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ORIGINAL ARTICLE

# Modelling and simulating knowledge diffusion in knowledge collaboration organisations using improved cellular automata

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**ABSTRACT**
Knowledge diffusion plays a vital role for the success of knowledge collaboration organisation (KCO). From the view of micro knowledge exchange activities, this paper aims to study the process and rule of knowledge diffusion in KCO. First, consulting the SEIR epidemic propagation model, this paper divides the individuals into different knowledge statuses, and depicts the process of knowledge diffusion. Considering the influence of individual heterogeneity and mobility on knowledge diffusion, this paper develops an improved cellular automata model with heterogeneity and mobility to study the knowledge diffusion in KCO. By using simulation method, we study the impacts of the distribution pattern of initial knowledge disseminator, knowledge accessibility among individuals, individual mobility and knowledge quitting rate on knowledge diffusion performance. The results reveal some valuable enlightenments about how to improve the knowledge diffusion performance in KCO, which are helpful to the managers to carry out knowledge management strategies and actions.

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**KEYWORDS**
Knowledge collaboration organisation; knowledge diffusion; SEIR model; heterogeneity and mobility; cellular automata

## 1. Introduction

With the tendency of global economic integration and the uncertainty of market competition environment, firms increasingly adopt collaborative knowledge innovation mode by cooperating with the research institutes, suppliers, customers, and other collaborators to obtain the knowledge complementary advantages (Nieves, Quintana, & Osorio, 2016). Aiming at collaborative knowledge innovation, the virtual enterprise alliance, collaborative product development union and cross-functional team, etc. all can be called as knowledge collaboration organisations (KCOs) (Feng & Fan, 2012). KCOs always consist of collaborative members with different backgrounds of organisations, knowledge domains, and even cultures. There are the asymmetries of knowledge structure and knowledge stock among members of KCO, which can lead to the frequent and extensive knowledge diffusion in KCO. In the context of KCO, knowledge diffusion is not only conducive to improving the knowledge stock of members and KCO, but also simulating the knowledge complementary advantages among members, which can enhance the knowledge innovation level of KCO (Roper, Love, & Bonner, 2017).

Recently, knowledge diffusion has been widely studied, such as the factors of knowledge diffusion (Joia & Lemos, 2010; Shi & Li, 2010), the approaches to enhance knowledge diffusion (Jeon, Kim, & Koh, 2011; Wu & Zhu, 2012) and the models of knowledge diffusion (Kim & Park, 2009; Wang, Guo, Yang, & Liu, 2015), etc. Although the significance of knowledge diffusion for organisational performance has been extensively investigated in various scenarios, we have seen few formal quantitative methods and models to study the knowledge diffusion process and rule, which is the foundational issue in the knowledge diffusion research. Furthermore, the existing research mainly focused on the qualitative analysis of knowledge diffusion process or the mathematical method research on knowledge diffusion from the macro-perspective. However, for the knowledge diffusion process in the context of KCO, the interactions among members show the features which are not shared by the knowledge exchange between the single knowledge sender and receiver. The fact that knowledge diffusion is a complex process generated by the micro-knowledge exchange activities among individual is also neglected by the existing research. Therefore, the purpose of this paper is to propose a systematic and quantitative model to investigate the knowledge diffusion process and rule in KCO. To do this, this paper adopts the complex system modelling method, that is, cellular automata (CA), to study the knowledge diffusion issue from the perspective of micro-knowledge exchange activity among members, which can shed a light on the better understanding of knowledge diffusion mechanism, and provide a theoretical support to improve the knowledge diffusion

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efficiency and knowledge management performance of KCO.

The remainder of this paper is organised as follows. Section 2 reviews the related literatures about the issue of knowledge diffusion. The improved CA model of knowledge diffusion is built in section 3. Section 4 adopts the simulation method to study some key factors' impact on the knowledge diffusion performance, and propose the knowledge management implications for KCO. Finally, the conclusions of this paper are outlined in section 5.

