Expert Systems With Applications 98 (2018) 242–256

Contents lists available at ScienceDirect

Expert Systems With Applications

journal homepage: www.elsevier.com/locate/eswa

Research on the characteristics of evolution in knowledge flow networks of strategic alliance under different resource allocation

Zhao Jianyu[a,*], Li Baizhou[a,*], Xi Xi[c], Wu Guangdong[d], Wang Tienan[b]

[a] School of Economics and Management, Harbin Engineering University, Harbin 150001, PR China
[b] School of Management, Harbin Institute Technology, Harbin 150001, PR China
[c] Management School, Harbin University of Commerce, Harbin 150028, PR China
[d] School of Tourism and Urban Management, Jiangxi University of Finance and Economics, Nanchang 330013, PR China

ARTICLE INFO

Article history:
Received 2 July 2017
Revised 5 November 2017
Accepted 6 November 2017
Available online 6 November 2017

Keywords:
Strategic alliance
Knowledge flow
Networks
Evolution
Resource allocation
Characteristics

ABSTRACT

This paper takes the four types of resource allocation (randomly oriented, relationship-oriented, cooperation oriented, and knowledge-embedded) as its premise and investigates the complex characteristics of knowledge flow network evolution in strategic alliances, taking into account the mutual variance effects of the evolution mechanism. Existing research has neglected the differences in resource allocation types, by and large employed statistical analysis methods, and identified only the linear relationships among experimental variances of cross-sectional data. The present study differs from existing research in the following ways: First, we thoroughly consider the multi-faceted nature of resource allocation. Second, we use the method of multi-agent imitation according to perspective of dynamic system evolution and the principle of phase theory, allowing the explicitly analysis of nonlinear functional logic, forms and patterns in the variance. Finally, we analyze the appropriateness of different resource allocation models. Our paper features several significant findings: (1) The evolution of the knowledge flow network of a strategic alliance can produce a bifurcation phenomenon composed of saddle-node bifurcation and transcritical bifurcation. (2) The number of nodes exhibits a logarithmic growth distribution, the connection intensity and the network gain exhibit exponential growth distributions, and the connectivity and knowledge flow frequency are mutually influential in the form of a power function. (3) Knowledge-embedded resource allocation is most effective for improving the knowledge flow rate of networks and can further supply ample impetus for evolution. (4) Cooperation-oriented resource allocation is most beneficial for quickly propelling the network into the evolution realm. (5) Relationship-oriented resource allocation can aid the network in capturing more profit. Furthermore, this research is beneficial for understanding the key problems of each resource allocation model and the evolution of strategic alliance in knowledge flow networks. Our proposed methods and framework can be more widely applied to the fields of complex networks, knowledge management, and strategic innovation.

1. Introduction

In the age of the knowledge economy, the strategic alliance has been adopted by enterprises as a new business model for understanding and dealing with murky and uncertain environments. The biggest advantage of the strategic alliance is the ability it gives alliance organizations to supplement their own capabilities and shortcomings and achieve strategic goals of mutual benefit through the multi-faceted knowledge flow networks formed by knowledge transmission and interaction (Schildt, Keil, & Maula, 2012; Zhao, Xi, & Su, 2015; Panico, 2017). In addition, considering that the differential resource allocation could influence the formation and effectiveness of knowledge flow networks, the problem of the evolution of knowledge flow networks in strategic alliances opens up the black box of the complex nature of network evolution. Therefore, research on different resource allocation models is extremely valuable for clarifying the emerging mechanism of network evolution as well as for propelling the stabilization, diversification, and continued development of the strategic alliance.

In conjunction with earlier research based on knowledge management theory (Hansen, Nohria, & Tierney, 1999; Gupta & Govindarajan, 2000; Phene & Tallman, 2014; Caner & Tyler,2015; Guan & Liu,2016; Zhang, Li, & Li, 2017; Geels,2017), recent studies have been influenced by the idea of “relationship-structure” in complex network theory. Scholars have mainly focused on the influence of network structure characteristics on the effectiveness of knowledge flow and that of network relationship characteristics

* Corresponding authors.
E-mail addresses: jianyu64@sina.com (Z. Jianyu), Libaizhou@126.com (L. Baizhou), cc_58@163.com (X. Xi), gd1984@163.com (W. Guangdong), WTN@hit.edu.cn (W. Tienan).

https://doi.org/10.1016/j.eswa.2017.11.012

on knowledge understanding and ties degree. Although the studies have differed in their approaches, their conclusions all showed the complexity manifested in the changes of knowledge flow networks and the uncertainty of network social relationship changes poses monumental challenges for researchers and practitioners of the strategic alliance. In fact, a number of theoretical perspectives related to the role of knowledge flow in complex networks have contributed to our understanding of strategic alliances. These theories include complexity systems, network embeddedness, resource-based views, knowledge management, strategy management, social capital, and technology innovation. However, most of the literature using these theories has been limited on three important fronts: content, method, and context.

First, in terms of research content, Sorenson, Rivkin, and Fleming (2006) noted that "while much of the knowledge networks and knowledge flow in strategic alliance research has dealt with the barriers to successful knowledge transfer and has investigated structural questions, little of the research has delved into the characteristics of networks evolution based on knowledge flow in strategic alliance." Likewise, Meier (2011) recognized that much research attention has been directed to trends in knowledge ambiguity in the strategic alliance, alliance formation, determinants of networks, the alliance network effect, and resource utilization in alliances, rather than questions related to evolution characteristics. Even, studies that focused on knowledge networks in the strategic alliance and network evolution fell short of linking emerging characteristics and evolution mechanisms. Instead, these studies turned to the role of network-specific variables such as average path length (Grigoriou & Rothaermel,2017; Paruchuri & Awate,2017; Wang et al.,2017), topological structure (Tan, Zhang, & Wang, 2015; Basole,2016), degree distribution (Graham, 2017; Baum, Calabrese, & Silverman, 2000), or organization heterogeneity (Moeen & Agarwal,2017; Lavie, Haunschild, & Khanna, 2012). However, scholars whose research focused on knowledge networks in the strategic alliance, all found that the characteristics of knowledge flow network evolution-such as bifurcation, mutation, node tie mechanism, and relationship between alliance organizations-clearly influenced the direction and effect of knowledge flow networks. And the important problem of explaining the characteristics of knowledge flow network evolution has received scant systematic attention. Beyond the analysis of the dual effect of knowledge flow, few studies have used appropriate methods to link the attribute variables (control variables) with the effect variable (state variables) to explain the characteristics of evolution.

Second, in terms of research method, much of the scholarship has focused on the theoretical aspects of conceptual research. From a holistic perspective on the network, few studies have employed computational simulation methods. Although ample research has been conducted on the knowledge management and knowledge network problem of strategic alliances, there still exists substantial research potential in quantitative fields of research. Similarly, the prevalent and foundational theory used to analyze the knowledge management problems of the strategic alliance seems to also have certain problems, as scholars have begun to realize that the most valuable and meaningful variance is often difficult to explain persuasively through theoretical analysis. Although prior researches proposed and demonstrated the hypothetical and empirical functions of such methods in the knowledge network and knowledge transfer problems of the strategic alliance, there are still shortcomings in these methods. First, the knowledge flow networks of the strategic alliance exhibit high degrees of information asymmetry, which causes many data capture and calculation deficiencies (or a lack of reliability and data loss) for researchers who employ structural equations and regression methods. Second, the knowledge flow networks of the strategic alliance are complex systems that exist within time and space-evolution occurs in continuous time and is a process that is clearly dynamic and uncertain. The existing studies that conducting statistical research through questionnaires or cross-sectional data were all conducted with the implied condition of being divorced from time, leading to a lack of precision in the analysis of the emergence traits of network evolution and a lack of reliability in their conclusions. Third, although empirical research methods with statistical analysis can indeed prove the logic behind the effects of independent and dependent variables, they cannot prove the characteristics, forms, or laws of the effects among variables, rendering practitioners unable to develop targeted and effective management policies. This study departs from theoretical speculation and empirically based on research that relies on cross-sectional samples or investigations based on a structural equation or regression approach. We use a multi-agent imitation method to investigate the evolution characteristics and principles of the knowledge flow networks of strategic alliances. The benefit of utilizing this method is that we can use a rigorous and intelligent programming language to define the rules of network evolution, to make continuous time a basic condition of a network's evolution, and to prominently feature the interdependent effects of variables.

Third, in terms of research context, among scholarship that pertains to the theoretical research of alliance networks and knowledge flow based on the resource-based view and the knowledge-based view, scholars have recognized the limited nature of resources, but they unfortunately have not considered the existing differences in the limited resource allocation and utilization methods of alliance organizations caused by differences in strategic targets and development directions (Klingebiel & Rammer,2014;Kogan, Papanikolaou, Seru, & Stoffman, 2017). This leads to the problem that scholars take one single resource allocation model only as their research context. Not only do they fail to notice the formation mechanism and influence model of multiple resource allocations, but fail to provide analysis of the effect of multiple resource allocations models on network evolution. As a result, the focus of the existing research has been entirely concentrated on the rate of alliance resource utilization, the integration of knowledge resources, and the influence of network structure on the transfer of knowledge resources, failing to investigate the potential guiding role exerted by resource allocation models on the network evolution of strategic alliances in knowledge flow. Therefore, this paper partitions the various resource allocation models that may be selected by strategic alliances according to the dual impact of knowledge flow, analyzes the knowledge flow evolution traits of strategic alliances based on these resource allocation models, and discusses the unique functions of each resource allocation model in network evolution.

To address the limitations of previous research and further our understanding of the characteristics of knowledge flow network evolution in strategic alliances under different resource allocation conditions, this paper will explain the content and function of different resource allocation models, analyze the key variables of knowledge flow networks in strategic alliances (node density, average network node degree, spatial distance, and connectivity), and, by utilizing the multi-agent imitative method, conduct analysis of the evolution traits of knowledge flow networks of the strategic alliance based on different resource allocations. This research elucidates the nature and laws of knowledge flow network evolution in strategic alliances under different resource allocation premises with limited resources as a condition and establishes a new research framework for related future research. This framework can shed light on three problems. First, different resource allocation models have different functions and levels of usability for the knowledge flow network evolution of strategic alliances. Second, under different resource parameters, the mutual effects of control factors and variable factors create special patterns for the evolution of networks. Third, in the discussion section, we examine the complex particularities (tie mechanism, bifurcation, growth of network revenue, knowledge flow frequency) of the emergence of knowledge flow network evolution in strategic alliances as well as their causes. This framework can be utilized in research on many knowledge flow networks. As such, the method proposed in this paper expands the knowledge range of knowledge management and complex networks and provides a basis for policy selections for strategic alliances.

