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*Research article*

# Study on the influence diffusion of SMEs in open-source communities from the perspective of complex networks

**Yingzi Li[1], Mingxuan Yang[1] and Shuo Zhang[2,*]**

[1] School of Economics and Management, University of Science and Technology Beijing, Beijing 100083, China
[2] School of Economics and Management, North China Electric Power University, Beijing 102206, China

* **Correspondence**: Email: zhangshuo@ncepu.edu.cn.

**Abstract:** In the era of digital economy, enterprise research and development (R&D) tends to be open-source. Due to their limited resources, small and medium-sized enterprises (SMEs) can join open-source platforms to get additional creative resources and technical support. In this context, from the perspective of complex networks, the influence diffusion of SMEs after embedding open-source innovation networks is studied in this paper. First, an integrated simulation model including a network model, agent model and innovative diffusion model is constructed. Second, the influence diffusion strategy is proposed considering initial impact, embedding timing and connection mode (same-match and heterogeneous) of the enterprise. Third, the dynamic simulation of the influence diffusion process of SMEs demonstrates that embedding timing has a significant impact. There is no significant difference in the influence diffusion at the early and mature stages in the evolution process of open-source innovation networks. The initial impact of enterprises has a significant influence on the diffusion during the developing period, but the effect on its influence diffusion at the initial and mature stages is not obvious. Finally, in light of experiment results, it is clear that the open-source platform plays an important role on the growth of SMEs as evidenced by the close correlation between the spread of SMEs' influence within the open-source innovation network and the community's stage of development.

**Keywords:** open-source innovation; SMEs; influence diffusion; complex network; agent-based modelling and simulation (ABMS)

## 1. Introduction

In the era of the digital economy, a series of changes have taken place in the internal management models of enterprises, among which innovation and R&D models tend to be open and open- source [1]. At present, with the development of Internet technology, enterprises have paid more attention to open-source the innovation model. More and more firms try to obtain more knowledge resources from open-source communities. Over the past decades, FLOSS (free/libre and open source software) has moved from an academic curiosity to a mainstream research focus [2], and with the development of the Internet, "open-source" has been applied to a broad range of fields, such as knowledge-sharing (e.g., Wikipedia), product design (e.g., Lego Mindstorms), hardware (Arduino) and so on. By this pattern, stakeholders can benefit from the modality by obtaining both higher performance and lower costs [3]. With the growing competition, the enterprise has paid more and more attention to obtain more and more innovation resources and ideas based on the mode of "open-source". Enterprise' participation in open-source innovation has gradually spread from the initial software field to the knowledge field, and to the manufacturing field. For example, Von Krogh et al. presented six ideas to help manufacturing companies open up their innovation process [4]. They recommended improving the organization's ability to absorb and implement ideas from external sources. They proposed that non-traditional sources of knowledge may spark process innovation and help overcome difficult problems. Stakeholders can benefit from the modality by obtaining both higher performance and lower costs [3]. Enterprises can get more creative resources from open-source communities to help them improve innovation efficiency and product competitiveness, which is one of the important reasons for the development mode to be open-source [5,6]. Generally, there are three ways for a firm to participate in open-source community [7]: (1) firm as a sponsor, they will provide reward to get more ideas by the platform, such as Innocentive, which is an intermediary platform with over 375,000 participants who are from 200 countries; (2) firms provide part codes (models) to start a new open-source project. For example, Microsoft has released its code to test unmanned aerial vehicles (UAV) and unmanned ground vehicles (UGV) in its open-source community, IBM and HP are developing open-source projects on the Linux platform; (3) Different from (2), some firms will construct their own open-source community instead of relying on existing platforms, such as Lego Mindstorm, Local motors, Baidu's Apollo driverless car platform in China and so on.

Since the 1990s, innovation by network cooperation has become a general mode of global enterprise organization development, and the research on enterprise innovation networks has rapidly become one of the hot spots of network research [8]. Up to now, the research of enterprise innovation networks has achieved fruitful results in the aspects of network construction and evolution mechanism [9,10], network characteristics and innovation performance [11,12], and internal mechanism of the network [13]. Enterprises make use of the creative resources in open-source communities so that the boundary of the enterprise innovation network is constantly expanded, and innovation agents are diverse [14]. Large enterprises with abundant capital, technology and talent can construct their own innovation platforms and attract more innovation resources through open-source to form an innovation network with diversified agents. However, small and medium-sized enterprises (hereinafter: SMEs) who are because of resource poverty, dependent on external input and cooperation with other companies [15]. In this context, this paper mainly explores how SMEs embed in open- source innovation networks. This mainly includes the following two issues:

(1) How can an enterprise embed in an existing open-source community network and quickly

spread its influence in the network?

(2) In the context of the dynamic evolution of the open-source community, what is the impact of the timing with which an enterprise embeds in a community network on the diffusion of influence?

Thus, this paper attempts to explore the influence diffusion of SMEs in open-source innovation networks, combined with a multi-agent simulation method. The second chapter is the literature review, the third chapter is the model description, the fourth chapter is the simulation study, and the last chapter is the conclusion and suggestion.

## 2. Related researches

(1) Status quo of SMEs participating in open-source innovation

Different from large enterprises, SMEs' participation in open-source innovation usually depends on platform enterprises or intermediary firms. Therefore, SMEs should emphasize the issues of internal innovation and external autonomy at the strategic level and consider how to improve efficiency, innovation ability and business growth, and then enhance their competitiveness from a tactical level. At a strategic level, managers can design open innovation strategies to maximize the absorption of relevant knowledge, but they should pay attention to the risk of knowledge leakage, especially for start-ups [16]. At a tactical level, Spithoven et al. have found that collaboration and external R&D have a positive impact on SME innovation performance [17]; Xie et al. have proposed that open innovation can improve R&D efficiency through complementary effect, incentive effect, learning effect, substitution effect, etc. and may also reduce efficiency due to the dependence effect and the adaptation effect [18]. However, when the external environment changes, such as large market fluctuations, strong technological fluctuations or fierce market competition, the role of team effectiveness in open innovation will be weakened to varying degrees [19]. In this context, many SMEs have to rely on large platforms for open-source innovation, but this is easy to generate path dependence.

