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Multi-agent Simulation on Original Innovations from the Knowledge Views

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Abstract: Original innovations are important for the technical progress and the economic growth of countries and constructing models to reveal their inherent factors, the interaction between those factors and their specific effects is becoming quite necessary. This paper proposed a multi-agent model on original innovations from the knowledge views. It analysed the relationships among the supporting knowledge system of the original innovation, its participators and the scientific collaboration network, designed agents' behaviours as well as their adaption rules and simulated the model on Swarm platform. It showed that the system with very few research directions tends to have the best innovation performance. As for systems with middle or higher amount of research directions, adopting the strategy prior to adapt original innovations initiated by other researchers as well as the strategy to introduce collaborations between experts may both improve the system innovation performance. These two strategies all have their individual advantages and it cannot be stated which one is always better than the other. This multi-agent model on original innovations is operable and applicable and the deductions drawn from its simulation results can be supported by practice and may contribute to our cognition of original innovations and their improvement strategies.

Key words: Original innovation, knowledge views, multi-agent simulation, scientific collaboration network

INTRODUCTION

Original innovations are mainly represented as great scientific discoveries, theoretical innovations, technological innovations, experimental methods and instrument inventions etc. They usually have high theoretical value, practical benefits and strong enlightening. Meanwhile, they often lead to a series of innovations to improve the current theory and technology, as well as researches which imitate their problem-solving approaches. Until now, several researchers have talked about original innovations from different angles. For example, Goldenberg *et al.* (1999) proposed a systematic framework for original incremental innovations, which come from examinations of patterns observable in the internal dynamics of the current innovations and they showed that these original incremental innovations may reduce the complexity of their systems rather than increasing it. Chen *et al.* (2005) focused on factors and performance of university original technological innovations and their quantitative analysis confirmed that project leader factor, team and organise factor, resource and policy factor and process factor all have correlation with university original technological innovation performance. Yixin (2011) argued that the cognition and evaluation of original innovations are facing the problem that lack of knowledge about their connotation, scientific evaluation methods as well as valid evaluation systems, so we should turn to fuzzy mathematics and system engineering theory and methods. Zhu *et al.* (2012) believed that technological original innovations are processes of enterprises making use of knowledge to create new technology. They used Mutation theory to analyze the evolution mechanism of technological original innovations and discussed the effects of institutional arrangement factor and organization operation factor under the changed values of the knowledge-technology conversion parameter. Lee and Rodriguez-Pose (2013) considered the influence of an urban location on whether innovations of SMEs are original or learnt and they showed that while urban firms tend to be both product and process innovators, they are extremely likely to introduce process innovations only new to themselves, rather than entirely original. However, simulation researches are not common in this field, due to lack of rational frameworks and operable parameters.

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Nevertheless, this kind of researches can provide us with various visual results demonstrating the system evolution processes as well as effects of different simulation parameters which denote the inner influence factors or those coming from the circumstance and this may contribute to our cognition of these original innovations.

This study proposes a multi-agent model on original innovations from the knowledge views. It analyzes the original innovation supporting knowledge, researchers and the collaboration network among them, completes the agent behaviour and adaption rule designs and then simulates the model on Swarm platform. By observing the simulation results, we find that the final performance of an original innovation is affected tremendous by the total number of the research directions belonging to its subject, which is also an indicator of the broad extent of the subject knowledge and also indirectly reflects the current evolution stage of this subject. Comparing the simulation results under the different values of this parameter, we can show its specific impact. Based on this, we further simulate two common original innovation improvement strategies by modifying the agent adaption rules, as well as the agent collaboration network structure. These works may enhance our understanding on these improvement strategies and help us choose the suitable one on changed circumstances.