## 2. Literature review

Knowledge diffusion is the process by which knowledge is communicated through certain channels over time among actors in a social system (Meng et al., 2003). As implied by the organisational knowledge-based research, the core competitiveness of organisations essentially depends on their capability of acquiring, diffusing, using and creating knowledge (Carneiro, 2013; Lee, Foo, Leong, & Ooi, 2016). Knowledge is increasingly diffused among organisationally dispersed members which generates more and wider mutual knowledge learning and collaboration to better encourage knowledge innovation (Su, Yang, & Zhang, 2017). Therefore, the issue of knowledge diffusion has been a hotspot in the current research. Among them, numerous scholars paid much attention on the factors of blocking and promoting knowledge diffusion. Haldin (2000) stated that the main obstacles to transferring and diffusing knowledge lay in the unconsciousness of knowledge and the difficulty to express it. In the context of knowledge collaboration, the efforts to diffuse knowledge are often impeded by individual tendencies to guard or selectively share their knowledge (Gilmour, 2003). Thus, Zahra and George (2002) and Su et al. (2017) suggested that organisations should carry out more effective approaches and routines to acquire, transfer, and share knowledge across the organisational boundary. On the individual level, many researches have focused on the factors of individual characteristic. For instance, the knowledge absorptive capacity enables people and organisations to identify and acquire the external knowledge resource (Cohen & Levinthal, 1990). In turn, the individuals involved in knowledge diffusion not only absorb knowledge, but also simultaneously transfer knowledge. Hence, Mu, Tang, and Maclachlan (2010) took into account the disseminative capability of knowledge holders and the absorptive capability of knowledge recipients simultaneously to get a full understanding of the knowledge transfer process. From the view of individual behaviour, Zhang, Qiao, and Wang (2008) investigated the impact of individual knowledge learning willingness and self-efficacy on knowledge diffusion performance. Meanwhile, the relationships and interactions among individuals also greatly affect the knowledge diffusion performance. Tamjidyamcholo, Baba, Tamjid, and Gholipour (2013) stated that the higher trust between people stimulated them to exchange and share knowledge more actively. Singh (2005) studied the influence of interpersonal tie, social distance, geographic localisation, and organisation boundary on the intra-regional and intra-firm knowledge diffusion. Considering the heterogeneity of knowledge, Hansen (1999) argued that strong relationships promoted the transfer of complex knowledge, while weak ties promoted the transfer of simple knowledge. The above works make us expecting that a comprehensive knowledge diffusion research should consider two important aspects: the individual knowledge absorptive capabilities and transfer capabilities, and the knowledge exchange relationships among individuals.

The other research stream focuses on using the mathematical method and the complex network method to model the knowledge diffusion process. Tsai (2008) introduced five kinds of knowledge diffusion patterns, including knowledge internalisation, knowledge externalisation, knowledge improvement, external knowledge acquisition, and internal knowledge release, to construct the knowledge diffusion model which integrated the intra-firm and inter-firm diffusion processes simultaneously. Qi et al. (2008) proposed a system dynamic model to study knowledge diffusion within enterprise, and discussed the rules of knowledge diffusion. However, in their conceptual model, the research elements are a little general and crude, and the important factors such as knowledge subject characteristic, knowledge diffusion mechanism, and channel are neglected. From the view of collaboration relationship, Ozel (2012) established a conceptual model of knowledge diffusion among research collaboration groups, and investigated the organisational structure characteristics with efficient knowledge diffusion and their knowledge diffusion strategies. Analysing the above works, we can get that the mathematical models of knowledge diffusion mainly study the process of knowledge diffusion from the top down, which focused on the macro-process and features of knowledge diffusion. Meanwhile, it is another important research branch to build the knowledge diffusion model using the complex network method. Kim and Park (2009) proposed a complex network model that integrated knowledge exchange and knowledge creation to reveal the connections among the network structure and the knowledge diffusion performance, and stated that the small-world network was the optimal network structure to facilitate knowledge diffusion. Considering the individual characteristic and their knowledge exchange relationships, Su et al. (2017) built a weighted network model to measure knowledge diffusion efficiency in R&D network, and draw a conclusion that the organisational structure, individual characteristic and knowledge exchange relationship were the significant factors affecting knowledge diffusion. Wang et al. (2015) presented a knowledge diffusion hyper-network model based on the idea that knowledge would spread from the target node to all its neighbours in terms of the hyper-edge and knowledge stock, and implied that the hyper-network model was faster to diffuse knowledge than the traditional knowledge diffusion model. The aforementioned efforts focus on the influence of network structure and network properties on knowledge diffusion performance, which contribute noticeably for the understanding of knowledge diffusion process and factors in the context of networks. However, these works seldom studied the process and rules of knowledge diffusion from the view of micro-knowledge exchange among individuals inside collaboration organisations.

