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RESEARCH ARTICLE

# The Evolution and Knowledge Change of Innovation Cooperation Network in Platform Ecosystem: A Computer Simulation From Complex Network Perspective

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**ABSTRACT** Platform ecosystems, as a new organizational form, provide enterprises with new contexts for innovation and entrepreneurship. However, due to a lack of dynamic data, we do not understand how the platform ecosystem evolves. Because the traditional methods have limitations, this study uses computer simulations to investigate the evolution and knowledge change of innovative cooperation networks in the platform ecosystem from the perspective of complex networks. The results indicate that the platform ecosystem's innovation cooperation network evolves around initial network enterprises. The degree of enterprise cooperation shows a trend of decreasing first then increasing, but the efficiency of enterprise cooperation gradually decreases. Second, as the network evolves, the knowledge level rises, whereas the knowledge growth rate falls in the platform ecosystem. Meanwhile, the impact of network structure on knowledge change is unclear, whereas enterprise knowledge creation capability, knowledge absorption capability, and competitive pressure all have a significant impact on knowledge change.

**INDEX TERMS** Platform ecosystem, innovation cooperation network, network evolution, knowledge change, enterprise capability, computer simulation.

## I. INTRODUCTION

The emergence of the Internet and information technology has given rise to a new organizational form, the platform ecosystem, which has quickly become a driving force for social and economic development [1]. Many global enterprises, including Amazon, Apple, and Facebook, own digital platforms and implement ecosystem strategies. Platform ecosystems are emerging networks in which platform enterprises use digital technology to link interdependent bilateral or multilateral users, resulting in many ecological participants [2]. Many enterprises are flocking to the platform ecosystem to participate in innovation and entrepreneurship [3]. For example, just around the anchors, the TikTok platform has spawned enterprises of various sizes, including operation management, video services, live e-commerce, and auxiliary logistics. Platform ecosystems have evolved into a significant social and economic development engine.

Many enterprises in the platform ecosystem collaborate to create value, share resources, and innovate. Connecting enterprises promotes the evolution of the innovation cooperation network, inducing knowledge creation and flow, thus improving overall innovation output [4]. However, due to the long growth cycle of the platform ecosystem, complex influencing factors, and difficulty in obtaining complete dynamic data, most existing research focuses on internal innovation and entrepreneurial behavior [5], [6], with insufficient attention paid to the ecosystem level. How does the innovation cooperation network of a platform ecosystem evolve? How does knowledge emerge and spread in the network of innovation

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cooperation? Existing research has not yielded a clear answer. Resolving these issues is critical for promoting the healthy development of the platform ecosystem, which has theoretical and practical implications.

Complex network simulation has become one of the most widely used methods for investigating network evolution [7] and providing a viable path for resolving network complexity in platform ecosystems in recent years. For example, Xu et al. [8] investigated the dynamic evolutionary characteristics of organizational groups in a platform network. Zhou et al. [9] developed a symbiotic evolution model based on ecological agents and described the key competitive factors that influence the dynamic evolution of platform ecosystems. However, simulated analyses of a platform ecosystem's innovation cooperation network are generally sporadic and disjointed.

This study used Python software in the context of the platform ecosystem to investigate the evolution and knowledge change of innovation cooperation networks from the perspective of complex networks. It focuses on two specific aspects: (1) How does the platform ecosystem's innovation cooperation network evolve? (2) How does knowledge change in the platform ecosystem's innovation cooperation network? Then, we discuss the following in detail: (1a) What kind of evolution model is the platform ecosystem's innovation cooperation network? (1b) What are the characteristics of cooperation's degree and efficiency in the evolutionary process? (2a) How do the average knowledge level and knowledge growth rate change in the platform ecosystem's innovation cooperation network? (2b) How dose network structure, firm knowledge creation capability, knowledge absorption capability, and competitive pressure impact knowledge change? This study differs from previous innovation network simulation analyses in several ways. First, it constructs a network evolution model from the perspective of complex networks, a novel concept in most platform evolution research. Second, this research focuses on the impact of the competitive environment on knowledge creation and flow, emphasizing the uniqueness of networks in platform ecosystems. Third, this study encourages a focus on innovation activities from knowledge creation and flow standpoint, which raises the importance of knowledge management in the platform ecosystem. Furthermore, the findings not only add to complex network theory but also provide recommendations for promoting platform ecosystem innovation and development.

## II. THEORETICAL FOUNDATION

### A. COMPLEX NETWORK THEORY

A complex network has some or all of the following characteristics: self-organization, self-similarity, attractor, small-world, and scale-free [10]. Complex networks in daily life include transportation, power, computer, and social networks. The development of computer simulation methods based on complex networks has made it more efficient to investigate these network phenomena [11].

In general, complex networks include random, scale-free, and small-world networks. In the case of node isomorphism, the random network generated by the random graph algorithm is usually uniform and can accurately represent network evolution. For instance, in a random network of $N$ nodes, the probability of cooperation between any two firms is $p \in [0,1]$ and the number of generating edges is variable [12]. The scale-free network assumes that most real-world networks are not random because a few nodes frequently have many connections, and node degree distributions in a scale-free network conform to the power–law distribution [13], [14]. Small-world networks are networks that exist between regular graphs with high clustering coefficients but average path intersections and random graphs with low clustering coefficients but short average paths, and it has both a high clustering coefficient and a short path, which are both common features of real networks [15]. Watts and Strogatz [15] started with a regular network and randomly added edges to get to the Watts–Strogatz (WS) small-world network model. According to the WS small-world model, the probability of edge addition $p = 0$ corresponds to a completely regular network, $p = 1$ corresponds to a completely random network, and $p = 0.01$ corresponds to the most obvious small-world network. By varying the $p$ values, different types of network structures can be created. A large amount of statistical data shows that many network models have "small-world" characteristics in real life, so the small-world network model is widely used in enterprise complex network simulations [16].