2. Theoretical foundation

2.1. Different resource allocation

The theory of the resource-based view holds that the strategic alliance is a product of pursuing reciprocal benefits and symbiotic goals in the context of incomplete agreements. If the alliance attempts to supplement its own deficiencies by means of the knowledge flow cooperation relationship to target the uncertainties and instabilities of the external environment (Blake & Moschieri,2017; Pontikes & Barnett,2017), then the heterogeneity and transfer intensity of knowledge resources in networks will be important for the coexistence and cooperation among alliance organizations (Rodan & Galunic, 2004; Wassmer, Li, & Madhok, 2017). However, under the limited nature of alliance organization resources (Trigeorgis & Reuer, 2017; Xia, 2011) and the simultaneous influences of organizational differences and coexistence relationships (Panico, 2017; Lavie et al., 2012), different models and types of alliance organizations must evaluate the allocation of limited resources when participating in technological collaboration activities and social capital investments (Zhao et al., 2015; Agarwal, Anand, Bercoviz, & Croson, 2012; Hansen et al., 1999). If alliance organizations paid more attention to the establishment and maintenance of social relationships in networks and attempted to increase network profit based on stable and good social relationships, then the emphasis of their resource allocation would veer toward social capital investment (Koka & Prescott, 2002; Hansen et al., 1999). If alliances paid more attention to R&D activities that targeted innovating new knowledge and attempted to improve their competitive advantage through technological innovation, then they would be more likely to invest limited resources in knowledge flow activities concerned with technological innovation (Vanhaverbeke, Belderbos, Duysters, & Beerkens, 2015; Meier, 2011; Lahiri & Narayanan, 2013). Thus, we hold that the evolution of knowledge flow networks in strategic alliances can explain the different resource allocation models of different alliance organizations as well as the dynamic process of the alliances' holistic technological progress and social cooperation development within the selection of technological innovation and social capital investment. To specify evolutionary characteristics of knowledge flow network in strategic alliance under different resource allocations, as well as specific functions of different resource allocations, we divide the resource allocation into four types as following according to previous researches and knowledge-based view (KBV) from Zhao et al. (2015), and tie-principle of each resource allocation modes is designed.

(1) Randomly oriented resource allocation: The alliance organizations that use this model believe that the two resource allocation strategies-technological innovation collaboration and social capital investment-have no direct relationship with or influence on each other. We call tie mechanism of alliance organizations that adopt this resource allocation modes as random ties. Theoretically, this resource allocation is appropriate for firms that future developing direction are temporarily uncertain, such as new venture as well as small and micro businesses. This kind of resource allocation represents alliance organizations without a clear development direction. This type of alliance allocates its resources without bias, and the connectivity of knowledge flow has no specific target. Based on the principle of proximity (Capaldo & Petruzzelli, 2014; Baum, Cowan, & Jonard, 2010), we assume that this type of organization builds knowledge flow ties with the alliance organization that is the closest spatially and has an expected revenue ratio higher than the -loss ratio. Using the topological distance method to construct a neighborhood set (Cowan, Jonard, & Özman, 2004; Morone, 2004), we then take alliance organizations with topological distances to a random ties alliance organization x_i smaller than the average path length of the network as the realm ofx_i. Therefore, alliance organization and others establish a knowledge flow ties that can be expressed with the equation

$$ties = \begin{cases} 1, \left\{ x_i, x_j \in V \middle| d_{ij} < d \right\} \\ 0, others \end{cases} \tag{1}$$

(2) Relationship-oriented resource allocation: The alliance organizations that use this model believe that participating in technological innovation collaboration based on knowledge flow will not influence the accumulation of social capital; that is, the two strategies are mutually independent, and the alliance organizations will devote more effort to maintaining and improving social relations. This resource allocation mode is more suitable for firms that have already occupied certain share in the market and try to consolidate their position and establish more stable supply chain by good social relations. Based on the characteristics of this type of resource allocation mode, we define the tie-principle as ties that favors social capital investment. This category represents alliance organizations whose primary target of resource allocation is investing in social capital. According to the principle of "perimeters" in the connectivity principles of social networks (Uzzi, 1999; Shirver, Nair, & Hofstetter, 2013; Aral & Walker, 2014), we utilize the method of node degree to measure the structural capital of alliance organizations. Following the rule, within knowledge flow networks, a higher degree node of the alliance organization would lead to the establishment of a stronger or weaker link, and the greater importance of the social status in the strategic alliance. Correspondingly, other alliance organizations will tend to establish knowledge flow relationships based on social capital accumulation with organizations of greater node degrees within a given topological distance. We represent this ties relationship with Eq. (2), which is the function used to calculate the node degree of the network:

$$ties = \begin{cases} 1, Max f(q) \\ 0, others \end{cases} \tag{2}$$

(3) Cooperation-oriented resource allocation: Unlike the alliances that use relationship-oriented resource allocation, the alliance organizations that use this model believe that the accumulation of social capital will not impact technological innovation and collaboration; such alliance organizations are more willing to utilize a multitude of methods to participate in the cooperation activities of technological innovation based on knowledge flow. This type of resource allocation can be common with knowledge-intensive firms or high-tech firms which focus on R&D or takes technological innovation as the core competitive advantage. We define tie-principle in this type of resource allocation mode as ties that favors technology. This category represents alliance organizations that take investing in technology innovation and collaboration as their main objective in resource allocation. Ac-

cording to the spread and overflow principles of innovation networks (Singh, 2005; Phene & Tallman, 2014), we measure the innovation investment of revenue toward alliance organizations and establish that within knowledge flow networks. A higher revenue of an alliance organization would bring it higher capacity for technology innovation, and more prominent technological innovation advantages in strategic alliances. Correspondingly, other alliance organizations will tend toward build knowledge flow relationships with the strongest-capacity organizations within its topological distance. This tie is represented by Eq. (3) to calculate the revenue of the nodes, where $S(q)$ represents the capacity function of the alliance organization:

$$ties = \begin{cases} 1, MaxS(q) \\ 0, others \end{cases} \quad (3)$$

(4) Knowledge-embedded resource allocation: This model of resource allocation manifests the dual function characteristic of knowledge flow. The alliance organizations that use this model believe that participating in technological innovation and collaboration and investing in social capital have a mutually beneficial relationship. Firms that adopt knowledge-embeddedness resource allocation mode are relatively mature transnational corporation, business group or alliance firms in new technology industry which own typical technical advantages and are in need of expanding market. For the characteristics of this type of resource allocation mode, we define the tie-principle as combination ties. It represents alliance organizations that believe in the mutually encouraging positive effects of technological innovation investment and social capital investment. We combine ties favoring social capital and that favoring technological innovation to describe a knowledge flow network ties based on knowledge-embedded resource allocation. We set the probability of using social capital merit as P_{TR} and the probability of using technological innovation as P_{TS}, where $P_{TR}+P_{TS}=1$. At the same time, in order to clarify it for alliance organizations choosing combination ties, the existence of both social capital and technological innovation merit is key, and we stipulate the distribution interval between the two probabilities to be [0.45, 0.55].

2.2. Variables of knowledge flow networks

According to Gulati (1999), the strategic behaviors of alliance organizations are impacted by network attribute variables and the strategic behaviors form the fundamental characteristics of the network, such as network node density (Baum et al., 2000), spatial distance (Schilling & Phelps, 2007), boundary density (Gilsing & Nooteboom, 2005; Dyer & Nobeoka, 2000), and connectivity (Uzzi & Spiro, 2005). In terms of the knowledge flow networks of strategic alliances, the network's attribute variables determine the index of network structure and profit and can influence the synergy effectiveness among alliance organizations (Gulati, 1998; Gupta & Govindarajan, 2000).

The node density is determined by the quantity of network nodes and the connection preference of the nodes. It is an important criterion for evaluating the connection mechanisms of the knowledge flow networks of strategic alliances and for judging the effectiveness of knowledge capture and interaction (Uzzi, 2002). On the one hand, a dense network connection mechanism is ideal for the foundation of effective communication and knowledge flow within strategic alliances. By establishing knowledge flow connectivity with resource-rich partners, alliance organizations increase the exchange speed of knowledge resources and more efficiently realize the mutually beneficial cooperation purpose (Reagans & McEvily, 2003). On the other hand, the different strategic objectives of alliance organizations lead them to adopt different resource allocation models (Hitt, Dacin, Levitas, Arregle, & Borza, 2000). Different resource allocation models determine the different connection preferences of alliance organizations and influence the target and efficiency of knowledge exchange in a network (Zhao et al., 2015). The number of nodes corresponding to each type of resource allocation model represents the dynamic change process of the network connection mechanism under the function of that allocation model. We use the function $N(t)=sum(q)$ to describe node density, where t is time and $sum(q)$ represents the summation function of the connection node.

Boundary density, also known as average network node degree, is an important metric influencing network innovation spillover. Social network theory holds that the average network node degree influences the emergence of new technologies by changing the degree of network agglomeration and social relation connection (Cowan, Jonard, & Zimmermann, 2007). With respect to the knowledge flow networks of strategic alliances, a higher average node degree encourages the emergence and spread of new knowledge. With increasing network complexity, the average network node degree also increases, network centrality gradually becomes more latent, and the social statuses of alliance organizations become more differentiated (Ibarra, 1993; Batjargal, 2010). Alliance organizations with relatively higher social status possess more knowledge flow partners and can capture richer knowledge resources (Hallen, Katila, & Rosenberger, 2014); they also possess the informal power to direct network evolution direction, whereby they can create valuable new knowledge and drive the spread and spillover of new knowledge in networks. We use a function of time to describe the average node degree of the knowledge flow network of a strategic alliance. Since the smallest complete graph of a network requires at least two alliance organizations, we express the average network node degree with $D(t) = 2 \times \frac{sum(e)}{sum(q)}$, where $sum(e)$ represents the summation function of the network connection boundary numbers.

Spatial distance represents the relationship strength of alliance organizations participating in knowledge flow and is an important indicator in analyzing network revenue. According to Granovetter (1992), the different network connection models can change the strength of the relationships among main bodies and influence the network revenue. By strengthening knowledge exchange among alliance organizations, strong ties increases the rate of network knowledge innovation and knowledge spillover, which not only changes the relationship strength among alliance organizations, but also impacts the development of exploratory innovation activities (McFadyen, Semadeni & Cannella, 2009; Battilana and Casciaro, 2013). Weak ties, which depend on more connections, improve the social relationships of alliance organizations by increasing factors such as trust and reliability, expand the search and flow range of knowledge, shorten the spatial distance between organizations (Gilsing & Nooteboom, 2005; Levin & Cross, 2004), and influence the development of liberated innovation activities among organizations. As a result, despite their differences, both connection types can allow the main bodies of networks to supplement their knowledge differential, shorten spatial distance, create spillover of more valuable knowledge, and improve the positive impact of network revenue (Singh, 2005; Tortoriello, Reagans, & McEvily, 2012). To express the strength of network relationships, we use a function of time, $r(t) = \frac{sum(r_{ij}(t))}{sum(e)}$, where $r_{ij}(t)$ represents the spatial distance between alliance organization i and alliance organization j at time t, and $sum(r_{ij}(t))$ represents the summation function of the relationship strength.