Thus, SMEs need to maintain their own autonomy [20], and deploy their absorptive capacity to access valuable knowledge on collaboration innovation networks [21].

(2) Impact of network embeddedness on the innovation performance of SMEs

From the 1990s to now, construction of cooperation networks has become a general innovation mode of global enterprises, and the research on enterprise innovation networks has rapidly become one of the hot spots of network research [14]. SMEs usually join innovation networks through embeddedness. Network embeddedness can be divided into two categories: structural embeddedness and relational embeddedness [22]. Structural embeddedness is mainly about the enterprise position in the network, which has an important impact on the quality of innovation resources. The relational embeddedness means that the establishment and maintenance of a good cooperative relationship among enterprises can facilitate the enterprise to obtain real and reliable market and technical information in time. Scholars have conducted much research on the relationship between network embeddedness and innovation performance. Koka et al. [23] have proposed that a higher degree of network embeddedness implies greater opportunities and unique situations for accessing new knowledge that is conducive to creating radical innovative ideas and products. Lyu et al. have proposed that structural embeddedness directly affects innovation diffusion [24]. In addition, aimed at different innovation patterns, incremental innovation and radical innovation, some valuable research was explored. Han et al. have presented that open innovation can strengthen the relationship between network embeddedness and incremental innovation capability, and relational embeddedness is positively related to incremental innovation capability, while structural embeddedness exerts a negative effect [25]. Lyu et al. have found that network centrality plays a negative moderating role in the relationship between open innovation and innovation radicalness, whereas network reach positively moderates the relationship [26]. Xie et al. have proposed that enterprises should start with structural embedding and reconsider the position of enterprises in the network. They can gain a dominant position in the network to increase access to heterogeneous innovation resources [27]. Mazzola have studied that the influence of network embeddedness on new product development in biopharmaceutical industry [28]. For SMEs, previous studies have shown that network embeddedness has a significant impact on improving their innovation performance [29]; Liang et al. have demonstrated that SMEs' innovation can benefit from having sparse connections and interlocked connections [30]. However, at the same time, it should be noted that SMEs are usually in a marginal position in the network due to the limitations of their own capabilities and resources, and it is difficult to obtain key resources [31]. SMEs need to be more active in network innovation, rather than relying on core enterprises. Compared with SMEs that completely rely on network embeddedness, enterprises with a high level of network embeddedness and open innovation perform much better [29].

(3) Modeling and simulation

With the development of human society, the evolution trend of management practice and nature are presented from the systemic to the complexity [32]. However, enterprise innovation networks cannot be simply described by a linear system, chaotic system or other related theories because of their typical nonlinear and self-organizing characteristics [33], so it is more suitable to adopt the research methods of system modeling and dynamic simulation. ABMS (agent-based modeling simulation) is a bottom-up modeling approach which can easily incorporate micro-level drivers of adoption, bounded rationality, imperfect information, and individual heterogeneity in terms of attributes, behavior and linkages in a social network [34–37]. ABMS has been shown to deal with issues related to complexity and openness given the range of dynamic and unknown environments [38]. Most of simulation research on enterprise innovation network focuses on industrial innovation and cluster innovation. For example, Huang et al. have used ABMS to describe the enterprise innovation network and simulated its dynamic evolution characteristics [39]; Tan et al. constructed a simulation model based on multiple agents to analyze the evolution mechanism of industrial innovation network [33]. Wang et al. have simulated the formation mechanism of integrated innovation network for emerging industries [40]. The complex network analysis and network evolution in the above research is valuable for this paper. Furthermore, the simulation research on knowledge collaboration networks and open-source design are also promising. Zhou et al. have simulated and analyzed the impact of drain strategy for key nodes on robustness in the knowledge collaboration network [41]; Panchal presented an agent-based modelling approach, which enables modelling of the behavior of different entities within a mass-collaborative product development scenario [42]; Seo et al. have demonstrated that the effect of market dynamics and innovation management on performance in SMEs by using ABMS [43]; Zhang et al. introduced the ABMS method to describe the collaboration behaviors of participants in the open-source design process [44]. Most simulation studies on enterprise innovation networks focus on industrial innovation, cluster innovation, and other fields [33,40].

The above studies focus on innovative partnerships between enterprises. The partners are relatively stable. This paper mainly discusses the innovation activities of SMEs in the open-source community led by platform enterprises, and the diversity of agents in the open-source community makes the innovation network more dynamic and uncertain. In this context, the process of SMEs joining open-source innovation networks is full of self-organizing and non-linear characteristics, which can be described and studied by using ABMS.