### B. KNOWLEDGE NETWORK EVOLUTION

Enterprise survival and growth rely heavily on an organizational network built on cooperative relationships [17]. Localized learning networks with universities, institutes, government agencies, and other organizations, as well as vertical or horizontal business networks with suppliers, customers, and even competitors [18], can be formed by enterprises. Whether localized learning network or a vertical or horizontal business network, different network entities must have knowledge creation and flow activities. Supply chain, for example, acts as a regional supply network channel for information and knowledge exchange between companies, promoting organizational learning and knowledge diffusion across industries [19], [20]. Indeed, knowledge networks can be found in a wide range of organizational networks. Knowledge networks regard network nodes as knowledge carriers, achieving knowledge creation, flow, diffusion, and sharing through the activities of knowledge participants at different levels [21]. In today's digital economy, knowledge networks are frequently embedded in specific social networks. Enterprises must join knowledge alliances or embedded platforms to expand and acquire new knowledge. As a result, the knowledge network of the platform ecosystem has gradually entered the researchers' vision.

In fact, knowledge network research dates back to the mid-1990s [22]. Early research has focused on the constituent elements, evolution mechanisms, network boundaries, and cooperation mechanisms of knowledge networks. As research advances, more emphasis is being placed on enterprise–universities, enterprise–enterprise, individual–enterprise, and individual–individual knowledge flow [23], [24]. Many researchers have focused on cooperation benefits knowledge diffusion during this process [18], [25], [26]. First, cooperative relationships foster the development of trust among enterprises [27]. High levels of trust among enterprises can reduce opportunism and the possibility of one party exploiting valuable knowledge for personal gain, while increasing willingness to share knowledge [28]. Second, cooperative relationships foster information exchange among enterprises [27]. Active, timely, and accurate information exchanges among collaborators can improve mutual understanding of knowledge subjects and boost the effectiveness of tacit knowledge-sharing [29]. Third, cooperative relationships foster joint problem-solving [27]. Joint problem-solving enables enterprises to respond to rapidly changing technologies and markets by innovating and promoting knowledge creation and diffusion [30]. Platform ecosystem cooperative relationships formed around platform leaders based on digital technology enable faster knowledge diffusion. Knowledge network issues have become more complex as knowledge acquisition methods have become more diverse and intertwined.

To simulate knowledge diffusion, several studies have used complex network evolutionary algorithms. For example, Cowan and Jonard [31] modeled knowledge diffusion as a barter exchange process in which various types of knowledge are diffused in the node exchange process and the system exhibits "small-world" characteristics. Lin and Li [32] investigated knowledge diffusion and innovation in four representative network models, defining growth diffusion time and showing that scale-free networks can provide optimal knowledge transfer. Zhou and Jia [33] proposed a knowledge diffusion-based link prediction method in complex networks, and simulation results showed that it is more accurate than previous methods. In summary, complex network analysis has become one of the mainstream knowledge network methods, and it can extract network evolution characteristics and trends in a more complex network environment, providing critical support for the discussion of knowledge diffusion in platform ecosystems.

## III. INNOVATION COOPERATION NETWORK EVOLUTION IN PLATFORM ECOSYSTEM

### A. SIMULATION PRINCIPLE AND PARAMETER SETTING

Collaboration between enterprises promotes network formation and evolution. There is a diverse range of individuals or organizations in the network for knowledge learning and exchange based on cooperation [18], [26], [27]. In other words, all the enterprises in the network engaged in innovative cooperation form a knowledge field in which the enterprises are knowledge subjects, and cooperation among various subjects promotes knowledge creation, sharing, and diffusion. Indeed, the innovation cooperation network is the carrier of knowledge diffusion, and the distance between cooperation relationships directly impacts knowledge diffusion efficiency [25], [26]. For example, direct cooperation clearly has a higher knowledge diffusion efficiency than indirect cooperation via a third-party. Enterprises in platform ecosystems have multidimensional characteristics. Multidimensional matching is frequently used to form an innovation cooperation network, which results in a differential clustering network model. To propose a network simulation model, we refer to the community network structure and similar growth network models [34] and modify the preferred node connection mechanism of nodes. The model's main parameters are as follows:

(1) $N$: the network scale, or the total number of network nodes $i, j, i, j \in [1, N]$.

(2) $K$: the number of new enterprises that join the innovation network, where $K_0$ is the number of nodes at the start of the network's establishment.

(3) $T$: the number of network connections. $T_i$ represents the number of network connections at node $i$.

(4) $C$: network-clustering coefficient. $C_i$ denotes the clustering coefficient of node $i$, and $C(N)$ denotes the network's average clustering coefficient, which reflects the degree of cooperation and closeness between enterprises. The greater a node's clustering coefficient, the stronger the node's connection to other nodes. A node's clustering coefficient is calculated by dividing the number of network connections at a given point by the maximum possible variable. The overall network-clustering coefficient is the average of the clustering coefficients at all points.

$$C_i = \frac{2 \times T_i}{K_i \times (K_i - 1)}$$

(5) $L(N)$: the average path length. The average path length represents the distance and efficiency of enterprise collaboration. The shorter the average path length, the lower the cost and the higher the efficiency of enterprise cooperation. This is calculated by dividing the sum of the shortest paths between any two nodes by the total number of network connections.

$$L(N) = \frac{1}{1/2N(N-1)} \sum_{i>j} d_{ij}$$

(6) $p(\theta_i)$: Cooperation probability, which represents the likelihood that a newly added node will connect to an existing node $i$ in the innovation cooperation network:

$$p(\theta_i) = T_i / \sum_{i \neq j}^{N} T_{ij}$$

In complex network calculations, many tools, such as NetworkX, Graph, and Gephi, are commonly used. Each tool has its own advantages when it comes to analyzing complex networks, and researchers can choose the tool that best meets their needs [35]. NetworkX, a software package based on the Python programming language, has grown in popularity in recent years [36]. It has strong network analysis capabilities, low development costs, and high scalability. As a result, we implement the platform ecosystem simulation design in Python 3.8, with the innovation cooperation network environment generated by the complex network modeling toolkit NetworkX. Invoking various NetworkX modules creates the specific network structure. The simulation design process is as follows.