Connectivity represents the number of effective connections in the network and is used to describe and analyze network structure and the rate of knowledge flow. Complex network theory maintains that when the network structure is superior, the connectivity of nodes can not only change the topological distance of networks, but also exert influence over the degree of centrality among collaboration partners, the frequency of knowledge exchange, and network innovation revenue (Schilling & Phelps, 2007). The more effective the connections are in a network, the more likely they are to form a dense connection cluster from which the network can change the range of its connection structure, contact, organization, and use of embedded knowledge, as well as the innovation potential of network knowledge (Uzzi & Spiro, 2005; Vandaie & Zaheer, 2015). We express network connectivity using a function of time, $n(t) = sum(n) = r(t) \times \frac{sum(e)}{N(t)}$, where $sum(n)$ is the summation function of effective connection. The rate of knowledge flow is determined by network connectivity. Based on Leenders, van Engelen, and Kratzer (2003) analysis of interaction concentration, we express the function of knowledge flow rate as $f(t) = \frac{\varepsilon}{n(t)}$, where ε is a constant.

Network revenue is a key index for determining whether strategic alliance knowledge flow networks can indeed innovate in new knowledge and bring the new knowledge to market, as well as how much technological innovation revenue (economic benefits) and social capital benefit (social benefit) they can obtain (Wassmer & Dussauge, 2011; Gulati, 1998; Stuart, 2000). In order to reduce the impact exerted by extreme exponential growth of network revenue on our research results, we have consulted and integrated measures of network revenue indices (patents, volume of new products, profit margin, etc.) and adopted a logarithmic analysis of the average increase of all node revenues in strategic alliance knowledge flow networks. We use a function of time t to represent network revenue: $b(t) = \log[\sum_{i\in N} (\frac{b_i(t)}{\sum_{i\in N} b_i(t)}) \times b_i(t)]$, where $b_i(t)$ represents the revenue obtained by alliance organizations in the knowledge network at time t.

3. Simulation design

According to the evolution principle of complex systems (Holland, 1995), when the environment changes, the subject will automatically adjust its own status according to the "stimulation" provided by the change in the environment by means of a targeted "response" behavior to adapt to the new environment. From the perspective of knowledge management, the knowledge flow network evolution of strategic alliances that use knowledge complementarity and qualitative improvement as targets fulfills the evolution principle of complex systems (Akbar, 2003; Sherif & Xing, 2006): On the one hand, the knowledge flow network of a strategic alliances comprises multiple alliance organizations with different resource allocation preferences, and every alliance organization represents different development demands and knowledge flow nodes, where the properties of the nodes thoroughly exhibit a multi-agent structure and diverse characteristics (Cummings & Teng, 2003). On the other hand, alliance organizations can be induced to exhibit the corresponding response (knowledge flow) behaviors according to changes in the environment and thereby drive the evolution of networks in order to adapt to the new environment. This type of social, self-adaptive, and self-evolved toward new stasis organization tendency adheres to the model and characteristics of multi-agent complex system evolution technology (Axelord, 1997). Therefore, we take the attribute structures of the multi-agent, consider the different resource allocation preferences of alliance organizations, and, according to the knowledge flow connection mechanisms among alliance organizations, establish an evolution model of the knowledge flow of strategic alliances and use simulation technology to conduct analysis on the complex traits of the evolution.

We use the software platform Netlogo to analyze the evolution traits of knowledge flow in strategic alliances based on different resource allocation models. First, we use the interface design function of Netlogo, following the basic attribute distribution of the independent agent in the agent simulation design principle, and set up the simulation interface for the evolution of knowledge flow in strategic alliances. Then, we use the procedure interface program's development function based on a macro model of the research on agent simulation framework design to conduct the simulation (macro system model sees Fig. 1).

According to the topological structure of the knowledge flow network of a strategic alliance, we partition the simulation subject into four alliance organizations (nodes) of resource allocation preferences and knowledge flow connections (sides) among organizations. As such, in accordance with the "stimulus–response" principle of the multi-agent simulation model, the agent type should include a randomly oriented resource allocation agent, a relationship-oriented resource allocation agent, a cooperation-oriented resource allocation agent, and a knowledge-embedded resource allocation agent, with the knowledge flow connections among the agents forming the sides of the network. Additionally, any complex system will have as its premise changes in the environment, whereby within the knowledge flow networks of strategic alliances, all basic attributes of agents, connection statuses among organizations, and connection relationships stem from the influence of environmental changes (Maes, 1994). Therefore, we use an environmental agent to control for the impact of environmental changes on network evolution, representing that as evolution takes hold, agents with different resource allocation preferences will establish knowledge flow relationships with other organizations in accordance with the environmental change.

After establishing the agents, we design the multi-agent simulation model's variables and variation relationships. Among these, resource allocation is the controller of the knowledge flow network evolution of strategic alliances, performing the function of inducing multi-agent connections in the form of random connections, social capital-preferring connections, technological innovation-preferring connections, and combination connections. The environmental agent acts as the controller of the knowledge flow network evolution of strategic alliances, performing the core function of controlling for the distribution of multi-agent attributes as well knowledge flow network connection design and adjustment. Network revenue b represents the comprehensive capability level of an alliance organization after establishing knowledge flow connections based on its own resource allocation preference at time t. The average network node degree (D, $D > 0$) represents the density of the knowledge flow network's "sides." The expected revenue ratio (PE, $PE \in [0, 1]$) represents the alliance organization's increase capability ratio. At the same time, taking into consideration the impact of opportunistic behavior on alliance network revenue and evolution (Das & Teng, 2001; Gulati, Nohria, & Zaheer, 2000; Inkpen & Beamish, 1997), we stipulate the net income loss ratio based on opportunism and self-interested maximization (PL, $PL \in [0, 1]$) to represent the decrease capacity ratio of the alliance organization. The topological distance (L, $L > 0$) of network nodes represents the spatial length of the knowledge flow connections established by alliance organizations. The resource capital (C, $C > 0$) represents the cost paid by alliance organizations to establish and maintain knowledge flow connections. The critical threshold (T, $T > 0$) represents the critical value of the capacity of the strategic alliance to induce qualitative network changes (technological emergence) under specific knowledge flow conditions. Furthermore, for alliance organizations that have already established connections, we calculate the expected income ratio and resource capital for these organizations' next interaction and, depending on the size of the resource capital, whether the organization will maintain or break off

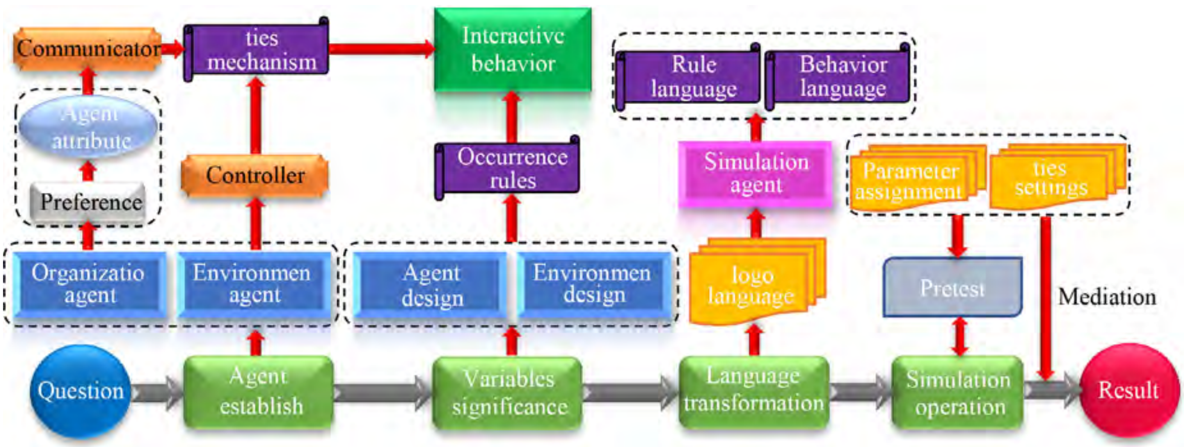

Fig. 1. Simulation macro system model.

Table 1
Simulation parameter design.

Parameter name	Stipulated value
Network node number	$N = 100$
Initial distribution of the node knowledge capacity	$E \in [0, 2]$
Average network node degree	$D = 8$
Expected revenue ratio	$PE = 0.5$
Revenue loss ratio	$PL = 0.3$
Topological distance	$L = 0.35$
Resource capital	$C = 8.5$
Threshold value	$T = 6.4$
Frequency constant	$\varepsilon = 1$

the connection. Empirically, we designed the simulation so that at every step, every agent can break at most one connection to ensure the orderly evolution of the network and prevent the abrupt decline of the network.

In order to transform the above-delineated multi-agent attributes and simulation design into a computational simulation model, we used logo language to program network connections based on each type of resource allocation preference and the multi-agent attribute simulation program, and thus completed the model initiation. Simultaneously, according to the initial design of the simulation, we conducted the simulation pre-test. A total of 40 trials were carried out, fulfilling the multi-agent simulation testing requirement proposed by Gilbert, Ahrweiler, and Pyka (2007). We then selected all the trial simulation results that had reached a stable simulation step ($SS = 275$) to be the formal simulation step and thereupon conducted the formal experiment.

According to the authoritative research which utilized Netlogo simulation with multi-agent design methods and the results of simulation pre-test, we established the network parameter for formal experiment as shown in Table 1. Specifically, network node number adopts the stable network node number setting proposed in the research of Phelps, Heidl, and Wadhwa (2012); initial distribution of the node knowledge capacity utilizes setting from Cowan et al. (2007) and Gilbert et al. (2007), ensuring that evolution of network will go on wheels and the phenomenon that energy is enable to spill over will not occur. To ensure that nodes in network are compatible and able to be connected in unit distance, average network node degree adopts the design standard from Park, Lee, Park, and Lee (2000), using stable value in network after pre-test's setting. Expected revenue ratio and revenue loss ratio of network are set according to revenue principle from Lopolito, Morone, and Taylor (2013) and Garcia, Rummel, and Hauser (2007), ensuring that every node in the network can be disconnected and reconnected if needed. Topological distance refers to Morone (2004)'s basic topological distance standard setting. Resource capital refers to Seo and Chae (2016)'s research, adopting average resource cost when all networks reach stable condition in the pre-test. Threshold value takes Gilbert et al. (2007)'s advice, using the value where network reaches one stable cycle of unit interval in the pre-test. At last, frequency constant refers to Grigoriou and Rothaermel (2017) and Paruchuri (2010)'s research, adopting the minimum frequency constant.

Furthermore, after completing the design of tie-principle, parameters as well as simulation parameters of the four resource allocation models, we describe the mechanism model of research shown in Fig. 2.

4. Result discussion and implications

In this article, we expect to use multi-agent method to analyze adaptivity of different resource allocation modes. Therefore, other than satisfying general complex network characteristics, knowledge flow network in strategic alliance need to meet the following hypotheses' condition:

H1: knowledge flow network in strategic alliance can always exchange material, information and energy, in other words, is an open complex system, allowing new nodes to enter as well as existing nodes to quit.

H2: under different resource allocation modes, the evolution of knowledge flow network in strategic alliance is non-reversible, so that network's evolution follows the general principle of complexity science. In one evolution cycle, network can fulfill the whole evolutionary process by evolving from low order to high. Meanwhile, evolution in knowledge flow network is dynamic and time-sensitive, unable to bring instant recession to the network evolution.