## 3. Model construction and strategy design

### *3.1. Integrated simulation model*

To describe SMEs' embedding process in open-source innovation networks, the participation of SMEs on an open-source innovation platform—Baidu's apollo platform is investigated. Baidu Apollo is an artificial intelligence open innovation platform released by Baidu on April 19, 2017. It provides an open, complete and secure software platform for partners in the automotive industry and autonomous driving field. It can help enterprises quickly build their own complete autonomous driving system by combining vehicles and hardware systems. According to Baidu Apollo's official website (https://apollo.auto), the institutions currently cooperating with Baidu Apollo include government (city), software enterprises, developer enterprises, OEMs (vehicle manufacturers), hardware enterprises, Tier1 firms, service providers, personal technicians, educational institutions, etc., covering the complete industrial chain of the automotive industry and becoming the most influential open innovation platform for intelligent driving in China. Up to now, based on the information from its official website (www.apollo.auto), Baidu Apollo has obtained a total of 3322 intelligent driving patents, a total of 700,000 lines of open-source code, more than 100,000 developers and more than 220 partners in 165 countries around the world. It is growing into the world's most active open platform for autonomous driving. Among the participants, SMEs account for the majority. We have observed that some companies join the open-source community at the beginning, while others only join the Apollo platform when it reaches a certain scale. At the same time, SMEs can connect software companies, developer companies, hardware manufacturers and many individual developers on the platform. The above enterprises may be famous or be in obscurity. Based on the above examples, the impact of embedding timing and methods on the influence diffusion of SMEs is explored by using the multi-agent model and network model.

Enterprise is embedded in the existing open-source innovation network to interact with the agents. With the spread of enterprise influence, the agents in the network will participate in tasks released by enterprises and provide creative ideas, and the enterprise will form its own subgroup in the network. In this evolutionary process, the enterprise, the agents and the network environment constitute a complex adaptive system. Among them, the agents voluntarily join withdraw from the open-source innovation network, independently choose whether to participate in the task released by the enterprise, voluntarily choose the task according to their own knowledge/skill level, participate in its development process, and constantly update the task information and status until the task is completed. In this process, the enterprise interacts with the agents constantly, and the agents also keep learning, enriching knowledge, improving skills, accumulating experience, and promoting the dynamic evolution of the whole system more effectively, as shown in Figure 1.

The integrated model consists of three parts: network model, influence diffusion model and agent model.

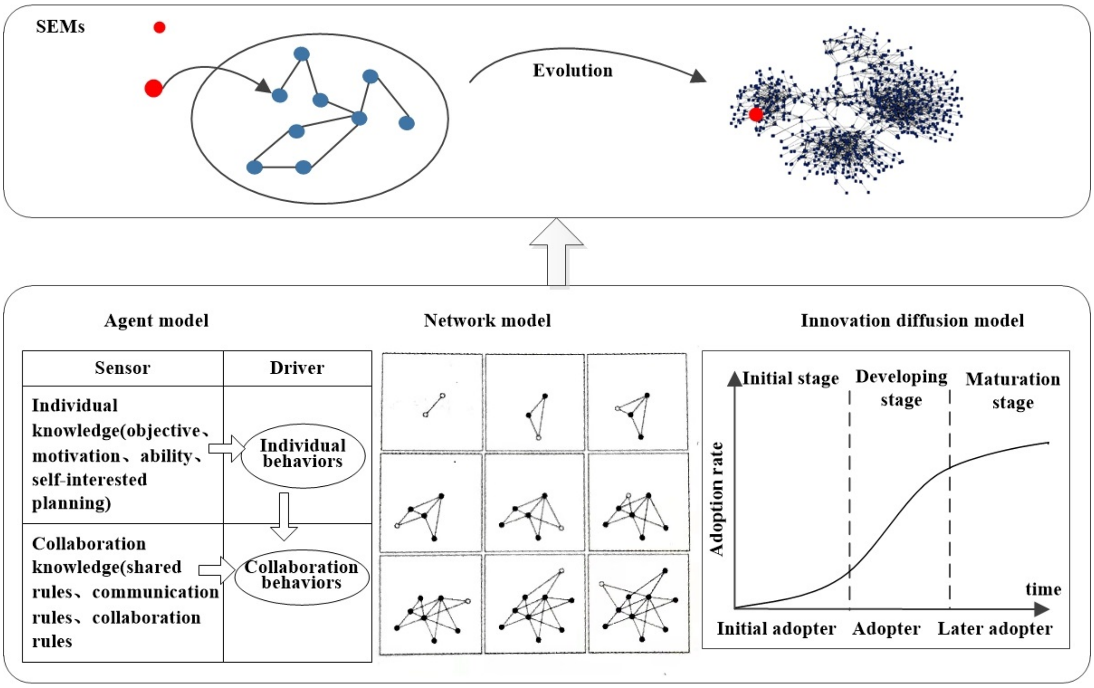


**Figure 1.** Integration model of an enterprise embedded in an open-source innovation network.

(1) Network model

The open-source community is rooted in the Internet, which fits for the scale-free network. Therefore, the BA (Balabasi-Albert) model [45], a classical scale-free network model, is introduced to describe the open-source innovation network. In this model, whenever a new node joins, the existing node in the network has the opportunity to increase its degree. The rate of node $i$ to obtain new links can be calculated by Eq (1):

$$\frac{dk_i}{dt} = m\Pi(k_i) = m\frac{k_i}{\sum_{j=1}^{N-1} k_j} \tag{1}$$

Here, $m$ is the $m$ links that each new node will bring, $\Pi(k_i)$ is the node connection probability with degree of $k_i$, and $k_i$ is the mean in multiple network growth. The BA model assumes that the first node grows continuously from $t = 1$ to form the network, and a new node is added at each time step. Thus, $N$ is equal to $t$. The summation term represents the degree of all nodes except the new node. According to Barabasi's derivation of the degree dynamics, it can be concluded that the degree of nodes in the BA model grows according to the power law, the growth is sublinear, and the nodes added earlier will have a higher degree of nodes due to preference. The speed at which node $i$ obtains new links is calculated by Eq (2):

$$\frac{dk_i(t)}{dt} = \frac{m}{2}\cdot\frac{1}{\sqrt{t_i t}} \tag{2}$$

Here, *t(i)* is the time when the *i-th* node joins the network. In addition, the degree distribution of the BA network obeys the power law distribution, as shown in Eq (3):

$$p_k \sim k^{-\gamma} \tag{3}$$

where $p_k$ is the degree distribution, $k$ is the degree, and γ is the power exponent.

