)$, and $F^{'}(0)<0$ , $F^{'}(1)>0$ , $a_1=0$ is an evolutionarily stable strategy.

(2) When $\alpha_2<C/(\Delta\pi_{X1}^{'}-\beta\Delta\pi)$, and $F^{'}(0)>0$ $F^{'}(1)<0$ , $a_1=1$ is an evolutionarily stable strategy.

(3) When $\alpha_1>C/(\Delta\pi_{X2}^{'}-(1-\beta)\ \Delta\pi)$ , and $F^{'}(0)>0$ , $F^{'}(1)>0$ , $a_2=0$ is an evolutionarily stable strategy.

(4) when $\alpha_1<C/(\Delta\pi_{X2}^{'}-(1-\beta)\ \Delta\pi)$ , and $F^{'}(0)>0$ , $F^{'}(1)<0$ , $a_2=1$ is an evolutionarily stable strategy.

According to Equation (9) and the establishment conditions of the stable solution, in the evolution process of knowledge transfer, there are five equilibrium points in the dynamic replication system of knowledge transfer between the core organization and the node organization, respectively $A_1(0,0)$ , $A_2(0,1)$ , $A_3(1,0)$ , $A_4(1,1)$ and $A_5(a_{12}^{*},a_{21}^{*})$ . The following is an analysis of the evolution conditions of these five equilibrium points.

The above conclusion is represented in a coordinate plane, as shown in Figure. 3:

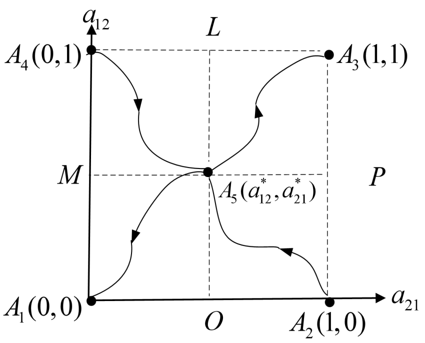


Figure. 3 Evolution Trend of Knowledge Transfer Decision Path

As shown in Figure.3, the five equilibrium points divide the decision-making willingness of the two into four regions:

When $\beta\Delta\pi>(\Delta\pi_{x_1}^{'}-C)(1-\beta)\Delta\pi>\Delta\pi_{x_1}^{'}-C$ , an initial decision point locates in the region $MA_1OA_5$ , at this time $a_1=1$ and $a_2=1$ . it is an evolutionarily stable strategy. The core and node organizations choose knowledge transfer and eventually reach equilibrium $A_4(1,1)$ . Through knowledge transfer, each subject evaluates differences in the marginal utility of knowledge, thereby facilitating knowledge transfer among different entities. Furthermore, implementing knowledge resource transfer compensation constrains opportunistic behavior, ensuring a high level of knowledge transfer under the incentive and constraint of distributing benefits $\beta\Delta\pi$ and liquidated damages C.

When $\beta\Delta\pi<(\Delta\pi_{x_1}^{'}-C)(1-\beta)\Delta\pi<\Delta\pi_{x_1}^{'}-C$ and the initial decision point locates in the region $LA_3PA_5$ , which indicates that the knowledge transfer willingness of the core organization and the node organization gradually decreases over time and finally evolves towards non-transfer. $a_1\to 0$ and $a_2\to 0$ . Finally, reach the equilibrium point $A_1(0,0)$ , when the distribution coefficient $\beta$ value is meaningful, the value of liquidated damages. C is relatively small, which fails to effectively restrain the opportunistic behavior of both partners, thus leading to the interruption of knowledge transfer behavior, and it is not easy to form a high-level knowledge transfer.