H3: under different resource allocation modes, nodes in knowledge flow network in strategic alliance are able to be disconnected and reconnected, namely when satisfying tie-standard of nodes, reconnection choice will be made in nodes according to the network space environment.

H4: under different resource allocation modes, state variable of evolution of knowledge flow network in strategic alliance is non-unique. Critical value of network instability corresponds to the threshold of evolution. Evolutionary characteristics of network is jointly decided by control variable and state variable.

Based on the hypotheses, we complete the formal simulation experiment. Fig. 3 depicts the structural graph of the knowledge flow network evolution of strategic alliances under the guidance

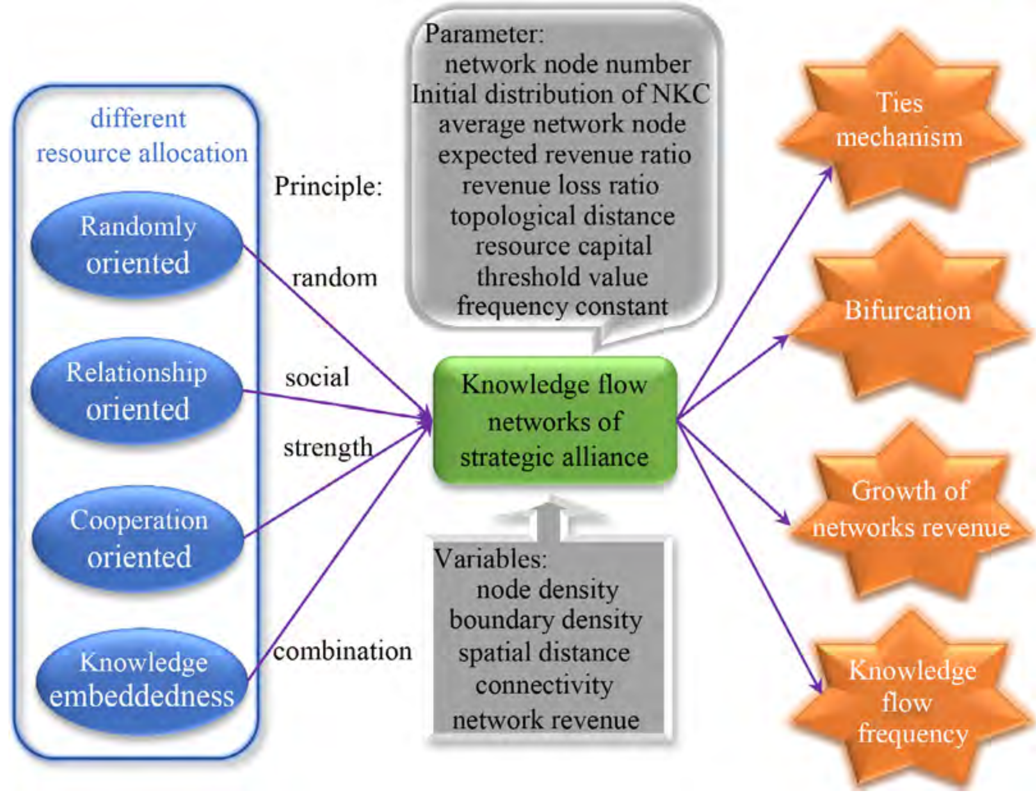

Fig. 2. Mechanism model of research.

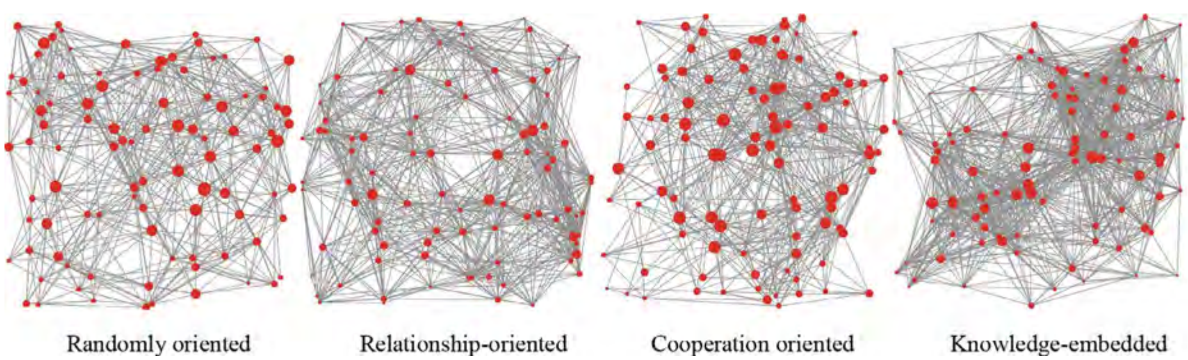

Fig. 3. Structural simulation of the knowledge flow networks of strategic alliances under different resource allocation models.

of different resource allocation models, where the complete graph of each network is composed of at least two alliance organizations. According to Fig. 3, as evolution progresses, the complexity of the network increases. In the case of relationship-oriented and knowledge-embedded influences, the knowledge flow network connections exhibited greater boundary density, demonstrating more vibrant knowledge flow among alliance organizations. Under cooperation-oriented resource allocation and knowledge-embedded resource allocation, network realms had more dense connections, demonstrating that under these two models of resource allocation, the push-and-pull effect among alliance organizations allows the network to more easily generate an agglomeration effect.

As a typical complex system, the evolution of complex networks possesses the characteristic of system state transition with the passage of time (Easley & Kleiberg, 2010; Albert & Barabási, 2002). As North and Macal (2007) pointed out, when analyzing the issue of the evolution of commercial complex systems, one should take the subject preference in dynamic time as a fundamental research premise and, by analyzing the interaction among important system variables, identify and summarize the evolution traits and laws. In order to reveal the mutual interaction and influence patterns of the state variables and control variables of knowledge flow networks in the context of resource allocation, further identify the contributions of different resource allocation models to network evolution, and confirm the emergence traits of knowledge flow networks under the mutual interaction of variables within a certain temporal range, we use the design stipulations of Butts (2001) and Barabási and Albert (1999), setting the observed time change as a state variable and the adjustable (simulated parameter change) network attribute variable as the control variable.

At the same time, on the basis of the Netlogo simulation experiment results (Figs. 4–7), we adopt a phase theory of complex network evolution to explain the form of interaction among variables as well as the emergence and evolution characteristics, and proceed to draw some valuable conclusions.

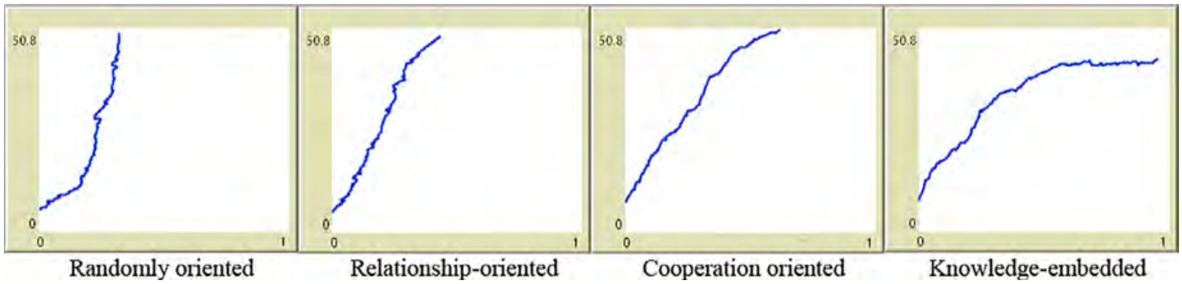

Fig. 4. Node connectivity mechanism simulation graphs of the knowledge flow networks of strategic alliances under different resource allocation models.

4.1. Ties mechanism

Fig. 4 displays the resource allocation model as the control variable (x axis), the network node connection mechanism as the state variable (y axis), and the nodes distribution in network of strategic alliance knowledge flow has differences in the states and trends. The randomly oriented resource allocation model exhibited the trend of relatively slower growth in the early stage, but rapid growth in the late stage. We believe the main reason for this is that because alliance organizations in this model have no apparent preference for resource allocation, within a short period, only a small number of alliance organizations establish knowledge flow connections. Once the main paradigm of the evolution is established, however, the alliance organizations take the initiative to rapidly and abundantly establish many node connections according to their knowledge flow needs and the guidance of the core organizations to establish and solidify their existing competitive advantage, leading to the rapid growth of node connections.

The node connection growth trends of relationship-oriented resource allocation and cooperation oriented resource allocation were similar, which demonstrates that for resource allocation models with an allocation preference, the number of node connections in the knowledge flow network of a strategic alliance is maintained and increased mainly by investment. However, under the influence of the resource investment preference, the connection tendency of alliance organizations (focused on social capital accumulation or technological cooperation innovation) becomes more prominent, causing the overall attributes of the network to increase along with node connection and evolve toward a particular direction until it evolves into a pure social network or technological network. Under relationship-oriented resource allocation, the knowledge flow network connection speed is faster, indicating that an increasing number of alliance organizations emphasize maintaining good social relationships with their cooperation partners and proactively establish multi-boundary knowledge flow connections with other organizations based on the principle of "innovation strength from social capital."

Under knowledge-embedded resource allocation, the network node connection first exhibits rapid growth, and in later periods exhibits relatively steady growth until it reaches saturation. This indicates that in the context of both technological innovation and social capital investment, on average, the alliance organization will increase the number of node connections in a knowledge flow network. After the connections are stabilized, consistent value tendency and mature organization learning mechanisms will form within the knowledge flow network, and alliance organizations will tend toward maintaining the present connection status of social capital accumulation and technological innovation cooperation and therefore form a threshold effect within a certain realm.

Furthermore, Fig. 4 shows that although knowledge flow networks form different node connection evolution trends under the four different resource allocation models, overall, they all exhibit near-logarithmic growth. According to the evolution phase theory, we describe the logarithmic relationship between the probability (p) of a node connection in the knowledge flow network of a strategic alliance and the dynamic coefficient (K) propelling knowledge flow network evolution as $K = \log_a p + K_0$, whereK_0represents the initial value of the evolution of the knowledge flow network and a is the growth coefficient. The smaller the growth coefficient, the steeper the slope of knowledge flow network node connection formation, which is not beneficial for knowledge flow network evolution. We can see from Fig. 4 that using randomly oriented resource allocation results in the steepest slope of node connection distribution. Correspondingly, using knowledge-embedded resource allocation results in the flattest slope and the highest probability of a positive trend in node connection and network evolution incentive. This phenomenon indicates that when node connection quantities increase in strategic alliances and connection development is uneven, alliance organizations should take advantage of the mutual influence between promoting technological innovation and promoting social capital in order to improve the internal power of network evolution. According to the above analysis, we identify the following finding:

Finding 1: The number of node connections in the knowledge flow network of a strategic alliances exhibits approximately logarithmic growth. Knowledge-embedded resource allocation can provide the ample internal power for the knowledge flow network evolution of strategic alliances.