For scale-free networks, the maximum degree is called $p_k$ natural truncation as shown in Eq (4):

$$k_{\max} = k_{\min} \cdot N^{\frac{1}{\gamma - 1}} \tag{4}$$

The power exponent $\gamma = 3.42$ which is set in light of the real Internet calculated by Balabasi [45], and the maximum degree $k_{\max}$ can be calculated by Eq (4), then the nodes in the network with degrees greater than $k_{\max}$ are hub nodes.

(2) Influence diffusion model

The diffusion of enterprise influence in the innovation network can also be considered as the recognition and acceptance from the members. Therefore, this paper adopts the hybrid model of innovation diffusion to describe the diffusion process of enterprise influence, shown as Eq (5):

$$\frac{dA(t)}{dt} = (\alpha + \beta A(t))[P - A(t)] \tag{5}$$

where, $\alpha$ is the coefficient of external influence, which represents corporate publicity. $\beta$ is the simulation coefficient, which represents the internal interaction. After the enterprise is embedded in the open-source innovation network, it will interact with the agents. It will gradually form its own sub-group so that its influence will continue to spread.

(3) Agent behavior function and influence diffusion

The agents in this paper are mainly divided into two categories: enterprise agent and member agents in open- source innovation networks. Among them, the enterprise will be embedded in the innovation network at a certain moment, and will release task requirements, and the member agent will choose independently to connect with the enterprise node. Therefore, this paper specifically describes the selection behavior of members in the agent model. Combined with the above network model and influence diffusion model, the choice behavior of the member agent can be described by the choice utility function, as shown in Eq (6):

$$T\_sel(i) = \mu \cdot Ind(i) + (1 - \mu) \cdot Soc(i) \tag{6}$$

$T\_sel(i)$ indicates that the *ith* agent has chosen the task released by the firm. $Ind(i)$ is the individual choice utility, which can be calculated from Eq (7), and $\mu$ is the weight of $Ind(i)$ which value is [0,1]:

$$Ind(i) = \lambda \cdot pre(i) + (1 - \lambda) \cdot match(i) \tag{7}$$

$pre(i)$ is agent $i$'s subjective preference for a task released by the enterprise with value [0,1], and $\lambda$ is the weight of$pre\ (i)$ with value [0,1]. $match(i)$ is the matching value of agent $i$ for the task, which can be calculated by Eq (8):

$$match(i) = \begin{cases} 1, requirement \le ability(i) \\ 0, requirement > ability(i) \end{cases} \tag{8}$$

Here, requirement refers to the level of ability or experience needed for a task, and *ability(i)* refers to the level of ability or experience of the agent $i$.

$Soc(i)$ is environmental utility. In this paper, we adopt the influence diffusion model to describe the utility. It includes external influence and internal influence (Eq (5)). The level of external influence mainly refers to enterprise's popularity where the value of $\alpha$ is [0,1]. Internal influence is from other members in the network. Therefore, the simulation coefficient $\beta$ can be calculated by the following Eq (9):

$$\beta = \frac{Neibor\_sel(i)}{Neibor\_T(i)} \tag{9}$$

$Neibor\_sel(i)$ is the number of tasks selected by the neighbors of agent $i$, and $Neibor\_T(i)$ is the total number of the *ith* agent's neighbors.

### *3.1. Influence diffusion strategy design*

SMEs lacks of enough capital, technology and talents, so they rely on platforms built by large enterprises to embed their open-source innovation network. In the network, SMEs should improve their influence to get more creative ideas. In this paper, the measurement of enterprise influence is not only the node degree, but also considers whether other agents are willing to choose the task of their release. Therefore, based on the evolution characteristics of open-source innovation networks, the strategy design is carried out from the perspective of embedding timing and connection mode.

#### 3.1.1. Embedding timing

As the open-source community continues to grow and as new members join, others will inevitably leave the network. Accordingly, this paper divides the evolution of the open-source innovation network into four stages, and the specific network evolution is explained as follows:

*Initial stage*: In this stage, the community members are few, the development speed is slow, and the new nodes are few. However, there are almost no exit nodes.

*Development stage*: In this stage, the community members show an accelerated growth trend, and the number of new nodes joining is far more than the number of nodes leaving.

*Mature stage*: In this stage, the speed of new nodes joining slows down, but the number of new nodes is still more than the number of exit nodes.

*Recession stage*: In this stage, the network scale is shrinking. Although there are still new nodes to join, the number is less than the number of nodes to exit.

It is important to note that this paper focuses on the first three phases, given that enterprises usually do not choose declining open-source innovation networks. According to the description of node deletion in literature [45], when the number of deleted nodes is less than new ones, the network is still fit for the characteristics of scale-free. Therefore, the network degree distribution at the three stages still conforms to the power-law rule. Normally, the more well-known the enterprise is, the greater its initial influence will be. The enterprise can quickly attract community members at the initial stage of entering the community and become an influential agent in the community. At that time, $\Pi(k) \sim A + k$, where $A$ is the initial influence.

3.1.2. Connection strategy

Considering the evolution stage of the open-source innovation network and the connection situation of enterprises, this paper designs the connection strategies according to degree correlation theory: heterogeneous connection, same-match connection and random connection. According to the definition [45], heterogeneous connection is defined in this paper such that the enterprises will connect with other agents with different influence to spread its influence in the network. Same-match connection is such that the enterprise chooses the nodes with the same influence to connect. Then at the different stages, the heterogeneous connection can be divided into the following two cases: (1) the enterprise is a node with small degree connecting to the hub node; (2) The enterprise is a hub node connecting to a minor node. The same-match connection refers to the interconnection between hub nodes and hub nodes, and the interconnection between minor nodes and minor nodes.