Knowledge diffusion is a complex process which is formed by the micro-knowledge interaction among individuals. From the micro-perspective of knowledge exchange among individuals, some scholars tried to use the complex system method and the epidemic spread theory to study the knowledge diffusion process and rule. Zhu, Lai, and Nie (2006) developed a CA model to study the technology spillover process, and got the conclusion that the R&D ability and absorptive capability were the key factors affecting technology spillover performances. Lai and Wang (2006) established a CA model for knowledge spread, and the factors and rules of tacit knowledge spread among individuals were simulated. On the other hand, considering the similarity with epidemic spread process, Eugster, Guerraoui, Kermarrec, Massoulieacute, and Massoulié (2004) developed an epidemic spread algorithm to investigate the process and mechanism of information dissemination in large peer-to-peer system. Using the thought of epidemic spread, Bass (1969) built an epidemic diseases model for innovation diffusion, and proposed a quantitative approach to monitor the diffusion process. Based on the above research achievements, this paper will adopt CA, which is a complex system modelling method from the bottom up (Lai & Wang, 2006), to study the knowledge diffusion in KCO from the micro-view of knowledge exchange among KCO members. Moreover, the thought of epidemic spread model is introduced to depict the knowledge diffusion process in KCO. On this basis, considering the influence of individual characteristic on knowledge diffusion, this paper will develop an improved CA model with heterogeneity and mobility to study the impact factors, process and rule of knowledge diffusion. Thus, this paper aims to shed some light on the quantitative analysis of knowledge diffusion process and rule in KCO, which will provide managers with a decision support to manage the knowledge diffusion process and forecast the trend of knowledge diffusion in KCO.

## 3. The improved cellular automata model of knowledge diffusion in knowledge collaboration organisation

### 3.1. *The knowledge diffusion process based on SEIR*

Researches have shown that the knowledge diffusion process can be approximately seen as an infection process (Kiss, Broom, Craze, & Rafols, 2010). There are many similarities between knowledge diffusion and epidemic spread. Knowledge diffusion is the process of increasing the total amount of knowledge, while the epidemic spread is the process of increasing the total amount of virus. Knowledge diffuses and shares through the exchange relationship between individuals, and epidemic spreads among organisms through air, food, body fluids, etc. From the perspective of information theory, knowledge diffusion and epidemic spread are essentially similar, which both consist of four elements: information, source, channel, and destination. In the study of epidemic spread, the SEIR model is a classic model for the epidemic with incubation stage. The SEIR model divides the crowd into four status, which respectively are the suspicious, the exposed, the infected, and the removed (Biswas, Paiva, & Pinho, 2014). Employing the thinking of SEIR model, the knowledge diffusion process can be described as follows: in the knowledge diffusion process, individuals communicate and exchange knowledge during collaboration, and the individuals with knowledge can "infect" the individuals without knowledge to understand, master the certain knowledge, and get the ability to "spread" knowledge. Similar with the "incubation stage" of SEIR model, the individuals without knowledge always need to further absorb and learn knowledge before gaining the ability to spread the knowledge. Only passing the "incubation stage" successfully can the individuals without knowledge diffuse the knowledge to other individuals. Meanwhile, similar with the "removed status" of SEIR model, knowledge forgetting is an inevitable phenomenon in the knowledge diffusion process. After individuals contacting and understanding the knowledge, there are always two forms of knowledge forgetting mechanism (Wensley & Navarro, 2015): the passive forgetting based on the forgetting mechanism of human brain and the active forgetting based on the judgment of knowledge value and learning cost. Based on the above knowledge diffusion process and the SEIR model, this paper classifies the individual knowledge status into five types: knowledge susceptible (S), knowledge contactor (E), knowledge disseminator (I), knowledge forgetter (R), and knowledge quitter (Q). Their definitions are shown as follows:

Knowledge susceptible (S): These individuals do not master the specific knowledge, and they can become the knowledge contactors (E) after exchanging the knowledge with knowledge disseminator (I).

Knowledge contactor (E): These individuals have preliminarily contacted and known the specific knowledge, while they don't have the ability to transfer and diffuse the knowledge.

Knowledge disseminator (I): These individuals have completely absorb the specific knowledge, and gained the ability to diffuse the knowledge. We suppose that the status of knowledge disseminator will maintain unchanged.

Knowledge forgetter (R): These individuals have forgotten their preliminarily contacted knowledge due to the passive forgetting mechanism, but they can still exchange knowledge with knowledge disseminator (I) to become knowledge contactors (E) again.

Knowledge quitter (Q): These individuals have abandoned their preliminarily contacted knowledge due to the active forgetting mechanism. In this work, we suppose the knowledge quitter will not continue to contact the knowledge, so their status will maintain unchanged.

Based on the above definitions, the knowledge exchange relationship and status transition among the above five types of individuals is shown in Figure 1.

As seen in Figure 1, the knowledge susceptibles (S) preliminarily contact and understand the specific knowledge via knowledge exchange with knowledge disseminators (I). After the knowledge exchange, the knowledge susceptibles (S) can become the knowledge contactors (E) with different probabilities. Through the further knowledge learning and absorption, the knowledge contactors (E) will transform into the knowledge disseminators (I) with a certain probability. Meanwhile, based on the passive forgetting or active forgetting mechanism, the knowledge contactors (E) may also turn into the knowledge forgetters (R) or knowledge quitters (Q) with certain probabilities. The knowledge quitters (Q) will not join the knowledge exchange, and their status will remain unchanged. The knowledge forgetters (R) will still seek the knowledge exchange with knowledge disseminators (I), and still stand a chance to become the knowledge contactors (E) again.

## 3.2. *Overview of cellular automata*

CA is a dynamic model which is discrete in space and time (Balzter, Braun, & Köhler, 1998; Su, Yang, & Yang, 2015). CA consists of a finite number of cells, and each cell is endowed with a state which would change at every time step according to a local transition rule. The local transition rule can evolve a global complex behaviour of macro-system as time goes on (Wolfram, 1984). Because of the discreteness, synchronisation, and locality of CA, it has significant advantages to investigate the spread and diffusion issues. The CA has been widely applied by scholars to the study of complex spread and diffusion problems such as epidemic spread (Khabouze, Hattaf, & Yousfi, 2015), fire spread (Iudin, Sergeyev, & Hayakawa, 2015), and innovation diffusion (Guseo & Guidolin, 2009). As for the knowledge diffusion problem, CA does not need to establish and solve the complex mathematical models. The advantage of CA (i.e., the local simple rules can evolve global complex behaviour) can depict the knowledge diffusion process on the micro-level. CA can model the micro-knowledge exchange activities among individuals through the local transition rules, and then get the knowledge diffusion process of the whole system via the multiple iterations and evolutions. Moreover, we can monitor the state of knowledge diffusion process at any time, so as to realise the visual analysis of the whole knowledge diffusion process. Based on the above analysis, CA is very suitable for the research of knowledge diffusion problems, and this paper intends to apply the CA to study the knowledge diffusion process in KCOs.