When $\beta\Delta\pi<(\Delta\pi_{x_1}^{'}-C)$ and $(1-\beta)\ \Delta\pi>(\Delta\pi_{x_2}^{'}-C)$ . The initial decision point represents a region, $OA_2PA_5$ , signifying that when the core organization's willingness to transfer knowledge is low, the node organization opts for knowledge transfer, ultimately reaching the equilibrium point. $A_2(0,1)$ . It means that when liquidated damages C are under the appropriate circumstances, the value of the benefit distribution coefficient $\beta$ is relatively large. As a result, the core organization will obtain higher benefits, while the node will benefit less. Therefore, the core organization insists on knowledge transfer, while the node organization chooses not to transfer knowledge.

when $\beta\Delta\pi>(\Delta\pi_{x_1}^{'}-C)(1-\beta)\Delta\pi<(\Delta\pi_{x_2}^{'}-C)$ , and the initial decision point is a region $A_4LA_5M$ , which means that when the knowledge transfer willingness of the node organization is low, the core organization chooses the knowledge transfer and finally reaches the equilibrium point $A_3(1,0)$ . Furthermore, it means that when the liquidated damages C are under appropriate circumstances, the value of the benefit distribution coefficient $\beta$ is relatively small, the core organization obtains less benefit, and the node organization obtains more benefits. Therefore, the core organization chooses not to transfer knowledge, while the node organization chooses to transfer knowledge.

According to the above analyses, the marginal utility of knowledge utilization and the distribution coefficient of both sides of the transfer will affect the decision-making willingness of the subject and may form an inefficient equilibrium. In addition, the value of liquidated damages can restrain opportunistic behavior to a certain extent. The results show that by coordinating the distribution and liquidated damages coefficients. The stronger the willingness on both sides to transfer knowledge $\alpha_i$ is, the greater the economic benefits and the higher the ecological level of knowledge transfer. . As a result, coordinating the values of $\beta\Delta\pi$ 、 $(1-\beta)\Delta\pi$ and the liquidated damages C, respectively, controlling $\beta\Delta\pi>(\Delta\pi_{x_1}^{'}-C)(1-\beta)\Delta\pi>(\Delta\pi_{x_2}^{'}-C)$ . It is expected to promote the decision-making of knowledge transfer among various subjects and form a high-level knowledge transfer ecology.

## V. Numerical Simulation and Analysis

### A. Case Background

Based on related literature [1] and field investigation, we propose the development of a numerical simulation to empirically validate the knowledge transfer mechanism within the context of open innovation. The research focuses on the new energy automobile industry, a key sector within strategic emerging industries. This industry encompasses various fields such as vehicle integration, battery systems, motor electric control, intelligent networking, etc. It is characterized by a lengthy innovation chain, specialized knowledge requirements, division of labor, and close collaboration. Based on field research data, the core organization, CAXNY, focuses on researching and developing core technologies of energy-saving and new energy vehicles, such as pure electric, hybrid, and fuel cells; system integration design, manufacturing of electric drive system components; and production and sales of pure battery sightseeing vehicles. The node organization, ZQY, is mainly engaged in work with high knowledge and technology content, such as product development, experimental research, an essential base for quality inspection, and technical support institutions in the automotive industry. The core and node organizations build a knowledge transfer ecosystem to implement open innovation.

Our case is based on expert consultation and literature review. The node organization, ZQY, has accumulated vital technologies such as experimental research and quality testing. Through high-quality knowledge flows, ZQY establishes a knowledge chain. It builds an open innovation ecosystem, which is expected to reduce the uncertainty of the core organization CAXNY in developing new energy vehicles, improve innovation efficiency, increase industrial knowledge reserves, and promote open industrial innovation.

### B. Example calculation

TABLE II
SETTING OF KNOWLEDGE TRANSFER PARAMETERS

| variable | parameter | value |
|---|---|---|
| Knowledge transfer parameters | $\varepsilon$ | 1 |
| | $A_{a1}$ | 0.35 |
| | $B_{a1}$ | 0.55 |
| | $A_{a2}$ | 0.35 |
| | $B_{a2}$ | 0.55 |
| | $N_1$ | 300 |
| | $N_2$ | 280 |
| | $n_1$ | 885 |
| | $n_2$ | 845 |
| | $n_1^* + \Delta m_1^*$ | 1565 |
| | $n_2^* + \Delta m_2^*$ | 1700 |

TABLE III
SETTING OF KNOWLEDGE TRANSFER UTILITY PARAMETERS

| variable | parameter | value |
|---|---|---|
| Knowledge transfer utility related parameter | $C$ | 50 |
| | $\beta$ | 0.5 |