## 4. Simulation and analysis

### *4.1. Simulation*

4.1.1. Simulation process

We have applied Netlogo 6.1.1 programming to build simulation model including 3 simulation stages shown in Figure 2.

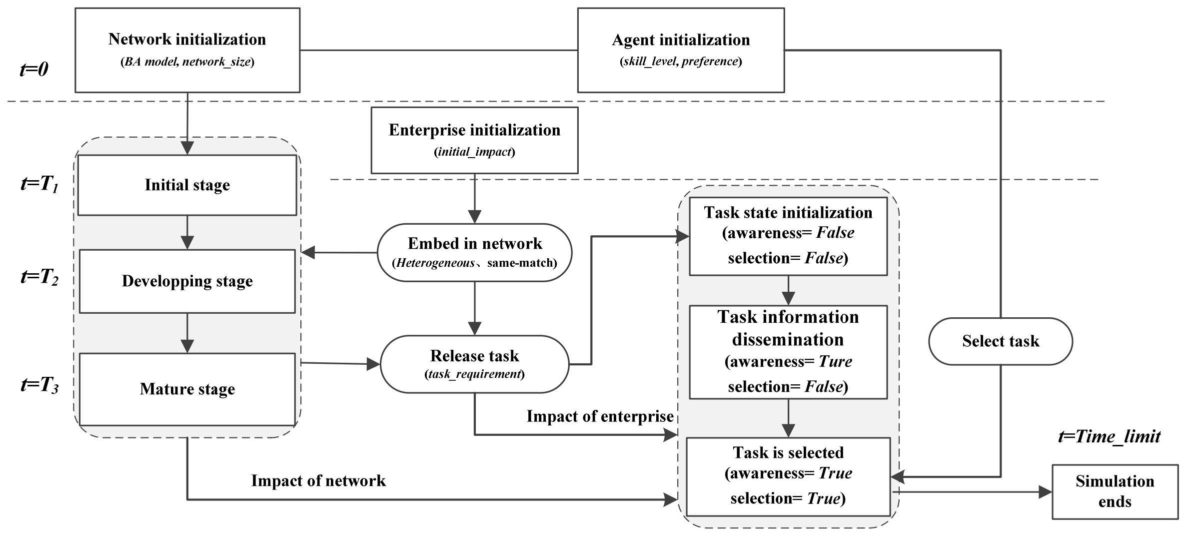


**Figure 2.** Simulation flow chart.

*Stage 1*: network initialization, member agent initialization.

When t = 0, the network is initialized, the community size network_size is set, and the BA network model is adopted. Nodes are members in the open-source community, so the member agent is also initialized and the skill_level and preference value interval are set.

*Stage 2*: the network evolution begins and the enterprise agent is initialized.

The network evolves continuously with simulation steps. Enterprise agents will embed the existing open-source innovation network in different stages with the initial impact initial_impact by the way of heterogeneous or same-matching.

*Stage 3*: task state initialization, enterprise influence diffusion.

After the enterprise is embedded in the network, it will release task information task_requirement, and the task information will be spread accordingly. The influence of the enterprise will gradually spread due to the network connection. The task state is also divided into "awareness" and "selection", which will change with the progress of the simulation step.

### 4.1.2. Simulation scenarios and parameters

The simulation scenarios are shown as Table 1 and the specific parameters are shown in Table 2.

**Table 1.** Simulation experiments design of SMEs' embedding in open-source innovation network.

| Scenarios | Contents | | Purpose | Output | |
|---|---|---|---|---|---|
| | Embedding time | Connection | | Static results | Dynamic results |
| Scenario A | Initial stage | A_1_S<br>A_2_He<br>A_3_R | With the different initial influences and different connection ways, the influence spread of enterprises which embed in the network in different community evolution periods is discussed. | Ratio of task selection | Network evolution process |
| Scenario B | Developing stage | B_1_S<br>B_2_He<br>B_3_R | | | |
| Scenario C | Mature stage | C_1_S<br>C_2_He<br>C_3_R | | | |

**Table 2.** Parameters of simulation experiments.

| Embedding time | Initial stage ($T_1$) | | Developing stage ($T_2$) | | Mature stage ($T_3$) | |
|---|---|---|---|---|---|---|
| scenarios | A_1 | A_2 | B_1 | B_2 | C_1 | C_2 |
| initial_impact | L:10 | H:30 | L:10 | H:30 | L:10 | H:30 |
| α | α = 0.3 | α = 0.7 | α = 0.3 | α = 0.7 | α = 0.3 | α = 0.7 |
| connection ways | Heterogeneous connection; Same-match connection; Random connection | | | | | |
| Hub node | degree > 9 | | degree > 12 | | degree > 15 | |
| rate of network growing | U(0,10) | | U(10,30) | | U(30,100) | |
| network_size | 200 | | | | | |
| Individual utility weight | μ=0.6 | | | | | |
| Preference weight | λ=0.3 | | | | | |
| Subjective preference | U(0,1) | | | | | |
| task_requirement | 10 | | | | | |
| skill_level | U(0,10) | | | | | |
| Hub node can be estimated by formula (4). | | | | | | |

## 4.2. Simulation model verification

(1) Network model verification

The network model in this paper is fit for "scale-free", whose degree distribution is power law. Figure 3 shows the initial network and the one after the enterprise agents are embedded in and they also conform to the power law distribution. It can be explained that the enterprise agent does not destroy the network characteristics. Taking scenario, A-1 as an example, when an enterprise with low initial impact chooses a same-matching connection strategy, there are many nodes connected to it, as shown in the blue edge in the figure. When it selects heterogeneous connection, only one node connects to the network because there are few hub nodes.