First, consider the initial network, $G_{(t)} = (N, T_{(t)})$. The platform ecosystem must go through a process from small to large. The platform typically comprises 3–5 enterprises in the early stages. New enterprises are drawn to the ecosystem as the platform evolves. This study establishes the initial network parameters as $K_0 = 5$ and $T(t_0) = 8$, implying that the initial network has five nodes (enterprises) and eight edges (connections) based on the actual situation.

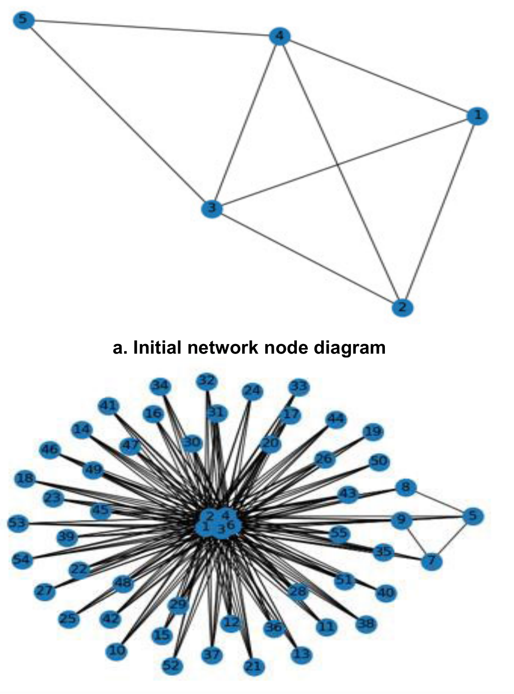
Second, it is assumed that new enterprises will continue to enter the platform ecosystem as time $T$ increases. To keep the simulation design simple, only one node was added each time ($t$). A newly added node has a certain connection probability $p(\theta_i)$ with the existing node. $p(\theta_i)$ represents the probability that a new node will choose to collaborate with a specific node $i$, which is proportional to node $i$'s existing network connections [12]. This means that the more existing connections an enterprise has, the more likely it is that new enterprises will collaborate later.

Finally, the generated network is left to evolve over time. After $T$ times, the platform ecosystem attracts $T$ new enterprises, and the innovation cooperation network evolves into a network with $N_0 + T$ nodes and $T_0 + M_i \times T$ edges ($M_i$ is the number of new edges created each time).

### B. SIMULATION RESULTS

First, we set the initial network $G(t_0) = (5, 8)$, and after $T = 50$, we obtained a 55-enterprise cooperation network, as shown in Figure 1. The network evolution diagram demonstrates that first-entry enterprises, particularly initial network enterprises, influence late-entry enterprises' partner selection. This is because platform leaders and key component providers are frequently the first participants, establishing and expanding the platform ecosystem [37]. These early participants not only provide a framework for other ecological participants to follow, but they are also the first to engage in competition and cooperation [37]. Consequently, subsequent ecological participants often form closer bonds with them, and the evolutionary path of the entire innovation cooperation network is also shown to revolve around the initial network enterprises.

Second, as shown in Figure 2, the network clustering coefficient decreased first and then increased. The network-clustering coefficient was lowest when $T = 8$. This demonstrates that cooperation was scattered and turbulent in the early stages of the platform ecosystem. Enterprise agglomeration emerged as the network evolved, and the degree of cooperation between enterprises increased. This is because cooperation in the platform ecosystem must be based on an




a. Initial network node diagram

b. Network evolution diagram when T = 50

**FIGURE 1.** Evolution diagram of innovative cooperation networks in the platform ecosystem.

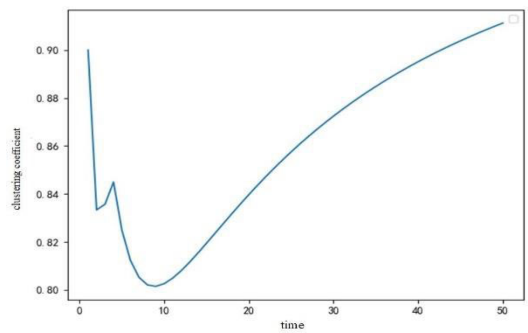



**FIGURE 2.** Evolution of network clustering coefficient.

agreement. The platform's ecosystem can only grow if other participants recognize and adhere to the platform's standards and rules [38]. Prior to the standard's formation, competition reigns supreme, and each key player strives to create the most beneficial product standard for itself, indicating a downward trend in cooperation closeness. However, when product specifications and standards are established, cooperation takes over, and the entire platform ecosystem will quickly provide complementary products based on a consistent standard, demonstrating that the level of cooperation among ecological participants gradually increases.

Finally, as shown in Figure 3, as the number of network subjects in the platform ecosystem grows, the network's average path length grows and eventually stabilizes at around 1.8. It is clear that as more enterprises join the network, the

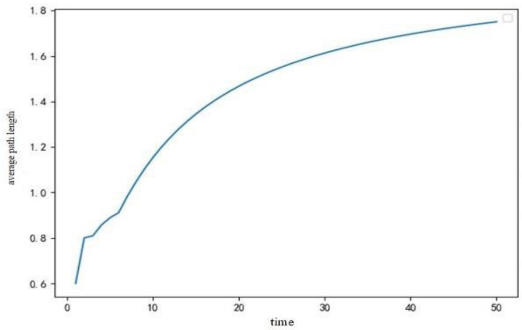



**FIGURE 3.** Evolution of average path length.

efficiency of network cooperation declines. This is because, unlike in other networks, the platform leader coordinates the activities of participants [39]. Because ecosystem participants are not under the platform leader's hierarchical control, platform leaders' coordination tasks become more difficult as the number of ecological participants increases [40]. Participants choose whether or not to join the platform ecosystem, as well as how to choose competition fields and partners. They frequently have dynamic and varied development objectives [41]. The amount of information surrounding platform leaders increases as the number of participants with strong autonomy increases, resulting in increased difficulty in network coordination and decreased overall cooperation efficiency.