4.2. Bifurcation

Fig. 5 shows that although alliance organizations have different preferences regarding resource allocation, with the average network node degree as the control variance (x axis) and the network revenue as the state variance (y axis), the simulation curve of the interaction between the two shows a clear inflection point; this means that alliance organizations with the objective of increasing network revenue will find a critical bifurcation in the evolution of their knowledge flow network. According to the bifurcation principle of complex network analysis (Mitchell, 2011; Tang, Lu, Lü, & Yu, 2012), network bifurcation can be divided into saddle-node bifurcation and transcritical bifurcation. When saddle-node bifurcation occurs, it means that there is a negative correlation between increasing average node degree and network revenue; when transcricritical bifurcation occurs, it means that there is a positive relationship between increasing average node degree and network revenue. This shows that the average node degree has two different effects on network revenue.

In the knowledge flow network of a strategic alliance using randomly oriented resource allocation, the average node degree is largest when the system evolution threshold is achieved, and its saddle-node bifurcation affects quite a large area. This indicates that when the average network node degree is smaller than the evolution threshold, the alliance organizations establish more connections within the network-and the fewer effective connections

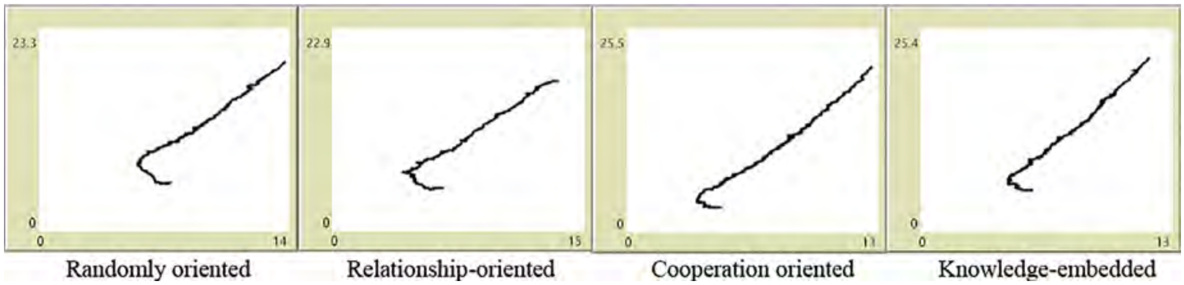

Fig. 5. Bifurcation simulation graphs of the knowledge flow networks of strategic alliances under different resource allocation models.

are made, the higher the likelihood of the adverse situation of network revenue decline.

In the knowledge flow network of a strategic alliance using relationship-oriented resource allocation, the area of saddle-node bifurcation is similar to that under randomly oriented allocation, but its average node degree is smaller. A possible reason for this is that when there is a preference for social capital accumulation, the early-stage evolution of alliance organizations will focus more effort on the maintenance of social relations, resulting in a higher boundary density within networks, but without prominent increase in innovation. Therefore, once stable social relationships are formed, the alliance organizations that maintain good social relationships will have more opportunities to interact with and capture implicit knowledge within networks, which can help shorten the period of breakthrough-style innovation, attract new organizations to enter the network, and rapidly create a positive relationship between average network node degree and network revenue.

Compared to the other three models of resource allocation, in knowledge flow networks that use cooperation-oriented resource allocation, the saddle-node bifurcation area is smaller, and transcritical bifurcation can occur when the average node degree and network revenue are relatively low. This indicates that with technological innovation cooperation as the preferred mechanism, alliance organizations can target the development of technological cooperation, and within the knowledge flow network, the mutual transfer and integration of heterogeneous knowledge can drive the emergence of innovation. In the stage of research and development and accumulation, network revenue may be slightly reduced due to the influence of knowledge viscosity, the time lag of knowledge creation, and the low effect of knowledge spread. However, as network evolution deepens, the knowledge viscosity will decrease, and more knowledge flow will occur among alliance organizations. After new knowledge and technology have been created, knowledge of higher complexity degree, higher value, and greater diversity will serve as a form of positive innovation feedback and help knowledge flow networks with a target of technological cooperation innovation to rapidly capture more revenue.

In knowledge flow networks that use knowledge-embedded resource allocation, the saddle-node bifurcation area is relatively small, but once the evolution threshold occurs, the average node degree and network revenue are higher than those in the cooperation-oriented model. We believe this is because in a context with no resource investment preference, the alliance organizations need a certain amount of time to simultaneously carry out mutual technological knowledge matching and social capital matching, causing the average node degree to influence network revenue within a short time span. When the alliance organizations form a sufficient number of boundaries, the network can then establish a coordinated effect of technological cooperation and social capital accumulation, from which it can realize the promotion of network revenue through the number of connection boundaries, leading the evolution into transcritical bifurcation. Furthermore, this coordination effect can help the knowledge flow network of a strategic alliance in the late stage of its evolution to maintain a higher degree of stability.

In addition, we analyzed the bifurcation laws of network evolution according to Lyapunov stability theory. We describe the saddle-node bifurcation formed by the average network node degree and network revenue in an idealized manner as $\overset{n}{B} = (B - B_m)^2 - Q_m$, where $\overset{n}{B}$ represents the network bifurcation effect, B represents network revenue, B_m represents the real number on the y-axis of the saddle-node bifurcation curve, and Q_m is the real number on the x-axis of the saddle-node bifurcation curve. Theoretically, as the knowledge flow network of strategic alliances continues to evolve, it will obtain two stationary and stable points: $B_1 = B_0 - \sqrt{Q_t}$ and $B_2 = B_0 + \sqrt{Q_t}$. In the case of transcritical bifurcation, the dynamic equation of the evolution is $\overset{n}{B} = (Q_n{+}2B_n)B - B^2 - (Q_n + B_n)B_n$, where B_n is the point at which the stable point B_2 meets a real number on the y-axis and Q_n is the corresponding x-axis real number of the transcritical bifurcation curve. At this point, two fixed points exist in the system $B_1 = B_n$, $B_3 = Q_n + B_n$: If $Q_n + 2B_n > 0$, then B_1 is not fixed, and B_3 is fixed; if $Q_n + 2B_n < 0$, then B_1 is fixed, but B_3 is not fixed. However, since $Q_n + 2B_n > 0$ and B_2 is the fixed point, we know that the evolution's transcritical bifurcation will certainly occur with stability. Based on the results of our derivation, we believe that because B_1 is not fixed, the lower the effect of network evolution on the threshold value, the higher the instability degree of the network, thereby increasing the probability of a positive effect on increasing the network's average node degree. According to Fig. 5, the threshold value of knowledge flow networks based on cooperation-oriented resource allocation is the lowest. Therefore, we arrive at the following finding:

Finding 2: The evolution of the knowledge flow networks of strategic alliances exists within the bifurcation phenomenon composed of saddle-node bifurcation and transcritical bifurcation. Cooperation-oriented resource allocation is more advantageous for pushing the knowledge flow network into the evolution realm.

4.3. Growth of networks revenue

Fig. 6 indicates that under the effects of the four different resource allocation models, where the relationship strength of alliance organizations is the control variable (x-axis) and the network revenue of the knowledge flow network is the change variable (y-axis), the simulation curve exhibits a trend of near-logarithmic growth. The revenue growth of knowledge flow networks under randomly oriented resource allocation is the slowest, and their revenue is the lowest, indicating that under the condition of lacking a resource allocation preference, alliance organizations remain in a contact stage of mutual interaction and trial for an extended period of time, making it difficult to select suitable partners to establish knowledge flow connections-and the greater

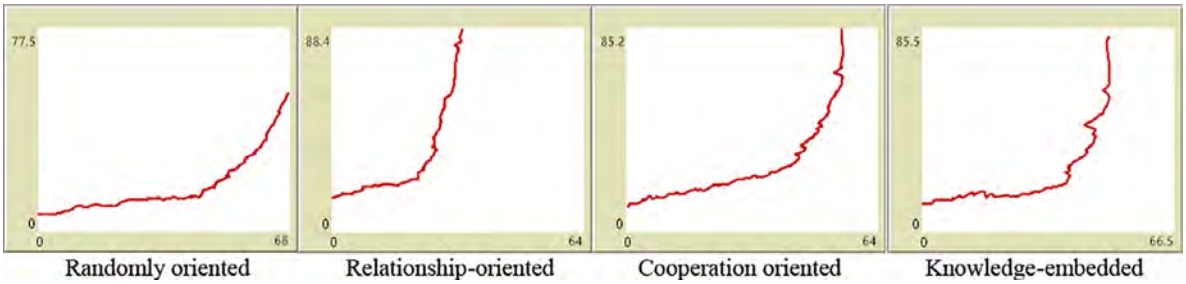

Fig. 6. Connection strength and network revenue simulation graphs of the knowledge flow networks of strategic alliances under different resource allocation models.

the spatial distance of networks, the lower the rate of agglomeration. As mutual interactions deepen, the core organizations of network evolution are established, and the knowledge flow path and direction among alliance organizations gradually become clearer; through this process, the network revenue will also gradually rise.

Under relationship-oriented resource allocation, the relationship strength and the simulation curve of network revenue rapidly increase in a short period of time. This indicates that when social capital accumulation is the resource allocation preference, the knowledge flow networks of alliance organizations can rapidly establish high relationship strength, making trust and reliability among alliance organizations relatively high, and thus encouraging the flow, spread, and spillover of abundant implicit knowledge formed within the knowledge network.

Compared to the simulation curve of relationship-oriented resource allocation, under the effect of the technological innovation and cooperation-oriented resource allocation model, the knowledge flow network revenue rapidly increases in the later stages of evolution. We believe the reason for this is that the early-stage knowledge flow connections are primarily built through formal and informal contracts with the objective of cooperation innovation. At this time, due to the viscosity and protectionism of knowledge, it is very difficult for alliance organizations to sufficiently trust one another and establish a mutual benefit-sharing atmosphere, such that although knowledge flow networks can capture revenue, its value is relatively low. As technological cooperation progresses, alliance organizations become more familiar with one another and develop mutual respect and recognition based on technological strength, and they will therefore more proactively contribute their own heterogeneous knowledge, causing the network revenue to rapidly increase in later stages.

Because knowledge-embedded resource allocation takes into account both technological innovation cooperation and social capital accumulation, the selection of knowledge flow partners for alliance organizations is more targeted, and in the early stage, the network connections help alliance organizations recognize and understand the necessity of knowledge flow collaboration, thus effectively decreasing the occurrence of opportunism and increasing the transparency of the alliance. Once the alliance organizations are fully aware of the mutual recognition of knowledge flow, the strategic alliance will internally establish a variety of formal and informal knowledge flow connections, and the strength of the relationships as well as the function of knowledge flow will improve significantly, causing network revenue to display a trend of rapid increase over a short period.

At the same time, the simulation curve indicates that although knowledge-embedded resource allocation can simultaneously promote the progress of technological innovation cooperation and social relationships, knowledge networks that put into practice this resource allocation model can face a time lag in network revenue; therefore, alliance organizations must speedily recognize and make use of the double function of knowledge flow in the early period of establishing connections.