To comprehensively analyze the evolution of knowledge transfer and the level of knowledge ecology in the open innovation process, we study open innovation carried out by the core organization CAXNY and the node organization ZQY through field research. In developing new self-driving vehicles, CAXNY takes advantage of R&D and design, and ZQY focuses on providing test scenarios. On the one hand, the study establishes the distribution of benefits through field research and assumptions. . Determine the distribution coefficient $\beta$ and the cost of default C. On the other hand, considering that it is not easy to quantify the relevant parameters of knowledge transfer in the open innovation process of SEI, combined with expert consultation, Referring to Long and Liu (2021) [29] and the hypothesis of the previous study, we set $n_1'$ and $N_1$ for the relevant parameter values of knowledge transfer, as shown in Table II and Table III.

(1) The influence of marginal utility of knowledge utilization, incentives, and constraints of knowledge transfer on knowledge transfer.

The calculation is based on the initial values provided in Table IIand Table III: Combined with formula (4), calculating the benefits of knowledge transfer chosen by the two organizations. Due to $\Delta\pi'_{x_1} = \Delta\pi'_{x_2} = 175$, it can get $\Delta\pi = 350$ after a single subject chooses not to transfer knowledge (default in the middle), and the income is $\Delta\pi_{x_1} = \Delta\pi_{x_1} = 200$, then $a_{12}^* = a_{21}^* = 0.67$. The payoff matrix of the two agents is shown in Figure. 4.

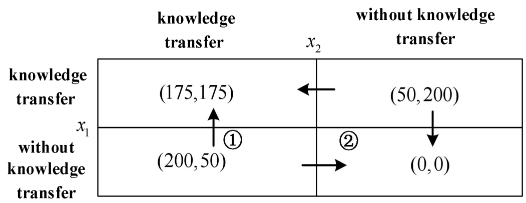


Figure.4 Profit Matrix of Knowledge Resource Transfer between Core Organization and Node Organization

As shown in Figure 4, scenarios with balanced distribution coefficients exhibited higher knowledge transfer efficiency, achieving equilibrium within fewer iterations. In contrast, coefficients below 0.3 led to system instability, highlighting the need for equitable benefit-sharing mechanisms. For instance, when $a_{12}$ does the initial value of 0.2 (hidden knowledge, at this time $a_{12} < a_{12}^*$), for the enterprise $x_1$, it exists $\beta\Delta\pi = 0.5 \times 350(\Delta\pi'_{x_1} - C) = 200$. For the enterprise $x_2$, it exists $(1-\beta)\ \Delta\pi = 0.5 \times 350 = 175$, and $C = 50$, then $(1-\beta)\ \Delta\pi > C$. Thus, the subject $x_1$ hiding knowledge, without knowledge transfer, will lead to the subject $x_1$ hide knowledge and then affect the overall revenue (Figure. 4 ①). Through negotiation, both sides carry out knowledge transfer simultaneously, which is conducive to increasing revenue (Figure 4 ②).

(2) The impact of knowledge transfer decisions and knowledge stock on knowledge ecology

To further discuss the ecological level of knowledge transfer in industrial innovation, the ecological level of knowledge transfer under different decisions is calculated based on the values determined above and the designed model, as shown in Table IV:

TABLE IV
THE IMPACT OF PARAMETER CHANGES ON KNOWLEDGE TRANSFER

| Model parameters | | | | | | | Ecological level of knowledge transfer | | |
|---|---|---|---|---|---|---|---|---|---|
| | $N_1$ | $N_2$ | $n_1$ | $n_2$ | $n_1^*$ | $n_2^*$ | $\eta_{12}^{'}$ | $\eta_{21}^{'}$ | $RHS$ |
| 1 | 300 | 280 | 885 | 845 | 865 | 1200 | 1 | 0.4 | 1.32 |
| 2 | 300 | 280 | 885 | 845 | 1265 | 1600 | 1 | 0.6 | 1.37 |
| 3 | 300 | 280 | 885 | 845 | 1565 | 1700 | 0.9 | 0.7 | 1.40 |