### C. CASE ANALYSIS

The relevant cases also support the above simulation results. In the 1980s, Microsoft and Intel formed alliances to challenge IBM's dominance [42]. Because of Intel's Moore's Law, Microsoft Windows system upgrades, and the support of other software and hardware suppliers, the Wintel platform ecosystem has dominated the desktop end of the personal computer market for more than 20 years [37]. However, with the advent of mobile Internet in 2010, the Wintel platform ecosystem began to show cracks and gradually lagged behind the ecosystems of IOS, Android, and other mobile platform.

In this process, the initial network enterprises that established the Wintel platform ecosystem are Microsoft and Intel, the platform leaders. To increase its influence during the ecological development process, Intel launched the "intel inside" campaign [43]; Microsoft also launched a global partner program to actively collaborate with ecosystem software and hardware manufacturers [44]. Indeed, the evolution of the Wintel platform ecosystem is centered on the two initial main bodies, Microsoft and Intel, which wield greater network influence over subsequent entrants. Second, Microsoft and Intel collaborated to promote personal computer (PC) standards, which increased ecosystem cooperation. Intel, for example, has created and defined interface standards for microprocessors to communicate with other components, and these interfaces are now part of the PC system [38]. Until standards are agreed-upon, the Wintel ecosystem cannot develop sufficient complementary and compatible products. Following the unification of the standards, participants' behaviors shifted from competition to cooperation, with the degree of cooperation gradually increasing. Third, as the mobile terminal market expanded, the Wintel ecosystem's overall cooperation path expanded while cooperation efficiency decreased. The Wintel ecosystem has gradually lost its competitive advantage in the emerging mobile terminal field. Microsoft, for example, began to seek collaboration with Arm, AMD, Qualcomm, and other chip manufacturers [45], as well as attempt to develop processors independently, to form new ecological advantages.

In summary, the platform ecosystem's innovation cooperation network evolves around platform leaders and key component providers. Ecological participants were competitive prior to agreeing on platform standards and specifications, which caused the degree of cooperation to decrease as the number of participants increased. Cooperation dominates the ecological participants after reaching an agreement on platform standards and norms, causing the degree of cooperation to increase as the number of participants increases. However, as the platform ecosystem matures, the cooperation paths between participants expand, cooperation efficiency declines, and agility to respond to changes in the external environment declines, gradually increasing the gap with the new ecosystem.

## IV. KNOWLEDGE CHANGE OF INNOVATION COOPERATION NETWORK IN PLATFORM ECOSYSTEM

### A. SIMULATION PRINCIPLE AND PARAMETER SETTING

The simulation of the evolution of the platform ecosystem's innovation cooperation network shows that after a period of time, the network's clustering coefficient is stable at approximately 0.9, and the path coefficient is stable at approximately 1.8. According to the data, network evolution has a "small-world" characteristic [12]. Consequently, a small-world model was selected to build an innovative cooperation network and simulate knowledge changes. The specific simulation steps are as follows:

(1) Constructing a model of a small-world network model. A network $G_{(t)} = [N, E]$ was created using the NW network model, and the connection probability ($p$) between network nodes was set.

(2) Each network node represents an enterprise. To begin, there are three enterprise knowledge change characteristics: basic knowledge (ken), knowledge absorption capability ($\alpha$), and knowledge creation capability ($\beta$). The enterprise's basic knowledge represents its starting point, knowledge absorption capability represents its ability to learn and transform new knowledge from other enterprises in the network, and knowledge creation capability represents its own ability to create new knowledge. Second, enterprises suffer from knowledge loss and are affected by platform competition. The knowledge loss coefficient ($\theta$) is typically set to 0.1 because it

is a nonlinear function. A competitive environment is a level playing field on a platform. According to Cai et al. [46], this competitive environment is described by the value of $\varepsilon$, where the larger $\varepsilon$, the more platform competition there is.

(3) Knowledge flow occurs when network nodes are connected (i.e., when cooperation occurs), but the following conditions must be met. For starters, knowledge can only flow from nodes with a high-knowledge base to nodes with a low-knowledge base, implying that knowledge-sharing is restricted to Ken($j$) – Ken($i$). Second, enterprise willingness to share influences knowledge flow, and competitive pressure ($\varepsilon$) influences the willingness to share of nodes with a large knowledge base. Third, nodes with a low knowledge base have a limited knowledge absorption capability ($\alpha$), which may not be fully utilized. As a result, at some point in time, the enterprise's knowledge acquired from a node is $\mathrm{KS}_{(i,t)}$.

$$\mathrm{KS}_{(i,t)} = \begin{cases} \alpha \times \left(K_{j,t-1} - K_{i,t-1}\right), \\ \text{when the enterprise is willing to share} \\ 0, \\ \text{when the enterprise refuses to share} \end{cases}$$

(4) Enterprises create their own knowledge. $\beta \times K_{t-1}$ knowledge is created at each stage. However, knowledge will also be lost, specifically the $\theta \times K_{t-1}$ knowledge. Consequently, at a certain point in time, enterprise created knowledge is $\mathrm{KC}_{(i,t)}$.

$$\mathrm{KC}_{(i,t)} = K_{(i,t-1)} \times (1+\beta) \times \theta$$

(5) As a result, the total amount of knowledge at any node in time is the knowledge created plus the knowledge acquired through cooperation. The total quantity of knowledge is $K_{(i,t)}$.

$$K_{(i,t)} = K_{(i,t-1)} \times (1+\beta) \times \theta + \sum [(1-\varepsilon) \times \alpha \times (K_{(j,t-1)} - K_{(i,t-1)})]$$

We chose the average knowledge level and knowledge growth rate to measure the knowledge change in the platform ecosystem. The average knowledge level is the average value of all nodes' knowledge levels in the network, and it is $\overline{K_t}$.