Furthermore, although increasing the knowledge flow network connection strength of strategic alliances can increase network revenue, the magnitude of exponential network increase differs under different resource allocation models. We describe the idealized evolution relationship of exponential increase between relationship strength (r) and network revenue (b) as $b = b_0 \times e^{s \times r}$, where b_0 represents the initial value of knowledge network revenue and s is the simulation increase magnitude. The higher the increase magnitude, the more apparent the effect of relationship strength on increasing network revenue, and the higher the concavity of the curve of simulated phase evolution.

According to Fig. 6, the concavity between relationship strength and network revenue is the greatest under the effect of relationship-oriented resource allocation, indicating that relationship strength has the most significant effect on promoting network revenue. Correspondingly, under the effect of randomly oriented resource allocation, the concavity of network revenue and relationship strength is not marked, indicating that the mutually stimulating sensitivity is low and that relationship strength has a relatively low impact on increasing network revenue. Based on the above analysis, we arrive at the following finding:

Finding 3: The relationship strength of the knowledge flow network of a strategic alliance has a near-exponential influence on network revenue. Relationship-oriented resource allocation promotes an amplified effect of relationship strength, causing the knowledge flow networks of strategic alliances to capture more revenue.

4.4. Knowledge flow frequency

Knowledge flow frequency refers to the number of times knowledge flow occurs within a strategic alliance, and has important value for assessing the innovation capacity and knowledge spread of an alliance. The simulation curve of Fig. 7 shows that under the four different resource allocation models, where the connectivity of knowledge flow networks is the control variable (x-axis) and the network knowledge flow frequency is the change variable (y-axis), there exists a sharp negative correlation between the two variables.

Under randomly oriented resource allocation, the knowledge flow frequency fell to its lowest level as connectivity increased. This indicates that although knowledge flow networks can increase connectivity by establishing many knowledge flow connections, because the alliance lacks a unified strategic vision, the knowledge flow networks experience cyclical interruptions; the number of redundant connections increase, and alliances cannot establish channels that allow for effective knowledge flow, spread, and spillover, causing the frequency of knowledge flow to drop to a very low level.

Under relationship-oriented resource allocation, the knowledge flow frequency and connectivity simulation curve shows that with social capital accumulation as the preferred mechanism, in order for alliance organizations to shorten their mutual social distance in the early stages of evolution, interaction centralization and rel-

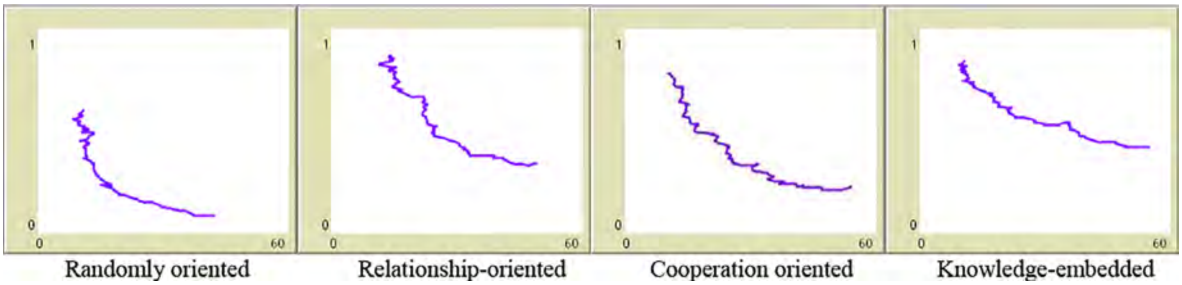

Fig. 7. Connectivity and knowledge flow frequency simulation graphs of the knowledge flow networks of strategic alliances under different resource allocation models.

atively high frequency of knowledge flow occur. When alliance organizations within a network form social relationship of mutual trust and mutual reliance, the increase in network connectivity will increase the already stable topological structure of social connection and gradually slow down the frequency of knowledge spread. At the same time, because the alliance organizations prefer social capital investment, they will tend to spend more time, effort, and resources in dealing with relationships, potentially causing the knowledge flow rate to begin decreasing when the network connectivity is relatively high (after the stabilization of social relationships) because the alliance organizations lack knowledge flow tools based on a unified technology paradigm.

Under cooperation-oriented resource allocation, increased network connectivity causes a sharp decrease in knowledge flow frequency. We believe that as the evolution of such a knowledge flow network progresses, the technological cooperation relationships among alliance organizations based on innovation as the preferred mechanism have already stabilized, and the core organizations that occupy the “structural gap” begin to holistically direct the model of knowledge flow. In this situation, the innovation outlooks of alliance organizations tend to converge, and their technological flow models and knowledge levels become more similar. Alliance organizations believe that it will be very difficult for them to make use of the heterogeneous knowledge of breakthrough innovation obtained through knowledge flow to influence new product development and the quality of technological innovation, causing the significant decrease in knowledge flow frequency.

Compared to the simulation curves of the three other resource allocation preferences, under knowledge-embedded resource allocation, knowledge flow frequency gradually decreases with increasing network connectivity. This indicates that under the condition of simultaneous allocation resources for technological innovation cooperation and social capital investment, alliance organizations can make use of the dual function of knowledge flow and promote the depth of technological innovation development while shortening the social distance among organizations, thereby realizing a win–win scenario of technological innovation cooperation and improved social relationships, within which they can effectively avoid the rapid decrease of knowledge flow frequency caused by paradigms lacking in knowledge flow technology and knowledge homogeneity.

Furthermore, although the knowledge flow frequency of a strategic alliance exhibits a near-power function relationship with average network connectivity (as long as connections exist, the network will necessarily develop connectivity, indicating that $x > 0$) under each of the four models of resource allocation, there exist some differences in the degree of influence. We use phase theory to describe the idealized relationship between knowledge flow network connectivity (n) and knowledge flow frequency (f) as $f = e^b/(n - n_0)$, where n_0 is the initial value of knowledge flow network connectivity and b is the reduction coefficient of the simulation curve. The smaller the reduction coefficient, the greater the concavity of the simulation curve (phase track), causing decreased knowledge flow frequency under the same conditions of knowledge flow connectivity.

According to Fig. 7, for knowledge flow networks under knowledge-embedded resource allocation, the simulation curve (phase track) of increasing network connectivity and increasing knowledge flow frequency has the smallest concavity, indicating that connectivity has only a minor influence on knowledge flow frequency. Correspondingly, under cooperation-oriented resource allocation, the increasing connectivity of knowledge flow networks and the knowledge flow frequency form the phase track with the greatest concavity, indicating that for strategic alliance knowledge flow networks that prioritize technological innovation cooperation, increased connectivity leads to an increase in higher-homogeneity organizations in the network, causing the convergence of innovation outlooks among alliance members and potentially impacting the innovation capacity of the alliance organization. Based on the above analysis, we arrive at the following finding:

Finding 4: The connectivity of the knowledge flow network of a strategic alliance exhibits a near-power function relationship with knowledge flow frequency. Knowledge-embedded resource allocation is more beneficial for improving the knowledge flow frequency of the knowledge flow network of a strategic alliance.

4.5. Implications

4.5.1. Theoretical implications

The purpose of our study is to theoretically, methodologically and practically improve our identification and understanding of evolution characteristics of knowledge flow network in strategic alliance guided by different resource allocation models. It may be of great potential value for us to understand the applicability of different resource allocation models and the evolution characteristics emerging in the knowledge flow network in strategic alliance with the method of supplementing theory, advancing method and discussing results,

Theoretically, compared with existing researches, the added value of this paper is all-round. First, the detailed literature review shows that in the field of resource-based view, knowledge management, complex network theory as well as strategic management, there is few literature that takes into consideration the different resource allocations adopted by alliance firms. Almost all of the current literature pays attention to the influence of certain resource allocation on evolution of complex network. However, this paper has made some supplement. Based on resource-based view and strategic management theory, we have put forward that resource allocation models may be adopted by firms in strategic alliance with different development goals and wishes. Also, we have discussed the influence of these resource allocation models on knowledge flow network in strategic alliance, emphasizing the importance to study the resource allocation models as a unit instead of studying one of them. Second, evolution principles of knowledge flow network in strategic alliance have been provided in some of the previous researches, but in the premise of different resource allocation models, there are limitations to identifying and understanding rules emerging in the evolution. Different from the existing researches, this paper, based on the knowledge flow interaction mechanism of “technological power” and “social reputation”, considers and discusses the characteristics of knowledge flow network in strategic alliance in complex network environment full of uncertainty in the premise of interaction between state variable and control variable in the strategic alliance knowledge flow network, advancing our understanding in the academic black-box, namely the evolution principle of knowledge flow network in strategic alliance. Third, this research helps us further understand the applicability of different resource allocation models on the evolution of knowledge flow network in strategic alliance. In the existing researches, it has been defaulted that the choice and role of resource allocation model may be fixed in the evolution of alliance network. However, a new attempt has been made in this paper. We have considered the condition where the multiple resource allocation models oriented by strategies. In this paper, not only is the influence of each resource allocation on network evolution verified, but also some interesting and novel conclusions are founded, especially the complex evolution characteristics of knowledge flow network in strategic alliance, which has not been studied in the previous research.

Methodologically, defects of studying method in existing researches are overcame. Statistical research has been used in existing researches which are related to our research subject, which fails to show the evolution rules in an intuitive and explicit way, so we have made supplement in it. Also, in this paper, we have adjusted the existing measures and made new simulation variables and experiments based on previous findings, which are conducive to reveal the interaction between state variable and control variable in the process of network evolution. What’s more, in this paper, problems such as the subjectivity of data in empirical study have been eliminated, which enables us to reveal, in a more objective way, the evolution characteristics of knowledge flow network in strategic alliance under the guidance of different resource allocation models.

4.5.2. Practical implications

Also, there are some conclusions which are of importance for managers and practitioners in strategic alliance, combining the “theoretical simulation” with “practice implications” more or less. And we will illustrate it from three aspects with practices of firms.

First of all, the practically managerial meaning in this paper is that strategic alliance firms should maintain sufficient knowledge values, which asks the alliance firms to promote their core competence advantages through continuous activities such as knowledge creation. It has been found in our research that the change of resource allocation models is subject to the strategic preference of firms and environment. Analyzing from the perspective of practice, start-up firms or small and medium firms are confused by the choices, for the external environment is ambiguous and uncertain, and they are unable to make a right judgement on their development directions according to their own practices and experiences. In addition, lacking of technological accumulation and social capital makes them unable to establish knowledge flow joint with other advanced firms. On this condition, random resource allocation model may help these firms in the initial stage, and they will have a clearer understanding to the environment and their own willing. Compared with start-up firms or small and medium firms, those, equipped with certain basis, who need to make a decision on investment direction would have more choices. For firms preferring to technology innovation, such as technological knowledge-intensive firms and high-tech firms, they attempt to share the limited knowledge resources with others by technological cooperation, thus tending to cooperation-oriented resource allocation model aiming at technological cooperation. In accordance with the simulation results, our suggestion for these firms is that in the management and practice, they ought to choose firms who enjoy the same innovation level with them or that who are able to establish formal contract with them, which is not only conducive for them to maximize the performance of cooperation oriented resource allocation model, but enables them to share the resources and prevent from opportunistic behaviors. For alliance firms preferring to maintaining stable social relations, such as social service firms in the structural hole or vertical supply chain firms, they expect to improve and enhance their social relations and status through social capital investment, and they hold that their technological advantages could be promoted in the relation accumulation. Thus, relationship-oriented resource allocation model is more suitable for their development. For this kind of firms, the suggestion is that they ought to make full use of the characteristic of relationship embeddedness and embed the relationship resource into alliance further so as to promote the trust between them and others. It is because that in this way, the relationship between alliance firms could be improved, which is positive to promote network profit and avoid innovation risks. Finally, for firms like mature international firms, knowledge-embedded resource allocation model is more conducive for them to exert their advantages. It is known to us that many of international firms would both invest in technology R&D and establish healthy coexistence relationship with local firms. And our suggestion for these firms is that their resource investment should be based on alliance culture, which is because that if we want to make the knowledge flow play its mutual role, the cultural paradox between alliance firms should be lower, which is the key to improve knowledge flow frequency and provide sufficient endogenous power for the network.