(2) Validation of innovation diffusion model

In this paper, we used adopter model to describe the innovation diffusion process. The influence diffusion of enterprises after embedding in the initial, development and maturity stages roughly conforms to the curve trend of the adopter model, especially in the early stage of community evolution. As shown in Figure 4, the trend of degree distribution and innovation diffusion can explain the rationality and effectiveness of the simulation model in this paper.

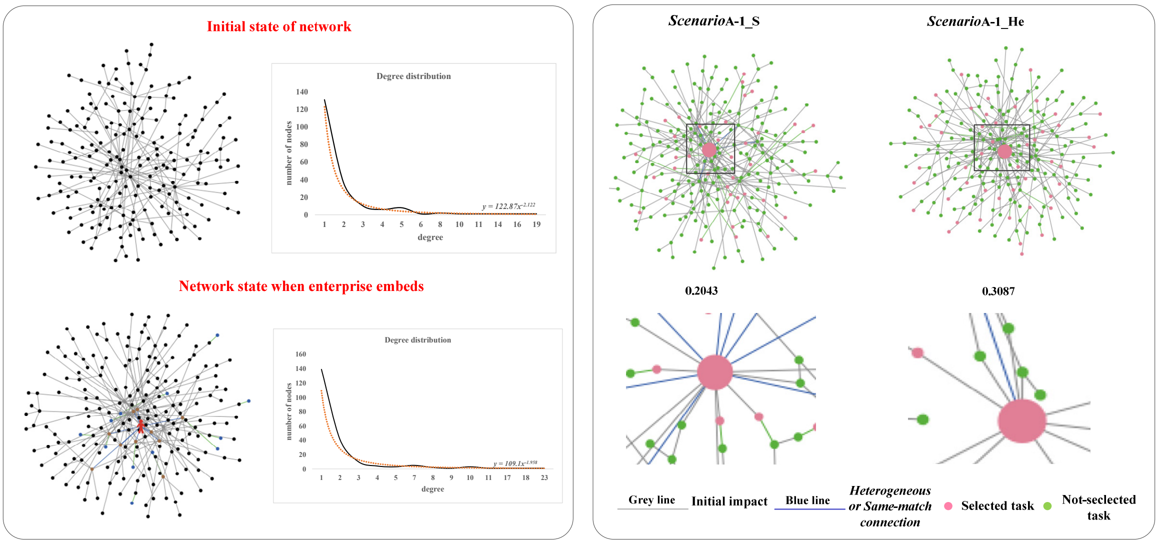


**Figure 3.** Comparison of network status before and after enterprise embedding.

## 4.3. Simulation results and analysis

### 4.3.1. Connection ways and influence diffusion

Table 3 reports the simulation results about the relationships between connection methods and influence diffusion. It suggests that there is no significant difference in either connection or stage for enterprises with low initial impact for which the *p-values* of the two-tailed *Z-test* are 0.072, 0.377 and 0.304 respectively. For enterprises with higher initial influence, at the developing phase, the same-matching connection method is better than the heterogeneous connection method (mean 0.715 > 0.686, $p$ = 0.032); However, at early and mature stages, the effect of connection methods on influence diffusion is not significant, and the two-tailed *p-values* of *Z-test* are 0.306 and 0.428, respectively.