THE MULTI-AGENT MODEL ON ORIGINAL INNOVATION FROM KNOWLEDGE VIEWS

According to Chen *et al*. (2003) original innovations are to explore the phenomenon of things, structure, movement and their interaction laws by scientific experimental and theoretical studies, or apply scientific theories to solve key scientific and technological issues in the economic and social development. Based on this, these original innovations can be further divided into basic researches and applied basic researches, where the former focus on scientific experimental and theoretical studies to explore the phenomenon of things, structure, movement and their interaction laws, while the latter include the use of scientific theory to solve key scientific and technological issues in the economic and social development. Shu and Gao (2008) pointed that according to the knowledge perspective, original innovation itself contains two inseparable: the generation of new knowledge and the use of new knowledge, where the former corresponds to basic researches, while the latter corresponds to applied basic researches. Through further analyse, we find that both of them are supported by knowledge in different research directions of the specific subject knowledge systems. For example, quantum mechanics, rising in the beginning of the 20th century, was firstly triggered by fails of classical mechanics to explain some experimental phenomenon and finally successfully proposed based on the knowledge of electrodynamics, thermodynamics, statistical physics and other physical sub-disciplines. For applied basic researches, their successes depend on developing a set of techniques to solve all aspects of sub-problems encountered (Arthur, 2007); behind this there must be knowledge of all aspects of the subject. Thus, the multi-agent model (Fig. 1) should reflect the knowledge view discussed above, assuming that all the supporting knowledge of an original innovation is totally limited in a subject and all the subject internal knowledge can be further divided into knowledge in different research directions.

Since the subject knowledge can be divided into knowledge in different research directions, a researcher in this subject may have knowledge in more than one direction. It means that an original innovation is a teamwork which can be carried by different researchers with knowledge in complementary research directions.

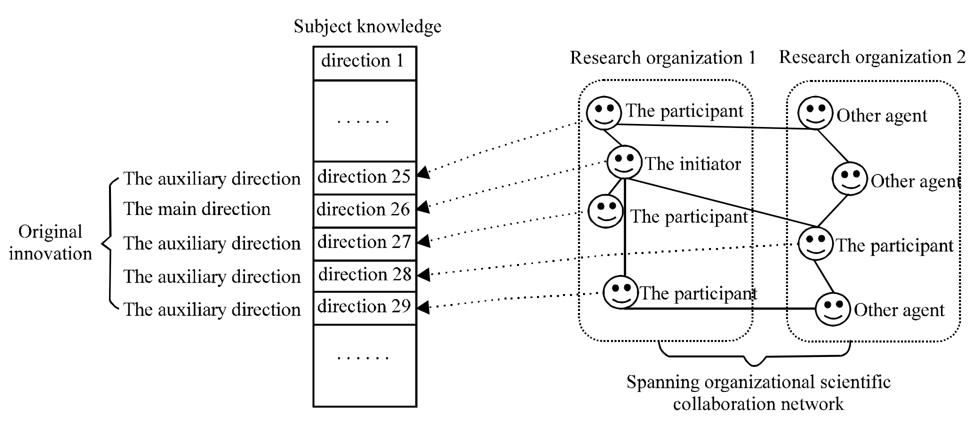

Fig. 1: Multi-agent model on original innovations

The key members of these original innovation teams are also very important. They are usually initiators and leaders of these teams and their academic standards as well as strategic visions determine the success or failure of the original innovations. So we further divided the team members into the initiator and participants (Fig. 1).

For a researcher agent in the multi-agent model on original innovations, which other researchers he can communicate is determined by his location in the scientific collaboration network and his vision. In general, researchers tend to find partners within the same organization but in recent years, some literatures argued that innovation collaborations across the organizations are more and more common (Zucker *et al*., 2007). Therefore, in our multi-agent model, the scientific collaboration network is also composed of researchers from diverse scientific research organizations (Fig. 1). Here, we use the visible distance to measure the vision of agents. When the visible distance of an agent is 1, he can only work with his direct neighbours, when it is 2, we imply that his direct neighbours may also introduce their own neighbours to this agent, so he can work with both of them.

Finally, if two agents all have the knowledge in the same research direction and they are not too far away in the network, there may be a competitive relationship between them. At this moment, the agent with the higher level of this kind of knowledge may have priority to be invited to become the participant of an original innovation. So it also requires agents to take the necessary adaption improvement to rationally adjust the levels of knowledge in all research directions they have.

AGENT BEHAVIOUR DESCRIPTION AND ADOPTION RULE DESIGN

First of all, we assume that all researchers and their original innovation behavior are limited into the same subject and the knowledge of this subject will be further divided into the KN specific research directions with the number from 1 to KN. Here we use the adjacency of the research direction numbers to represent the correlation degree of these directions. For instance, research direction 26 is closer to direction 25 than direction 27. We also adopt an annular design which assumes direction KN is adjacent to direction 1, so that all research directions are in the equivalent positions and the special treatment for the fringe directions such as direction 1, 2,KN-1 and KN can be left out.