Secondly, the practically managerial conclusion is that for the alliance firms, they’d better ensure that the strategy has certain flexibility when making resource allocation model strategy. It is because that in accordance with strategic management theory and knowledge-economy theory, the alliance firms could adjust resource allocation model in line with their development condition and the macro environment if the resource allocation model is flexible. Meanwhile, a flexible model enables alliance firms face less innovation risks, also, the negative effect of uncertain and ambiguous environment on knowledge flow network evolution will be decreased significantly. In addition, we hold that when developing, the alliance firms should control the knowledge flow joint in a reasonable range. According to our simulation results, though the knowledge flow joint could increase the alliance’s income, the number of efficient joint and frequency of knowledge flow are decreased with the increase of the number of joints, indicating that excessive knowledge flow joint will result in network redundance, which would not only affect network innovation income, but also bring negative influence such as the fault caused by innovation results spillover. Meanwhile, our suggestion is that the managers of alliance firms should adopt knowledge incentive in the internal to promote knowledge resource upgradation, for a higher heterogeneous knowledge is not only conducive to the development of the alliance firms, but is the foundation to facilitate alliance innovation.

Finally, the practically managerial implication of this article is that, based on the experience and previous research, inspiring the alliance firms to design and adjust resource allocation models may be good for improving the coexistence structure of alliance partners and facilitating the alliance’s development. Especially, in the current environment, strategic alliance would not be formed by one type of firms, so characteristics and development status of each type pf firm would influence alliance innovation. Hence, it is of great importance for them to have a resource allocation model suitable for their own development and to foster ability to adjust resource allocation according to the environment. In line with our simulation results, we hold that if the alliance firms are able to establish a relationship sharing both benefit and risks, it would be of great help for the evolution of the knowledge flow network. What's more, the simulation results also provide some implications to the government. The suggestion is that the government should play its role of supervision to control the number of network joint and strengthen supervision. For firms newly entering the alliance, the government should offer support in terms of capital and resources; and for core firms, the government should adopt knowledge incentive policies to encourage them to provide knowledge of higher value actively, so as to facilitate the evolution of the knowledge flow network in strategic alliance towards a healthy direction.

5. Conclusions

The aim of this study was to advance our understanding of the characteristics of knowledge flow networks evolution in strategic alliances under different resource allocation conditions. We regularized the complex knowledge flow behavior of strategic alliances and used a multi-agent model and Netlogo simulation to establish a simulation model of knowledge flow network evolution under different resource allocation conditions. Additionally, we made use of complexity theory and phase theory to conduct analysis of the node tie mechanism, bifurcation, growth of network revenue, knowledge flow frequency, and other complex traits of network evolution, thereby elucidating the principles of knowledge flow networks in strategic alliances.

This paper overcame some of the shortcomings of traditional knowledge foundation theory in strategic management theory and statistical analysis, such as limited perspective and irrational methods. In contrast to earlier research, this study featured three clear innovations. First, within existing research, researchers have predominantly used regression and other statistical methods to analyze the structure, effects, and relationships among internal variable changes of network evolution. These methods are flawed in that they can only show whether there exists a linear relationship between variables, but are unable to clarify the exact types of trends that exist. We used the multi-agent simulation method and, on the basis of rigorously defined subject behavior, not only verified the nonlinear relationships between variables, but also directly demonstrated the forms and patterns of the roles of variables by using new simulation technology, making up for the deficiencies of existing research. Second, we consistently took the knowledge flow network of a strategic alliance as a complex system, set previously uninvolved network attribute variables as control variables, and explained some of the complex traits and mutual effect patterns that emerge in the process of network evolution from a dynamic process perspective. Third, we fully considered the impact of different resource allocation models on network evolution and showed that different resource allocations impact the coevolution of the knowledge flow networks of strategic alliances. In particular, we deconstructed the different suitabilities of each resource allocation model based on the demonstrated traits of network evolution, which provides evidence for managers seeking to determine strategy and incentive policies.

This paper makes two important contributions to the research on knowledge flow networks in strategic alliances. First, we utilized a simulation method that is easier to understand and analyze than previously used methods and that considers the dynamic and comprehensive nature of network evolution. The model and analysis framework we established can aid researchers facing limited resources and the complex nature of knowledge flow networks. Our study identified the different types of nonlinear patterns among a network's control variables (node density, boundary density, spatial distance, and connectivity) and change variables (tie mechanism, bifurcation, growth of network revenue, knowledge flow frequency), which further clarify the principles of network evolution.

Second, we distinguished our research from the narrow perspective and approach of empirical studies that demarcate variable dimensions by directly taking as an entry point the holistic nature of network evolution and using a dynamic systematic analysis and phase theory to test for the unique emergence traits of networks undergoing evolution. At the same time, we compared and contrasted the network evolution patterns under four different resource allocation models and explained the impact of each model on network evolution. Our research has not only achieved a basic theory of resources that unifies knowledge management theory and complex network theory, but also provided a new line of thinking for managers searching for the optimal strategy to overcome the adverse effects of knowledge flow network evolution.

In this paper, there are some limitations that need to be completed in future study. First, we used simulation to analyze the function of different resource allocation modes, which is based on hypotheses settings. Although our conclusions reveal the adaptability of different resource allocation modes and clarify some characteristics in evolution of knowledge flow network in strategic alliance from the non-linear perspective, further empirical and statistical tests are still needed. And by the reason that our method and research model are adaptive for many sectors, we expect to choose industries (such as the high-end medical equipment industry, the electronic information industry and the low-carbon technological innovation industry) to collect data and conduct empirical study, aiming to analyze and improve the model proposed in this paper and elaborate some influencing factors more in detail with actual information and evolution characteristics and principles of cases, so as to make the research more specifically and empirically, and make it a link between the preceding and the future researches.

Acknowledgments

We hereby thank Professor Lean Yu of School of Economics and Management, Beijing University of Chemical Technology. This article has been partly funded by the National Natural Science Foundation of China (IDs: 71602041, 71602042); National Social Science Key Project of China (ID: 14AGL004); Natural Science Foundation of Heilongjiang Province of China (ID: QC2017082); Social Science Foundation of Ministry of Education of China (ID: 14YJC630142); Fundamental Research Funds for the Central Universities of China (ID: HEUCF170904).

References

Agarwal, R., Anand, J., Bercoviz, J., & Croson, R. (2012). Spillovers across organizational architectures: The role of prior resource allocation and communication in post-acquisition coordination outcomes. *Strategic Management Journal, 33*(6), 710–733.

Akbar, H. (2003). Knowledge levels and their transformation: Towards the integration of knowledge creation and individual learning. *Journal of Management Studies, 40*(8), 1997–2021.

Albert, R., & Barabási, A.-L. (2002). Statistical mechanics of complex networks. *Reviews of Modern Physics, 74*, 47–97.

Alelord, R. M. (1997). *The complexity of cooperation: Agent-based models of competition and collaboration*. New Jersey: Princeton University Press.

Aral, S., & Walker, D. (2014). Tie strength, embeddedness, and social influence: A large-scale networked experiment. *Management Science, 60*(6), 1352–1370.

Barabási, A.-L., & Albert, R. (1999). Emergence of scaling in random networks. *Science, 286*, 509–512.

Batjargal, B. (2010). The effects of network's structural holes: Polycentric institutions, product portfolio, and new venture growth in China and Russia. *Strategic Entrepreneurship Journal, 4*(2), 146–163.

Battilana, J., & Casciaro, T. (2013). Overcoming resistance to organizational change: Strong ties and affective cooptation. *Management Science, 59*(4), 819–836.