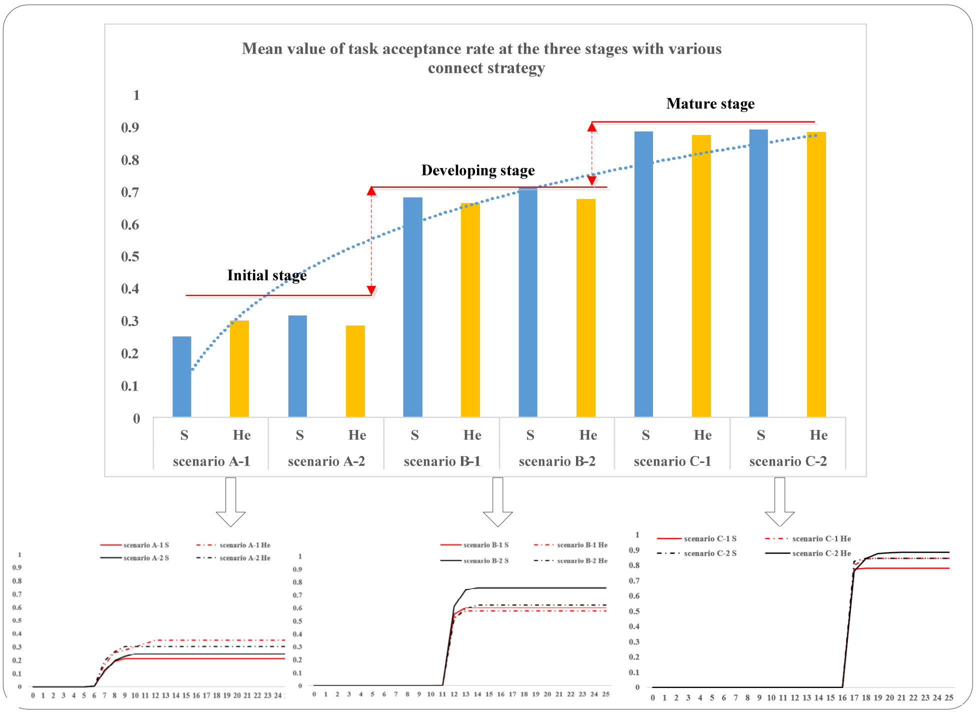


**Figure 4.** Task selection ratio and diffusion curve under different connection ways in different periods.

**Table 3.** Statistical results of task selection proportion under different connection ways in different periods.

| | Initial stage | | | | Developing stage | | | | Mature stage | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Scenario A-1 | | Scenario A-2 | | Scenario B-1 | | Scenario B-2 | | Scenario C-1 | | Scenario C-2 | |
| | S | He | S | He | S | He | S | He | S | He | S | He |
| Mean | 0.251 | 0.298 | 0.315 | 0.284 | 0.682 | 0.663 | 0.715 | 0.686 | 0.886 | 0.874 | 0.892 | 0.884 |
| Cov | 0.013 | 0.023 | 0.030 | 0.015 | 0.0128 | 0.001 | 0.011 | 0.002 | 0.004 | 0.003 | 0.003 | 0.003 |
| Observed value | 50 | | | | | | | | | | | |
| Assumed MD | 0 | | | | | | | | | | | |
| z | –1.797 | | 1.023 | | 0.884 | | 2.136 | | 1.029 | | 0.792 | |
| p(Z <= z) one-tailed | 0.036 | | 0.153 | | 0.188 | | 0.016 | | 0.152 | | 0.214 | |
| z one-tailed threshold | 1.645 | | | | | | | | | | | |
| p(Z <= z) two-tailed | 0.072 | | 0.306 | | 0.377 | | 0.032* | | 0.304 | | 0.428 | |
| z two-tailed threshold | 1.960 | | | | | | | | | | | |

*The significance level of the mean difference is 0.05

### 4.3.2. Embedding timing and influence diffusion

Next, the relationship between embedding timing and influence diffusion are analyzed. In this experiment, low-initial-impact enterprises to conduct same-matching connections are chosen and the specific results are shown in Table 4.

**Table 4.** Statistical results of task acceptance ratio at different evolutionary phases.

| Task acceptance ratio at different evolutionary phases (low-initial-impact and same-matching) | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Description | | | | | | LSD | | | | |
| Scenario | Samples | Mean | S.D. | Min. | Max | (I) | (J) | (I-J) | S.E. | Sig. |
| ScenarioA | 50 | 0.251 | .113 | 0.105 | 0.802 | A | B | -.431* | .0197 | .000* |
| ScenarioB | 50 | 0.682 | .113 | 0.476 | 0.910 | | C | -.636* | .0197 | .000* |
| ScenarioC | 50 | 0.886 | .060 | 0.762 | 0.973 | B | A | .431* | .0197 | .000* |
| Total | 150 | 0.606 | .283 | 0.105 | 0.973 | | C | -.204* | .0197 | .000* |
| | | | | | | C | A | .636* | .0197 | .000* |
| ANOVA | | | | | | | | | | |
| | S. S. | Freedom | M.S. | F | Sig. | | | | | |
| Inter group | 10.527 | 2 | 5.264 | 543.403 | .000 | | | | | |
| Within group | 1.424 | 147 | .010 | | | | | | | |
| Total | 11.951 | 149 | | | | | | | | |
| *. The significance level of the mean difference is 0.05 | | | | | | | | | | |

Table 2 shows the statistical results, we can find that the embedding timing has significantly different effects on their influence diffusion in either stage, all with *p-values* of 0.000. Figure 1 shows the obvious result.

### 4.3.3. Initial impact and influence diffusion

Finally, the relationship between initial impact and influence diffusion is tested. From Figure 5 and Table 5, only in the developing stage, the level of initial impact has a significant influence on the diffusion, with mean values of 0.708 and 0.641, respectively. The two-tailed *p-value* of the *Z-test* is 0.02. In the other two periods, the change of initial impact did not affect the diffusion of enterprise influence, with *p-values* of 0.687 and 0.230 respectively.

Through the above simulation results, the following conclusions can be drawn:

(1) Embedding timing. Based on the simulation results, it can be seen that enterprises' embedding in the network at a different evolution phase has a significant impact on its influence diffusion. It is more important for SMEs to choose the embedding time, that is, the maturity of the platform itself is more important. This is also in line with that mentioned in the literature in that platforms can empower SMEs and promote them to carry out market innovation, product innovation, channel innovation, R&D innovation and organizational innovation [46]. This is because the network external effect can promote all kinds of enterprises to carry out resource cooperation and collaborative innovation, which provides a good cooperation environment for SMEs.