For all researcher agents, we assume that they have the same total number of research directions (RKN) at the beginning of the simulation and all of their direction numbers are randomly chosen from 1 to KN (RKN<<KN). Here, we use Rl_i ($1 \le i \le N$) to represent the level of the knowledge in direction i, where RL_i is an integer generated randomly between 0-100. Further, we set $\Sigma RL_i = 100$ for every agent and it hints that they have the equivalent sum of all their knowledge levels but the different knowledge level in each research direction.

For an original innovation, we know that it is usually initiated and led by a key member and the initiator or leader must have a higher level of knowledge in the main research direction. In addition, the success of this original innovation requires that the knowledge of its team covers a variety of research directions, which are referred to as the auxiliary research directions beside its main research direction. For each agent, we prescribe that if one of his knowledge levels is higher than OL ($OL \le 100$), it will initiate an original innovation. At the same time, the program will generate a sequence of research direction numbers, randomly, which includes 5 consecutive numbers, one is the main direction number, the other four are taken as the auxiliary direction numbers. For example, an agent launches an original innovation with direction 1 as its main direction and the direction sequence generated may be KN, 1, 2, 3 and 4, where KN, 2, 3 and 4 denote auxiliary directions. Then the initiator will search for four participants in all of its potential partners with the knowledge in all of these auxiliary directions. Meanwhile, for each participant, its knowledge level in the specific auxiliary direction must reach PL (PL<<OL) at least which hints it is more difficult to be an initiator or leader than a participant and in the rest of this paper, agents who can initiate original innovations will be also named as experts. Finally, if the initiator manages to find all its participants with the necessary research directions as well as knowledge levels, its original innovation will be judged as successful.

As previously discussed, our agent cooperation network is a cross-organizational collaboration network. Based on this fact, we design it as an "interacting network" (Leicht and D'Souza, 2009). We assume that the entire network contains GS groups which represent different research organizations or institutions. Each group consists of the GN agents and each agent has BI ($BI \le GN-1$) neighbors inside its own group, BO ($BO \le BI$) neighbors outside that group (there will be an edge between an agent and each of its neighbor). In subsequent simulations, the values of GS and GN are not so large, thus this design can avoid the excessive gap between the neighbor numbers of different agents. Its defect lies in that a few agents may not get enough neighbors inside their groups due to all of other agents inside the same groups already have enough neighbors and this can be negligible. Here we also setthe visible distance of all agents to 2 and that means an agent can work with both its neighbors and the neighbors of its neighbors.

In this study, the adaption target of every agent is to initiate its own original innovation or participate in original innovations launched by others. Once any of these two takes places, the agent will not make any adaptation improvement; otherwise, the agent will adjust its knowledge levels in different directions. The adjustment is increasing the knowledge level in one direction by 1, meanwhile decrease the knowledge level in another direction by 1. So the sum of all knowledge levels of the agent is still 100 and we also require that the knowledge levels in any directions should remain non-negative after the adjustment.

When an agent is going to take the adjustment talked above, it must decide which research direction should be enhanced. The direction with the highest knowledge level is obviously one of the options. Here, we use imax to represent that research direction and let Di_{max} = OL-RL_{imax} be the gap between the current and target knowledge levels. Meanwhile, if a research direction of an agent is one of the auxiliary directions of the original innovation launched by its potential partner but this agent fails to achieve the necessary knowledge level PL or its knowledge level is below its competitor who has the same direction but higher knowledge level, this research direction will also become one alternative. Now the gap between the current and target knowledge levels is D_i = PL-RL_i, or $D_i = RL_i^{co}-RL_i$ (if RL_i^{co}>PL), where, RL_i^{co} denotes the knowledge level of its competitor. Finally, the agent with many alternatives may choose the direction i on the probability:

$$p_i = \frac{\frac{1}{D_i}}{\sum \frac{1}{D_i}}$$

and that means the direction with smaller gap is more likely to be enhanced. Then the agent may choose one of the directions left with the lowest knowledge level to impair.

ANALYSIS OF PARAMETERS AND SIMULATION RESULTS

In this Study, Swarm platform is used to implement the simulation and descriptions as well as values of part of parameters are given in Table 1.