Baum, J. A. C., Calabrese, T., & Silverman, B. S. (2000). Don't go it alone: Alliance network composition and startups' performance in Canadian biotechnology. *Strategic Management Journal, 21*(3), 267–294.
Baum, J. A. C., Cowan, R., & Jonard, N. (2010). Network-independent partner selection and the evolution of innovation networks. *Management Science, 56*(11), 2094–2110.
Basole, R. (2016). Topological analysis and visualization of interfirm collaboration networks in the electronics industry. *Decision Support Systems, 83*, 22–31.
Blake, D. J., & Moschieri, C. (2017). Policy risk, strategic decisions and contagion effects: Firm-specific considerations. *Strategic Management Journal, 38*(3), 732–750.
Butts, C. T. (2001). The complexity of social networks: Theoretical and empirical findings. *Social Networks, 23*(1), 31–72.
Caner, T., & Tyler, B. B. (2015). The effects of knowledge depth and scope on the relationship between r&d alliances and new product development. *Journal of Product Innovation Management, 32*(5), 808–824.
Capaldo, A., & Petruzzelli, A. M. (2014). Partner geographic and organizational proximity and the innovative performance of knowledge-creating alliances. *European Management Review, 11*(1), 63–84.
Cowan, R., Jonard, N., & Özman, M. (2004). Knowledge dynamics in a network industry. *Technological forecasting and Social Change, 71*(5), 469–484.
Cowan, R., Jonard, N., & Zimmermann, J.-B. (2007). Bilateral collaboration and the emergence of innovation networks. *Management Science, 53*(7), 1051–1067.
Cummings, J. L., & Teng, B. S. (2003). Transferring R&D knowledge: The key factors affecting knowledge transfer success. *Journal of Engineering and Technology Management, 20*(1–2), 39–68.
Das, T. K., & Teng, B.-S. (2001). A risk perception model of alliance structuring. *Journal of International management, 7*(1), 1–29.
Dyer, J. H., & Nobeoka, K. (2000). Creating and managing in high performance knowledge-sharing network: The Toyota case. *Strategic Management Journal, 21*(3), 345–367.
Easley, D., & Kleinberg, J. (2010). *Networks crowds and markets: Reasoning about a highly connected world*. Cambridge University Press.
Garcia, R., Rummel, P., & Hauser, J. (2007). Validating agent-based marketing models through conjoint analysis. *Journal of Business Research, 60*(8), 848–857.
Geels, F. W. (2017). From sectoral systems of innovation to socio-technical systems: Insights about dynamics and change from sociology and institutional theory. *Research Policy, 33*(6-7), 897–920.
Gilbert, N., Ahrweiler, P., & Pyka, A. (2007). Learning in innovation networks: Some simulation experiments. *Physica A: Statistical Mechanics and its Applications, 378*(1), 100–109.
Gilsing, V., & Nooteboom, B. (2005). Density and strength of ties in innovation networks: An analysis of multimedia and biotechnology. *European Management Review, 2*(3), 179–197.
Graham, B. S. (2017). An econometric model of network formation with degree heterogeneity. *Econometrica, 85*(4), 1033–1063.
Granovetter, M. S. (1992). Problems of explanation in economic sociology. In R. Nohria, & R. Eccles (Eds.), *Networks and organizations: Structure, form and action*. Boston (MA): 7 Harvard Business School Press.
Grigoriou, K., & Rothaermel, F. T. (2017). Organizing for knowledge generation: Internal knowledge networks and the contingent effect of external knowledge sourcing. *Strategic Management Journal, 38*(2), 395–414.
Guan, J.-C., & Liu, N. (2016). Exploitative and exploratory innovations in knowledge network and collaboration network: A patent analysis in the technological field of nano-energy. *Research Policy, 45*(1), 97–112.
Gulati, R., Nohria, N., & Zaheer, A. (2000). Strategic networks. *Strategic Management Journal, 21*(3), 203–215.
Gulati, R. (1998). Alliance and networks. *Strategic Management Journal, 19*(4), 293–317.
Gulati, R. (1999). Network location and learning: The influence of network resource s and firm capabilities on alliance formation. *Strategic Management Journal, 20*(5), 397–420.
Gupta, A., & Govindarajan, V. (2000). Knowledge flows within multination corporations. *Strategic Management Journal, 21*(4), 473–493.
Hallen, B. L., Katila, R., & Rosenberger, J. D. (2014). How do social defenses work? A resource-dependence lens on technology ventures, venture capital investors, and corporate relationships. *Academy of Management Journal, 57*(4), 1078–1101.
Hansen, M. T., Nohria, N., & Tierney, T. (1999). What's your strategy for managing knowledge? *Harvard Business Review, 77*(2), 106–116.
Hitt, M. A., Dacin, M. T., Levitas, E., Arregle, J. L., & Borza, A. (2000). Partner selection in emerging and developed market contexts: Resource-based and organizational learning perspectives. *Academy of Management Journal, 43*(3), 449–467.
Holland, J. H. (1995). *Hidden order: How adaptation builds complexity*. New York: Basic Books.
Ibarra, H. (1993). Network centrality, power, and innovation involvement: Determinants of technical and administrative roles. *Academy of Management Journal, 36*(3), 471–501.
Inkpen, A. C., & Beamish, P. W. (1997). Knowledge, bargaining power and the instability of international joint ventures. *Academy of Management Review, 22*(1), 177–202.
Klingebiel, R., & Rammer, C. (2014). Resource allocation strategy for innovation portfolio management. *Strategic Management Journal, 35*(2), 246–268.
Kogan, L., Papanikolaou, D., Seru, A., & Stoffman, N. (2017). Technological innovation, resource allocation, and growth. *The Quarterly Journal of Economics, 132*(2), 665–712.
Koka, B. R., & Prescott, J. E. (2002). Strategic alliances as social capital: A multidimensional view. *Strategic Management Journal, 23*(9), 795–816.
Lahiri, N., & Narayanan, S. (2013). Vertical integration, innovation, and alliance portfolio size: Implications for firm performance. *Strategic Management Journal, 34*(9), 1042–1064.
Lavie, D., Haunschild, P. R., & Khanna, P. (2012). Organizational differences, relational mechanisms, and alliance performance, *Strategic Management Journal*, 33(13):1453–1479.
Leenders, R. Th. A. J., van Engelen, JoM. L., & Kratzer, J. (2003). Virtuality, communication, and new product team creativity: A social network perspective. *Journal of Engineering & Technology Management, 20*(1), 69–92.
Levin, D. Z., & Cross, R. (2004). The strength of weak ties you can trust: The mediating role of trust in effective knowledge transfer. *Management Science, 50*(11), 1477–1490.
Lopolito, A., Morone, P., & Taylor, R. (2013). Emerging innovation niches: An agent based model. *Research Policy, 42*(6–7), 1225–1238.
Maes, P. (1994). Agents that reduce work and information overload. *Communications of the ACM, 37*(7), 30–40.
McFadyen, M. A., Semadeni, M., & Cannella, A. A., Jr (2009). Value of strong ties to disconnected others: Examining knowledge creation in biomedicine. *Organization Science, 20*(3), 552–564.
Meier, M. (2011). Knowledge management in strategic alliances: A review of empirical evidence. *International Journal of Management Reviews, 13*(1), 1–23.
Mitchell, M. (2011). *Complexity: A guided tour* (1st ed.). Oxford University Press.
Moeen, M., & Agarwal, R. (2017). Incubation of an industry: Heterogeneous knowledge bases and modes of value capture. *Strategic Management Journal, 38*(3), 566–587.
Morone, P., & Taylor, R. (2004). Knowledge diffusion dynamics and network properties of face-to-face interactions. *Journal of Evolutionary Economics, 14*(3), 327–351.
North, M. J., & Macal, C. M. (2007). Management business complexity. Oxford University Press.
Panico, C. (2017). Strategic interaction in alliances. *Strategic Management Journal, 38*(8), 1646–1667.
Park, K. C., Lee, K. S., Park, S. S., & Lee, H. S. (2000). Telecommunication node clustering with node compatibility and network survivability requirements. *Management Science, 46*(3), 363–374.
Paruchuri, S. (2010). Intraorganizational networks, interorganizational networks, and the impact of central inventors: A longitudinal study of pharmaceutical firms. *Organization Science, 21*(1), 63–80.
Paruchuri, S., & Awate, S. (2017). Organizational knowledge networks and local search: The role of intra-organizational inventor networks.Strategic Management Journal, 38(3):657–675.
Phelps, C., Heidl, R., & Wadhwa, A. (2012). Knowledge, networks, and knowledge networks: A review and research agenda. *Journal of Management, 38*(4), 1115–1166.
Phene, A., & Tallman, S. (2014). Knowledge spillovers and alliance formation. *Journal of Management Studies, 51*(7), 1058–1090.
Pontikes, E. G., & Barnett, W. P. (2017). The coevolution of organizational knowledge and market technology. *Strategy Science, 2*(1), 64–82.
Reagans, R., & McEvily, B. (2003). Network structure and knowledge transfer: The effect of cohesion and range. *Administrative Science Quarterly, 48*(2), 240–267.
Rodan, S., & Galunic, C. (2004). More than network structure: How knowledge heterogeneity influences managerial performance and innovativeness. *Strategic Management Journal, 25*(6), 541–562.
Schildt, H., Keil, T., & Maula, M. (2012). The temporal effects of relative and firm-level absorptive capacity on interorganizational learning. *Strategic Management Journal, 33*(10), 1154–1173.
Schilling, M. A., & Phelps, C. C. (2007). Interfirm collaboration networks: The impact of large-scale network structure on firm innovation. *Management Science, 53*(7), 1113–1126.
Seo, Y.-W., & Chae, S.-W. (2016). Market dynamics and innovation management on performance in SMEs: Multi-agent simulation approach. *Procedia Computer Science, 91*, 707–714.
Sherif, K., & Xing, B. (2006). Adaptive processes for knowledge creation in complex systems: The case of a global IT consulting firm. *Information and Management, 43*(4), 530–540.
Shriver, S. K., Nair, H. S., & Hofstetter, R. (2013). Social ties and user-generated content: Evidence from an online social network. *Management Science, 59*(6), 1425–1443.
Singh, J. (2005). Collaborative networks as determinants of knowledge diffusion patterns. *Management Science, 51*(5), 756–770.
Sorenson, O., Rivkin, JanW., & Fleming, L. (2006). Patent collaboration and international knowledge flow. *Research Policy, 35*(7), 994–1017.
Stuart, T. E. (2000). Interorganizational alliances and the performance of firms: A study of growth and innovation rates in a high-technology industry. *Strategic Management Journal, 21*(8), 791–811.
Tan, J., Zhang, H-J., & Wang, L. (2015). Network closure or structural hole? The conditioning effects of network-level social capital on innovation performance. *Entrepreneurship Theory and Practice, 39*(5), 1189–1212.
Tang, L.-K., Lu, J.-A., Lü, J.-H., & Yu, X.-H. (2012). Bifurcation analysis of synchronized regions in complex dynamical networks. *International Journal of Bifurcation and Chaos, 22*(11), 1–14 1250282.
Tortoriello, M., Reagans, R., & McEvily, B. (2012). Bridging the knowledge gap: The influence of strong ties, network cohesion, and network range on the

transfer of knowledge between organizational units. *Organization Science, 23*(4), 1024–1039.
Trigeorgis, L., & Reuer, J. J. (2017). Real options theory in strategic management. *Strategic Management Journal, 38*, 42–63.
Uzzi, B., & Gillespie, J. J. (2002). Knowledge spillover in corporate financing networks: Embeddedness and the firm's debt performance. *Strategic Management Journal, 23*(7), 595–618.
Uzzi, B., & Spiro, J. (2005). Collaboration and creativity: The small world problem. *American Journal of Sociology, 111*(2), 447–504.
Uzzi, B. (1999). Embeddedness in the making of financial capital: How social relations and networks benefit from firms seeking financing. *American Sociological Review, 64*(4), 481–505.
Vandaie, R., & Zaheer, A. (2015). Alliance partners and firm capability: Evidence from the motion picture industry. *Organization Science, 26*(1), 22–36.
Vanhaverbeke, W., Belderbos, R., Duysters, G., & Beerkens, B. (2015). Technological performance and alliances over the industry life cycle: Evidence from the ASIC industry. *Journal of Product Innovation Management, 32*(4), 556–573.
Wang, C.-C., Sung, H.-Y., Chen, D.-Z., & Huang, M.-H. (2017). Strong ties and weak ties of the knowledge spillover network in the semiconductor industry. *Technological Forecasting and Social Change, 118*, 114–127.
Wassmer, U., & Dussauge, P. (2011). Value creation in alliance portfolios: The benefits and costs of network resource interdependencies. *European Management Journal, 8*(1), 47–64.
Wassmer, U., Li, S., & Madhok, A. (2017). Resource ambidexterity through alliance portfolios and firm performance. *Strategic Management Journal, 38*(2), 384–394.
Xia, J. (2011). Mutual dependence, partner substitutability, and repeated partnership: The survival of cross-border alliances. *Strategic Management Journal, 32*(3), 229–253.
Zhang, S., Li, N., & Li, J.-Z. (2017). Redefining relational rent. *Technological Forecasting and Social Change, 117*, 315–326.
Zhao, J.-Y., Xi, X., & Su, Y. (2015). Resource allocation under a strategic alliance: How a cooperative network with knowledge flow spurs co-evolution. *Knowledge-Based Systems, 89*, 497–508.