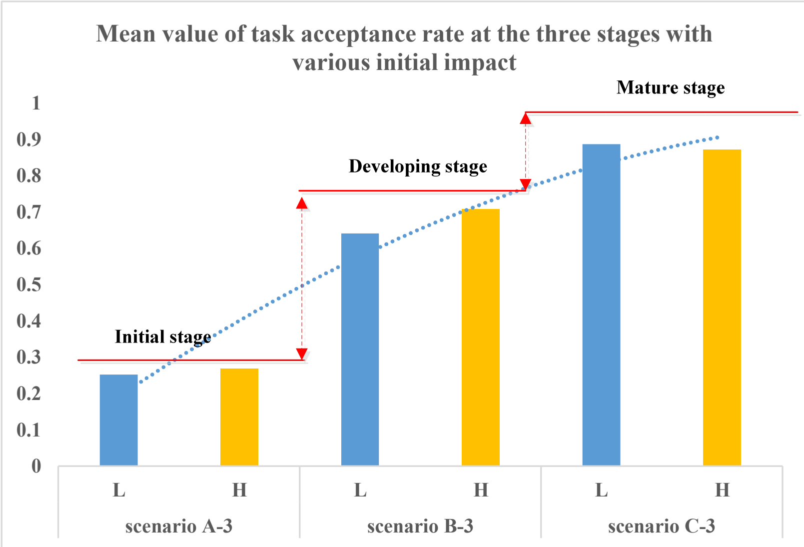


**Figure 5.** Comparison of initial effects in different periods.

**Table 5.** Statistical results of initial impact in different periods.

| | Initial phase | | Developing phase | | Mature phase | |
|---|---|---|---|---|---|---|
| | ScenarioA_3 | | ScenarioB_3 | | ScenarioC_3 | |
| | Low | High | Low | High | Low | High |
| Mean | 0.252 | 0.269 | 0.641 | 0.708 | 0.886 | 0.871 |
| Cov | 0.048 | 0.039 | 0.021 | 0.020 | 0.005 | 0.003 |
| observed value | 50 | | | | | |
| Assumed MD | 0 | | | | | |
| z | –0.403 | | –2.337 | | 1.200 | |
| p(Z <= z) one-tailed | 0.343 | | 0.010 | | 0.115 | |
| z one-tailed threshold | 1.645 | | | | | |
| P(Z <= z) two-tailed | 0.687 | | 0.020* | | 0.230 | |
| z two-tailed threshold | 1.960 | | | | | |

*The significance level of the mean difference is 0.05

(2) Connection method. When the enterprises embed in the community at early and mature stages, no matter what the initial impact it is and which connected strategy it chooses, it has no significant influence on the diffusion. This further confirms that the state of community is important. However, it can be seen that enterprises with low initial impact choose heterogeneous connections relatively better in the early evolution stage ($p$ = 0.036 for one side of the *Z-test*, but not significant for two sides). For high-impact enterprises embedded in the community development period, it is better to choose the strategy of same-matching, which is often mentioned in the paper [20] as the "strong cooperation" method.

(3) Initial impact. Initial impact has a significant influence on the enterprises embedded in the network during the community development period, which indicates that when the community is just starting up, the network scale is small, and the influence scope of the embedded enterprises is limited regardless of their own influence. On the contrary, when community development enters the mature stage, there are many participants and the network scale is huge, which also makes the effect of its

initial impact insignificant. However, at the developing phase, enterprises with high initial impact can establish connection advantages in the network, which has a positive effect on their influence diffusion ($p$ = 0.02 for two side of the *Z-test*).

In summary, it can be found that the role of the community as a platform is more significant than that of the enterprise itself. In addition, it is relatively better for enterprise to embed in the community in the developing phase. At this time, the community has a certain scale, which can provide innovation resources for enterprises, and still has the potential for continued development. Although in the experiment of connection mode, there are not many results with significant differences, it can be seen that connecting with hub nodes is a better choice. With many results with significant differences, it can be seen that connecting with hub nodes is a better choice.

## 5. Conclusions

### *5.1. Research results and management suggestions*

The internal management model of businesses has undergone a series of changes with the emergence of the digital economy, among which the innovation and R&D models tend to be open and open-source. SMEs always rely on the open-source platform constructed by major corporations to incorporate their open-source innovation network since they lack the necessary resources in terms of finance, technology, and skill. Based on the theory of complex adaptive systems, network science and innovation diffusion, the firm, nodes in the innovation network, and the open-source ecosystem are all viewed in this research as complex adaptive systems: the enterprise described by the intelligent hierarchy agents are embedded in the network at different stages of community evolution, which affects how much their influence diffuses. The integrated simulation model in this paper describes the interaction between enterprise and community members, the results of the embeddedness of enterprises with different initial influences in different evolution periods of community networks are discussed.

Based on the above research results, this paper puts forward the following management suggestions:

(1) Use the platform but do not depend on it. Combined with the existing research results and the simulation results of this paper, the importance of an open-source innovation platform is not to be doubted. Kapoor et al. [47] and Parker et al. [48] have also emphasized that platforms play an important role in the complex competitive environment. The platform can provide resources for SMEs to participate in commercial ecological co-construction and value co-creation [49]. However, innovation platforms also absorb the creativity and resources of SMEs, and it is easy for SMEs to over-rely on the platform, which will make it more difficult to carry out further independent innovation. Therefore, how to maintain independence and autonomy while relying on the platform is a big problem for SMEs. For example, the dependent upgrading strategy proposed by Chen et al. [20] includes three steps: mutual integration, symbiosis and independence, which is worthy of reference; Wang et al. [40] provide a network game to analyze the innovation network structure and in their network model, enterprises can actively choose to invest in R&D or establish links with others to absorb R&D spillovers.

(2) Both efficiency and cost. Through the study of this paper, it is found that choosing to embed the network in the mature stage or selecting hub nodes for connection can effectively improve the speed of influence diffusion. However, it is worth noting that in practice, the cost of connecting with

hub nodes, the cost of embedding in mature networks, and the maintenance cost after embedding in networks cannot be ignored. When considering practical issues such as cost, company development, etc., SMEs may join at any stage. Therefore, SMEs should make scientific decisions after assessing the above costs in combination with their own conditions. For example, in the early stages of development, the connection method does not have a significant impact on proliferation, so it is necessary to connect as many nodes with as small a degree as possible at a given cost thus connecting more community participants, which may be individuals or enterprises. Establish partnerships with them to provide more possibilities for subsequent business development. However, at the developing stage, connecting with hub nodes is better.

### *5.2. Limitations and prospect*

(1) Limitations. This paper assumes that all the connections of an enterprise embedded in the network exist at all times after establishment. However, the connection can be broken at any time in the actual open-source innovation. Furthermore, while the multi-agent simulation method can accurately predict the trend, it cannot provide correct data [50], necessitating further research by merging empirical investigations.

(2) Prospect. According to previous research, SMEs can boost their capacity for innovation and implement digital transformation by integrating an open-source innovation network. Future research will concentrate on the game between SMEs and platforms, cost management, and other elements.

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## Conflict of interest

The authors declare there is no conflict of interest.

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