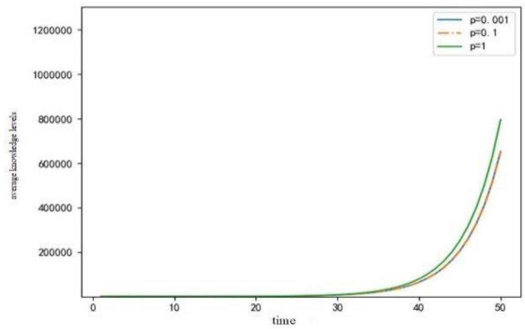
$$\overline{K_t} = \frac{1}{N}\left(\sum K_{i,t}\right)$$

The knowledge growth rate is the rate at which the network's overall knowledge level grows, and it is $\overline{U_t}$.

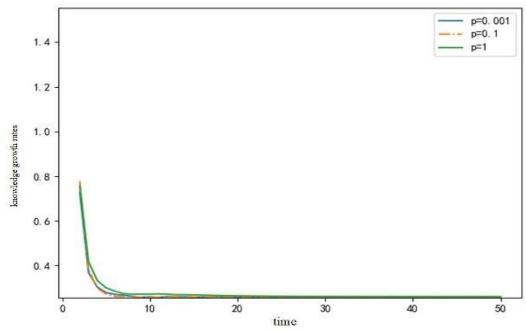
$$\overline{U_t} = \frac{\overline{K_t} - \overline{K_{t-1}}}{\overline{K_{t-1}}}$$

The impact of network structure, knowledge creation capability, knowledge absorption capability, and platform environment on knowledge change can be determined further by observing changes in knowledge level and growth rate in the platform ecosystem.

This study uses the number of small-world network nodes 200, and the connection coefficient $p \in [0,1]$ to determine the process involved in the simulation. The initial knowledge level of an individual is set as a random number between 0 and 10, that is, $K_{(i,0)} \in [0,10]$. Furthermore, an enterprise's absorption capability coefficient ($\alpha$) is 0.8, its knowledge creation capability coefficient ($\beta$) is 0.4, and its knowledge loss coefficient ($\theta$) is 0.9. Considering the competitive environments of different platforms and to avoid deviation of the results, we set the initial platform competition coefficient ($\varepsilon$) as 0.5, and the enterprise sharing willingness as 1-$\varepsilon$. The values of various parameters were then altered to investigate the impact of various factors on knowledge changes in the platform ecosystem.




**a. Comparison of average knowledge levels under different network structures**




**b. Comparison of knowledge growth rates under different network structures**

**FIGURE 4. Comparison of average knowledge level and knowledge growth rate under different network structures.**

### B. SIMULATION RESULTS

(1) The impact of network structure on knowledge change in innovation cooperation networks

To investigate the impact of different network structures on knowledge changes in the platform ecosystem, we changed the connection probability $p$ of each node in the network from 0 to 1 and the maximum evolution period $T = 50$, which increases the sufficiency of knowledge creation and flow.

The connection probability $p$ in this study's simulation model is 0.001, 0.1, and 1, following the general design of network simulation to generate a network to investigate the impact of regular network structures, small-world network structures, and random network structures on knowledge change. Figure 4 depicts the evolution of the average knowledge level and the rate of knowledge growth for the three network structures.

The average knowledge level of random networks ($p = 1$) was slightly higher than that of small-world networks ($p = 0.1$) and regular networks ($p = 0.001$), as shown in Figure 4a, but the difference was not significant. Figure 4b shows that the knowledge growth rates of the three network structures peak at around 0.78 at the start of network evolution, but the knowledge flow weakens as the network evolves.

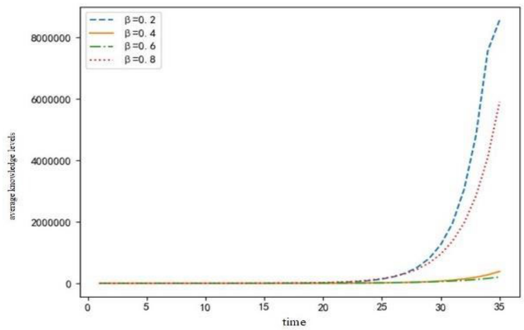
It can be seen that network structure has little influence on knowledge change, indicating that the overall ecology's average knowledge level is increasing while the average growth rate is gradually declining and stable at a low level. This is because platform leaders play a significant role in encouraging cooperation among ecological members. They actively seek knowledge creators while also providing a forum for participants to share their knowledge, such as online developer forums [47]. As the number of participants increases, they have the potential not only to generate more knowledge but also to increase the possibility of knowledge exchange, thereby raising the overall level of knowledge. However, as the number of participants grew, competition became more intense, and the rate of knowledge growth gradually slowed, indicating the ecosystem's maturity.

(2) The impact of knowledge creation capability on knowledge change in innovation cooperation network

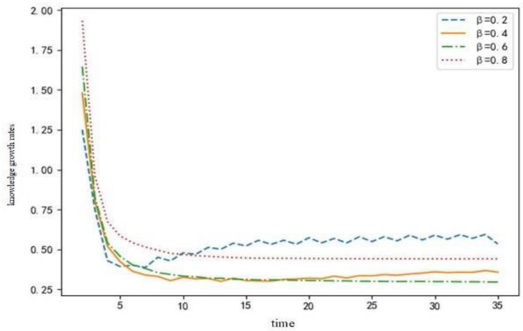
Knowledge creation capability is a fundamental capability of an enterprise and a critical component for an enterprise to achieve continuous innovation. This section employs a complex network simulation to explore the impact of enterprise knowledge creation capability on knowledge changes in the platform ecosystem. Because the network evolution in the platform ecosystem indicates that the network is ''small-world,'' the network structure is set as a small-world network model, and the network connection coefficient $p$ is set at 0.1. We measure the changes in the average knowledge level and knowledge growth rate of the innovation cooperation network by changing the data of enterprise knowledge creation capability $\beta$ (when $\beta$ is 0.2, 0.4, 0.6, and 0.8). Figure 5 depicts simulation results.