Figure 2 represents the evolution processes of the original innovation performance in systems with different

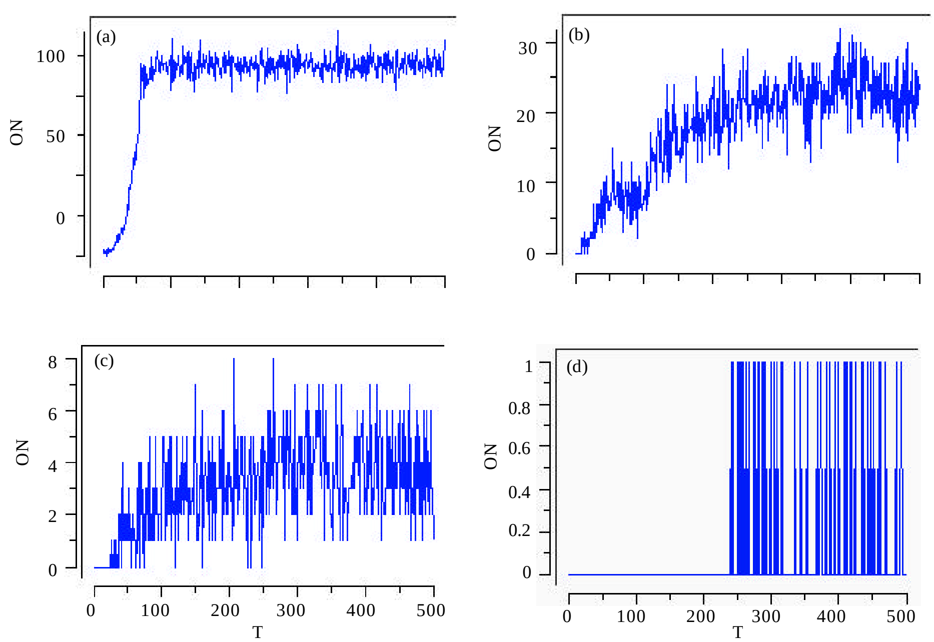

Fig. 2 (a-d): Evolution processes of the success number of original innovations ON in systems with different KN values and the total number of experts EN at 500th time step. In which (a) KN = 5, (b) KN = 50, (c) KN = 100, (d) KN = 350

Table 1: Parameters of the simulation

Parameter	Description	Value
KN	Total No. of research directions in the subject	5~400
LKN	Agent research direction number	5
RL_i	The knowledge level in research direction i	0~100
OL	The necessary knowledge level to initiate an original innovation	80
PL	The necessary knowledge level to participate in an original innovation	40
GS	Group number	10
GN	Group agent number	20
BI	Agent neighbor number inside the group	5
BO	Agent neighbor number outside the group	2

KN values, as well as their final expert numbers at 500th time step. From it, we can see no matter how the initial values of simulation parameters changes, the success number of original innovations overall the system ON will gradually increase untilit maintains relatively stable. Such a process can be regarded as the result of agent adaptation and the randomness in every original innovation direction sequence may account for the fluctuation of ON.

Figure 2 represents the evolution processes of the original innovation performance in systems with different KN values, as well as their final expert numbers at 500th time step. From it, we can see no matter how the initial values of simulation parameters changes, the success number of original innovations overall the system ON will gradually increase until it maintains relatively stable. Such a process can be regarded as the result of agent adaptation and the randomness in every original innovation direction sequence may account for the fluctuation of ON.

Figure 2 also show that KN has a significant influence on the final value of ON. We can conclude that systems with higher KN values tend to get the lower final ON values. The reason is that when the KN value is low, a lot of researchers may engage in few research directions and they are easily to form cooperation on innovation; further, due to the directions of agents tend to overlap with each other at this moment, the competitive intensity will enhance and it is beneficial to improve the knowledge level in all research directions. Figure 2a represented such a situation, where KN = 5 and this is also the number of research directions necessary to formation an original innovation, which means that the knowledge in every direction of an researcher can be used in original innovations launched by others, so it is very easy for initiators to find his partners. All these make the final value of ON much higher than other three systems. In the final state, EN = 200 means all researchers eventually become experts. In the real world, such a system is representative when some subjects just appear or in the early stage and a large number of researchers engage in only a few research directions to promote more original innovations in these research directions. The disadvantage is that such a state often can't last long,