Table IV shows the ecological level of knowledge transfer of the core organization and the node organization under different knowledge stocks (N) and willingness to make decisions ( $\alpha$ ). Based on the values presented in Table IV, we can determine the value of $\eta$ RHS at the equilibrium time of knowledge transfer. . It is not difficult to find that with the increase of the amount of transfer knowledge from the subject $x_1$ (e.g., rise of the willingness to make a decision $\alpha$ , $\alpha N$ become larger), the value of $n_1^* + \Delta m_1^*$ continues to rise when knowledge is balanced, and the ecological coordination degree of knowledge transfer (RHS) is expected to continue to rise. Therefore, in the open innovation process, the ecological level of knowledge transfer in the open innovation process is improved by selecting complementary and high-quality knowledge entities, giving full play to the utility of knowledge flow, formulating incentive and restraint mechanisms, and improving the decision-making willingness of the core entities and the node entities (As a result, the value of RHS increases), which verifies the conclusion of the previous mathematical derivation.

Thus, the ecological level of knowledge transfer can be enhanced by maximizing the marginal utility of knowledge utilization, fostering specialized division of labor and collaboration, ensuring incentive compatibility, strengthening the decision-making willingness of innovators within the knowledge chain, and promoting the flow of high-quality knowledge resources among them.

## VI. CONCLUSION AND RESEARCH VALUES

### A. Conclusion

This study integrates ecological theory, game theory, and knowledge management to construct a symbiotic coordination framework for analyzing knowledge transfer dynamics within the open innovation process of SEI. By employing an improved Lotka-Volterra model, the study quantitatively examines the evolutionary paths of knowledge transfer relationships and levels.

The results demonstrate that adopting knowledge transfer strategies significantly benefits both core and node entities in the SEI innovation ecosystem, compared to scenarios where knowledge transfer is not pursued. Specifically, the findings highlight that:

(1) Balanced distribution coefficients and optimized penalty mechanisms significantly enhance the efficiency and stability of the knowledge transfer ecosystem (as illustrated in Table IV).

(2) Incentive-compatible strategies reduce opportunistic behaviors and foster collaborative knowledge-sharing relationships, leading to higher innovation output (as illustrated in Figure 4).

(3) Coordinating knowledge transfer parameters within specific ranges accelerates the development of a high-quality knowledge transfer ecosystem, supporting sustainable innovation in SEI.

### B. Theoretical Values

This study advances the theoretical understanding of knowledge transfer dynamics in the context of strategic emerging industries (SEI) by integrating ecological theory, game theory, and knowledge management into a unified framework. The application of the Lotka-Volterra model offers a novel perspective for analyzing the evolutionary paths of knowledge transfer, addressing critical gaps in existing research.

(1) Unlike traditional models that primarily focus on linear or static relationships, this study incorporates ecological attributes such as mutualism, competition, and commensalism, providing a more nuanced view of the dynamic and interdependent relationships in SEI knowledge ecosystems.

(2) This research introduces the concept of high-quality knowledge transfer as a multi-dimensional construct, emphasizing the marginal utility of knowledge utilization and the ecological coordination of entities. It provides theoretical insights into how balancing these factors enhances innovation outcomes in SEI.

(3) By incorporating distribution coefficients and penalty mechanisms, the study extends existing game-theoretical approaches, offering a quantitative foundation for understanding how incentives and constraints influence knowledge transfer decisions and ecosystem stability.

### C. Practical Values

The study's findings offer actionable strategies for enhancing knowledge transfer in SEI. Policymakers and industry leaders can leverage insights into distribution coefficients and penalty mechanisms to design fair and enforceable agreements that foster trust and collaboration. Additionally, the research highlights the importance of optimizing knowledge resource allocation by strategically aligning entities with complementary capabilities. These recommendations support the development of robust, high-quality innovation ecosystems, enabling SEI organizations to achieve sustainable growth and competitive advantage in the era of open innovation.

## VII. Research Prospects

This paper constructs an evolutionary knowledge transfer model based on the evolutionary game and improved Lotka-Volterra model. It conducts empirical research on combining specific open innovation behavior and factors of SEI, focusing on the actual parameter values of knowledge stock, the marginal utility of knowledge utilization, incentives, restraint degree, etc. Future research should focus on integrating additional real-world parameters, such as cultural and policy influences, into the knowledge transfer model. Additionally, longitudinal studies examining the long-term evolution of SEI ecosystems would provide valuable insights into the sustainability of knowledge transfer strategies.

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