Figure 5 shows that when $T$ is less than 20, the network's average knowledge level dose not differ significantly, indicating a slow growth trend, whereas when $T$ is greater than 20, the change in knowledge level is quite different. When the creation capability is equal to 0.2 or 0.8, the average knowledge level continues to rise rapidly. Second, in terms of knowledge growth rate, the network knowledge growth rate corresponding to various creation capabilities is rapidly declining and tends to be stable over time. However, when creative capability is equal to 0.2 or 0.8, the knowledge growth rate remains higher.

It can be seen that the stronger or lower the enterprise's knowledge creation capability, the higher the average knowledge level and the rate of knowledge growth in the platform ecosystem. This is because participants have two main coping strategies for dealing with the platform ecosystem's competition and cooperation relationships: system strategy and component strategy [48]. The system strategy means that the enterprise's knowledge creation capability is relatively strong, and it can enter multiple component markets while minimizing cooperation. The component strategy implies that the enterprise's knowledge creation capability is relatively low, and it prefers to enter the single component market while maximizing cooperation. Enterprises that use the system strategy can increase their knowledge level and growth rate by creating more knowledge, that is, becoming more ''competition oriented.'' Enterprises that use the component strategy can improve their knowledge level and growth rate by leveraging external knowledge spillover, that is, ''cooperation oriented.''




**a. Comparison of the average knowledge level under different knowledge creation capabilities**

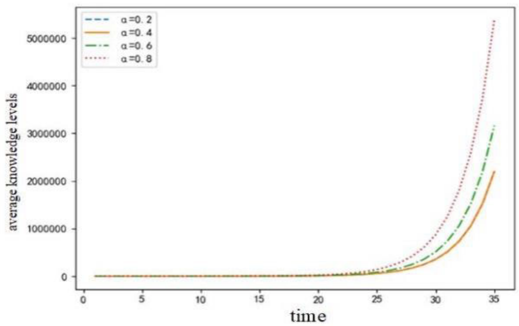



**b. Comparison of knowledge growth rates under different knowledge creation capabilities**

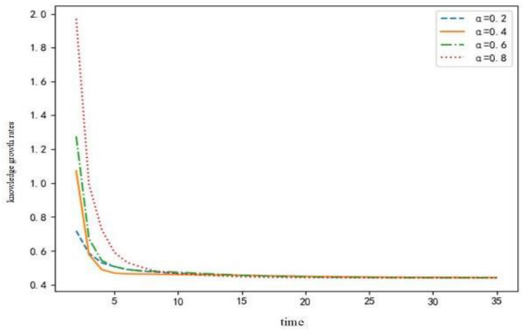
**FIGURE 5. Comparison of average knowledge level and knowledge growth rate under different knowledge creation capabilities.**

(3) The impact of knowledge absorption capability on knowledge change in innovation cooperation networks

Enterprises in the platform ecosystem must create new knowledge continuously and absorb new knowledge from external entities through innovative collaboration. What effect does a firm's absorption capability have on changes in network knowledge? This was the section's focus. We used a small-world network model for the network structure and set the network connection coefficient ($p$) to 0.1. We measured changes in the platform ecosystem's average knowledge level and knowledge growth rate by changing the value of enterprise absorptive capability $\alpha$ (when $\alpha$ is 0.2, 0.4, 0.6, and 0.8). Figure 6 shows the simulation results.

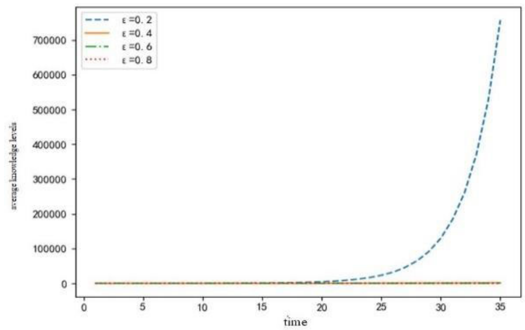



**a. Comparison of average knowledge level under different knowledge absorption capabilities**

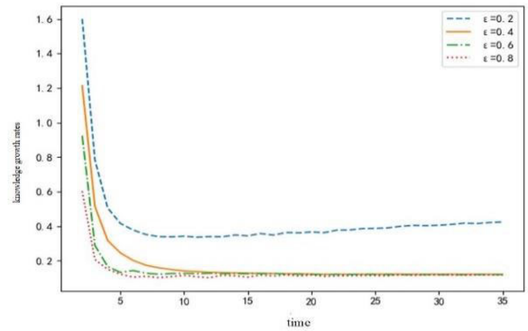



**b. Comparison of knowledge growth rates under different knowledge absorption capabilities**

**FIGURE 6. Comparison of average knowledge level and knowledge growth rate under different knowledge absorption capabilities.**




**a. Comparison of average knowledge levels under different competitive pressures**




**b. Comparison of knowledge growth rates under different competitive pressures**

**FIGURE 7. Comparison of average knowledge level and knowledge growth rate under different competitive pressures.**

As shown in Figure 6, when $T$ exceeds 23, the greater the absorption capability ($\alpha$) of the firm, the higher the average knowledge level; when $T$ is less than 10, the greater the firm's absorption capability ($\alpha$) and the higher the growth rate.