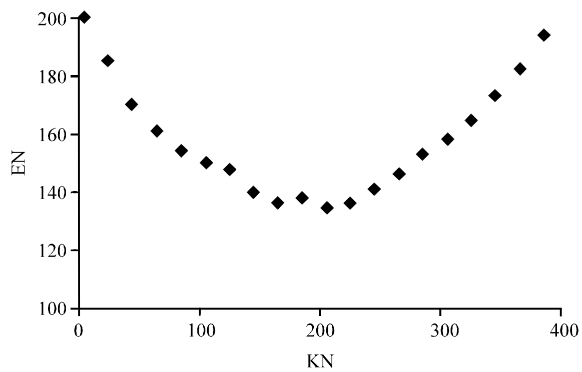

Fig. 3: Final EN versus KN. For each KN value, we randomly generate 100 systems. All results are collected at 500th time step and each EN value corresponding to the KN value is the average of the 100 values

when the research space and the potential in these directions is getting smaller and more valuable new research directions emerge, researchers will turn to other research directions. The final original innovation performance is the worst in the system (d), where KN (KN = 350) is much higher than the total number of researchers (10*20 = 200). In this system, researchers in many research directions are scarce and they cannot form an effective coordination. However, this situation is also not common in reality.

An interesting deduction we can draw from Figure 2 is that with the increasing of KN, the final value of EN firstly increases then decreases. Figure 3 shows the mean of EN in systems with different KN values at 500th time step and it confirms our deduction. But why systems with the moderate KN values have the lowest final EN values? The reason is as follows: When the KN value is very low, the directions of research among researchers can easily overlap; there exists competitions between agents with the same research direction. These competitions will compel researchers to enhance the knowledge they are good at until they become experts. As for systems with extremely high KN values, cooperation among researchers are quite inadequate and most researchers can only improve the knowledge with the highest level, which determines final EN values in these systems are quite high when ON values are quite low. Comparing with those talked above, in systems with the moderate KN values (presented in Fig. 2b, c), the number of researchers in the same direction is far less than in systems with low KN values and many initiators may find only one collaborator with the corresponding auxiliary research direction and the necessary knowledge level in their visions. So, the latter naturally becomes the participant, whose adaptation behaviours do not occur due to it is not necessary. Easily speaking, it is that lack of competitions determines the final values of EN are the lowest.

As discussed previously, systems with low KN values have optimal performance of original innovations but nowadays these systems are not common as systems with moderate KN values. Further, KN is a circumstance parameter that we cannot directly control and modify its value, thus, it is more realistic to study how to improve the original innovation performances in systems with moderate KN values.

The success of systems with low KN values may be attributed to the overlapping of researchers' directions and the intensive cooperation and competition caused by it. So it is reasonable for researchers to draw their research directions more closely to enhance the intensity of cooperation and competition and the strategy prior to adapt original innovations initiated by other researchers is in this manner. e.g. a researcher in the current time step is not an expert and meanwhile unable to participate in any original innovations in its sight due to its low knowledge level in the auxiliary research direction, this agent will no longer consider its own strongpoint but select one of auxiliary research directions initiated by other researchers and then enhance its knowledge level. This strategy induces researchers prior to enhance the research directions closer to other and in the system level it will gather the research directions in the subject. Comparing with it, the other strategy tries to modify the structure of the scientific collaboration network instead of the adoption rule of researchers. It introduces collaborations between experts by adding new links to the scientific collaboration network. In our simulations, if an agent successfully leads an original innovation (this agent must be an expert), it will have a chance to get a new collaboration network link, which points to another successful original innovation leader (experts). In the whole process, all agents can only have one chance to obtain a new link and if a new link issued by an agent has alternative multiple experts to be the endpoint, the agent will choose the expert whose strongest research direction is closer to its own. This strategy is designed for the following considerations: first of all, it needs to spend cost and effort to establish and maintain the new network link, so every agent has only one chance to do that; secondly, seeking experts as partners whose expertise is closer to its own may facilitate cooperation among experts as well as increase the possibility of competition between their partners; Furthermore, such a strategy is also relatively easy to implement in practice.