It can be seen that, within a certain range, the higher the absorption capability, the more helpful it increases average knowledge level and growth rate. This is because the greater the enterprise's ability to absorb knowledge, the more likely it is to realize the transformation from external to internal knowledge to enterprise innovation, which can maximize value creation through collaboration. Cooperative enterprises can gradually build trust, encourage information exchange, and eventually achieve joint problem-solving [27]. Innovation is a high-knowledge process [49]. To achieve innovation, ecological participants must acquire of tacit knowledge from platform owners or other participants, such as development knowledge. This tacit knowledge is frequently embedded in employees' skills, abilities, and perceptions, making cross-border communication difficult [50], [51]. However, through cooperative relationships, enterprises can transfer tacit knowledge in the joint problem-solving process, thereby stimulating learning and innovation [27], [52]. Therefore, if an enterprise has a strong knowledge absorption capability, it can better promote the exchange of tacit knowledge, thereby realizing the transition from external knowledge to internal innovation. As a result of knowledge creation, the ecological average knowledge level and growth rate improve.

(4) The impact of the competitive environment on knowledge change in innovation cooperation network

Platform ecosystems, such as the trading platform represented by Amazon and the innovation platform represented by Apple's APP store, have more pronounced participant competition. In this section, we examine at how a competitive environment affects knowledge changes in the platform ecosystem. We keep the network connection coefficient $p$ at 0.1 and leave the other parameters alone. That is, the enterprise absorption capability coefficient $\alpha$ is 0.8, the knowledge creation capability coefficient $\beta$ is 0.4, and knowledge loss coefficient $\theta$ is 0.9. We measured changes in the network's average knowledge level and knowledge growth rate by changing the competitive pressure data $\varepsilon$ (when $\varepsilon$ is 0.2, 0.4, 0.6, and 0.8). The simulation results are shown in Figure 7.

Figure 7 shows that when $T$ exceeds 20, the lower the competitive pressure ($\varepsilon$) in the platform ecosystem, the higher the average knowledge level, and the lower the competitive pressure ($\varepsilon$) throughout the interval, the higher the maximum value of the knowledge growth rate.

It can be seen that less competitive pressure promotes knowledge creation and flow. This is because a competitive environment influences enterprises' willingness to share knowledge [53]. When competition increases, firms are more likely to use intellectual property to protect their proprietary knowledge [54]. Conversely, firms are more likely to form cooperative relationships to facilitate knowledge exchanges when competition is reduced [55]. In other words, a competitive environment influences firm knowledge-sharing decision. When cooperation rules the network environment, knowledge subjects are eager to share their knowledge to further shared goals; however, when competition is fierce, opportunism rules, and knowledge subjects are frequently unwilling to share their knowledge to further their own interests [56]. In contrast, to gain a competitive advantage, enterprises require multiparty knowledge for innovation in a highly competitive environment [27]. Reduced willingness to share knowledge raises the risk of failure in innovation, creating a vicious circle of double decline in knowledge creation and flow. As a result, when there is a high level of competition pressure in the platform ecosystem, enterprises are hesitant to share knowledge and reduce the likelihood of knowledge creation, resulting in a decrease in the level of knowledge and the rate of growth. Platform leaders can significantly improve knowledge flow in an ecosystem by fostering a good environment for platform cooperation and reducing competitive pressure.

### C. CASE ANALYSIS

The relevant cases also support the above simulation results. To break through the game mode of physical CD sales, Valve officially launched Steam in September 2003 as an online channel to release games and push updates [57]. Steam initially operated independently until the first release of games developed by third-party manufacturers in 2005 [58], which marked the beginning of the Steam platform ecosystem's establishment. The Steam platform has gradually improved tagging, search, scoring mechanisms, online forums, community groups, cloud services, and so on, to improve user experience with third-party games [58]. The Steam platform has 120 million monthly active users by 2020, making it the world's largest game platform ecosystem with the fastest knowledge creation and flow.

During this process, the Steam platform first innovated the game distribution mechanism, promoted the release of new games, and realized knowledge growth. In 2012, the platform launched the "Green Light" program [59]. This mechanism allows game developers to publish game information to the "Green Light" interface, where popular games are reviewed for release. According to Steam DB data, following the implementation of this plan, the number of games released annually on the platform increased from 301 in 2012 to 4,683 in 2016, a 1,455.81% increase, which is a great success. To further shorten the release cycle, the platform introduced the "Steam Direct" mechanism in 2017 to replace the "Green Light," and the game was reviewed directly by the platform [59]. Following the implementation of this mechanism, the number of games released on the platform each year has increased from 6,966 in 2017 to 11,660 in 2021, encouraging the release of third-party games. However, the growth rate has slowed significantly to 67.38%, indicating that the Steam platform ecosystem is gradually maturing. Second, on the Steam platform, there are two types of ecological participants: game developers and game publishers. Enterprises can use the component strategy only as game developers to develop new game concepts and then find publishers for distribution [60]. These game developers frequently lack financial, sales, and marketing skills. However, by working together with publishers, these obstacles can be successfully overcome. If a company is large enough, it can use a system strategy to develop and publish games on its own [60]. These two modes coexist in the Steam platform ecosystem and promote knowledge creation and flow. Third, to boost user activity and gather feedback, the Steam platform has added a game discussion section to the player community module and granted the manufacturer community management rights [57]. If a game manufacturer has a high capacity for knowledge absorption, it is more likely to obtain useful information from user feedback and browsing behavior, promoting product improvement and game innovation, and thus raising the overall knowledge level. Fourth, the Steam platform combats piracy and reduces the competitive pressure caused by stolen games. Game developers face a higher risk of piracy and infringement due to the ease with which digital products can be copied and the lax enforcement of relevant laws, which increases competition and reduces the possibility of knowledge-sharing. In response to this situation, Steam offers digital rights management technology support to game developers [58]. Game developers use this technology to encrypt product packages before uploading and selling them, reducing the possibility of piracy and preserving platform knowledge.