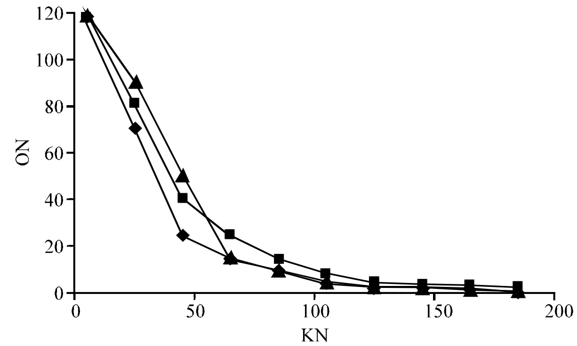

Fig. 4: Final ON versus KN under different strategies. Where diamonds denote ON under no strategies, squares denote it under the strategy prior to adapt original innovations initiated by other researchers and triangles denote it under the strategy to introduce collaborations between experts. For each KN value, we randomly generate 100 systems under every strategy. All results are collected at 500th time step and each ON value corresponding to the KN value is the average of the 100 values

Figure 4 gives final ON versus KN under different strategies at 500th time step. From it we can see that the final system innovation performance is improved significantly under the strategy prior to adapt original innovations initiated by other researchers in the systems with medium and relatively higher KN value (from around 20 to around 120), while the strategy to introduce collaborations between experts is only valid in the systems with medium KN value (from around 20 to around 60). That is because the success of the latter relies more on the inherent ON of the system than the former and when this measure is low (in systems with KN higher than 60), the number of new links introduced by the latter will be also quite few, which may impair the effect of this strategy. So the application scope of the strategy prior to adapt original innovations initiated by other researchers is more extensive than the strategy to introduce collaborations between experts. However, in systems with medium and relatively lower KN, the latter seems to have a better effect due to the relatively higher inherent ON (Fig. 4). Both the strategies are nearly invalid in systems with extremely low or high KN. In the first case, there is no need to gather the research directions of researchers as

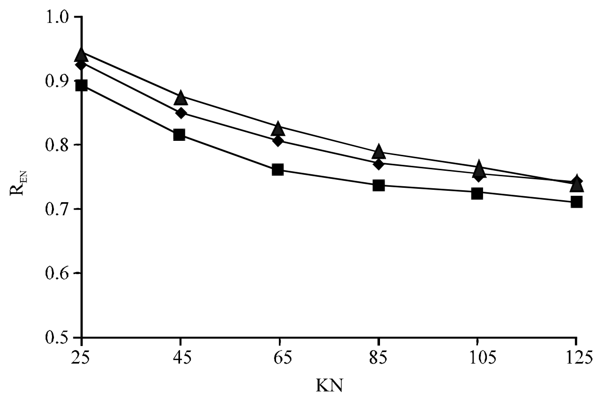

Fig. 5: Final R_{EN} versus KN under different strategies. Where diamonds denote R_{EN} under no strategies, squares denote it under the strategy prior to adapt original innovations initiated by other researchers and triangles denote it under the strategy to introduce collaborations between experts. For each KN value, we randomly generate 100 systems under every strategy. All results are calculated at 500th time step and each R_{EN} value corresponding to the KN value is the average of the 100 values

well as enhance the intensity of cooperation and competition, while in the second case the effect of any of them cannot counteract the scarcity of researchers in each research direction.

Another thing that draws our attention is the influence of those two strategies on the final number of experts. Figure 5 gives the final proportion of experts (R_{EN}) in systems with different KN values. From it, we can see that the strategy to introduce collaborations between experts may always train more experts than the original system due to the new competitions between the partners of those expertors. Meanwhile, the system under the strategy prior to adapt original innovations initiated by other researchers may have lower R_{EN} value than the original system, which means this strategy tends to sacrifice the final number of experts to create more innovation cooperation between researchers. Actually such a strategy has been adopted by many scientific research organizations spontaneously in reality. In these organizations, if a member becomes into an expert, other members will try to adjust their research directions to get close with the expert's, in order to make full use of the advantages introduced by cooperative innovations. Comparing with it, the strategy to introduce collaborations between experts is more effective in training experts, however this strategy will also need additional cost and effort to establish and maintain the new network link.

CONCLUSION

In this study, we proposed a multi-agent model of original innovations on swarm platform and our simulation results demonstrated that all researchers engage in few closely related research directions may take the advantages of knowledge complementary and competition, which is helpful to achieve higher original innovation performance, as well as train more experts. However, subjects with few research directions are not such common in reality as those with medium or even higher number of research directions. As for those systems, taking the strategy prior to adapt original innovations initiated by others as well as the strategy to introduce collaborations between experts maybe both valid. The former tries to gather researchers' directions and create knowledge complementary and competition in the smaller range without any additional connection costs. The latter is more effective for subjects which already have a certain number of successful original innovations and may train more experts. There is no absolute optimization between these two strategies.

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