In summary, as the platform ecosystem grows and matures, the knowledge level will improve significantly, but the rate of knowledge growth will gradually low and stabilize. In terms of knowledge creation capability, if an enterprise has a high level of knowledge creation capability, it can pursue a competitive system strategy. If its capacity for knowledge creation is limited, it can pursue a component strategy based on cooperation. Both strategies encourage the creation and flow of knowledge. In terms of knowledge absorption capability, the knowledge absorption capability of enterprises is relatively strong, which is conducive to transforming external knowledge to internal innovation, thereby improving ecological knowledge. In terms of a competitive environment, if an enterprise perceives little competitive pressure, it will be more willing to share knowledge and consider collaboration, which will promote an increase in the level and rate of growth of ecological knowledge.

## V. CONCLUSION AND DISCUSSION

### A. CONCLUSION

Using computer simulations, this study focuses on the evolution and knowledge changes of innovation cooperation networks in the platform ecosystem from a complex network perspective.

The following are the key findings regarding the evolution of innovation cooperation networks. First, the platform ecosystem's innovation cooperation network is evolving around initial network enterprises, such as platform leaders and key component providers. This finding shows the distinctiveness of the evolution of innovation cooperation networks in platform ecosystems. For example, industry–university–government networks can evolve in several ways, including enterprise-led, university-led, and government-led [61], [62]. Platform leaders and key component providers play an important role in knowledge creation and flow within the platform ecosystem [5], [56]. Second, prior to platform standard unification, the degree of network cooperation decreased, but it increased after standard unification. Because platform modularity is required, the development of an innovation cooperation network is based on a set of agreed-upon principles and standards [38]. Unlike supply chain networks [20], industrial cluster networks [63], alliance networks [64], and so on, which show a gradual upward trend as member interaction deepens, the platform ecosystem is dominated by competition before standards are formed, and by cooperation after standards are formed. Third, as platform leaders become more difficult to coordinate, network cooperation becomes less efficient. Coordination becomes more difficult as the number of participants increases, as it does in most enterprise networks [65]. The difference is that in the platform ecosystem, the platform leader is primarily responsible for coordinating participants who are not subject to hierarchical control or contract control, which complicates coordination and exacerbates the reduction in cooperation efficiency [39].

The key findings regarding knowledge change in innovation cooperation networks are as follows. First, the network structure has little effect on knowledge changes, showing an increasing trend of average knowledge levels and declining knowledge growth rates. As innovation collaborators increased in number, so did knowledge creators. The cooperative relationship fosters trust and information exchange [20], [56], which promotes knowledge-sharing and diffusion, and thus raises the overall knowledge level. The knowledge potential gap between collaborators narrows as the innovation network matures [66], causing the rate of knowledge growth to slow and eventually stabilize. Second, disparities in enterprise knowledge creation capability have resulted in two modes of knowledge change: "competition-oriented" and "cooperation-oriented." When an enterprise's knowledge creation capability is strong, it can enter multiple component markets and frequently employs a system strategy to achieve "competition-oriented" growth. By contrast, when the enterprise's knowledge creation capability is weak, it tends to concentrate on entering one component market, frequently employing a component strategy to achieve "cooperation-oriented" growth, and the rest of the required knowledge is frequently acquired through external cooperation [48]. Third, the greater an enterprise's capacity for knowledge absorption, the easier it is to realize the transition from external knowledge to internal innovation, thereby promoting network knowledge growth. Participants' innovation in the platform ecosystem is frequently inextricably linked to the platform owner's or other participants' tacit knowledge support [50]. The cooperative relationship established between enterprises enables joint problem-solving, facilitating the exchange of tacit knowledge [27]. Enterprises with strong absorptive capacities learn and absorb tacit knowledge more quickly, thereby accelerating the transformation of knowledge into innovation. Fourth, the less competitive pressure enterprises perceive, the more willing they are to share knowledge, thus promoting network knowledge flow. The competitive and cooperative environment of the network influences enterprises' willingness to share knowledge, and knowledge-sharing occurs more frequently when firms cooperate rather than compete [56]. In a highly competitive environment, a decreased willingness to share knowledge increases the likelihood of innovation failure [27], resulting in a double decline in knowledge creation and flow, which affects the platform ecosystem's knowledge level.

In its entirety, this study uses computer simulation to examine the evolution and knowledge changes of innovation cooperation networks in platform ecosystems based on enterprise entities. (1) The following are the main conclusions about how the innovation cooperation network evolves in the platform ecosystem. (1a) Different from networks like alliances, supply chains, and industry-university-government networks, innovation cooperation networks in platform ecosystems are primarily evolving around initial network enterprises like platform owners and key component providers. (2a) During the evolution process, the degree of cooperation shows a trend of first decreasing and then rising, while the cooperation efficiency shows a downward trend. (2) The following are the main conclusions about how knowledge changes in the platform ecosystem innovation cooperation network. (2a) The average knowledge level in the platform ecosystem innovation cooperation network is increasing, while the rate of knowledge growth is decreasing. (2b) The impact of network structure on knowledge change is unclear, whereas the enterprise's knowledge creation capability, knowledge absorption capability, and competitive pressure all have a significant impact on knowledge change. The findings presented above provide new ideas and inspirations for investigating the emerging phenomenon of platform ecosystems from the perspective of complex network theory.

### B. LIMITATIONS AND FUTURE RESEARCH

This study has the following limitations, which should be considered in future research. First, there are various types of platform ecosystems, such as commercial and industrial platforms. They are distinct in terms of structure, attributes, and operations. Future research should consider how differences in these platforms impact knowledge changes. Second, while enterprises are the primary source of knowledge creation and flow in the platform ecosystem, many potential users may also impact knowledge changes, which should be considered in future research. Third, the study's conclusions are primarily based on simulations and case analyses. Future research could use empirical methods to validate the findings and improve the model's generality and universality.

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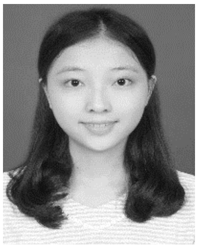

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