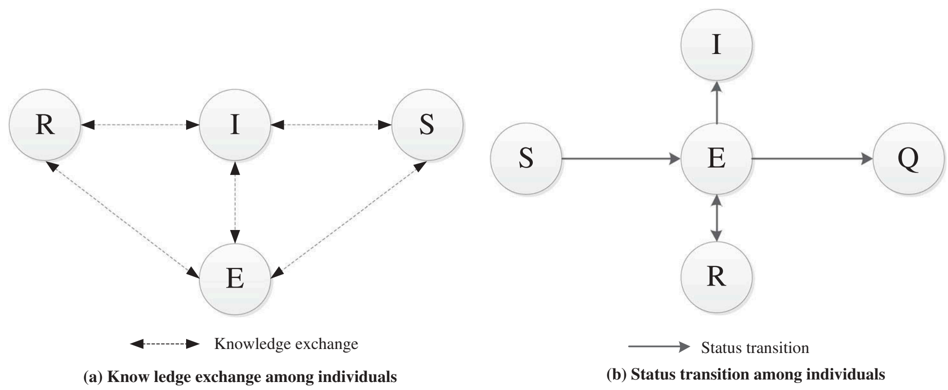



**Figure 1.** The knowledge exchange and status transition among the five types of individuals.

Structurally, the CA can be expressed by a four tuples.

$$C = (L, \Omega, V, F) \tag{1}$$

where, $C$ denotes the CA model, a cellular space L denotes the cellular space, $\Omega$ denotes the state space, $V$ denotes the neighbourhood template and $F$ denotes the local transition rule.

In the real-knowledge diffusion process, the involved individuals have heterogeneity, which reflects in the different knowledge transfer and absorption capacity, knowledge forgetting rate and the judgment of knowledge value and learning cost. However, in most CA-based researches, the cells are always regarded as the homogeneous objects, which imply that there is no difference among individuals involved in knowledge diffusion. Obviously, the homogeneous CA models are difficult to reflects the reality of knowledge diffusion. On the other hand, during the knowledge diffusion process, individuals are always in the status of moving to better exchange knowledge with each other. Therefore, the mobility of individuals also should be given enough attention in the process of knowledge diffusion. Based on the above analysis, this paper will propose an improved CA model considering the individual heterogeneity and mobility to study the knowledge diffusion in KCOs, which can better reflect the reality of knowledge diffusion in KCOs.

### 3.3. *The improved cellular automata model of knowledge diffusion*

The improved CA model of knowledge diffusion considering the individual heterogeneity and mobility is built as follows.

#### 3.3.1. *Cellular space L*

Suppose that $L$ is a two-dimensional cellular space with $\mathrm{n} \times n$ cells, and $L$ represents the whole KCO. The cell $L(i,j)$ in $L$ denotes the individual in KCO. The cellular space $L$ can be denoted by the following equation:

$$L = \{L(i,j) | 1 \le i \le n, 1 \le j \le n\} \tag{2}$$

where, $i$ and $j$ are respectively the coordinate value of $L(i,j)$ in L.

In the cellular space $L$, we can further propose a concept of "cell distance." The cell distance represents the organisational hierarchy distance and interpersonal distance among individuals, which reflects the strength of knowledge exchange relationship. The shorter the cell distance is, the stronger the strength of knowledge exchange relationship is. The cell distance $\mathrm{d}_{L(i,j)}^{L(k,l)}$ between cells $L(i,j)$ and$L(k,l)$ can be denoted by their Euclidean distance:

$$\mathrm{d}_{L(i,j)}^{L(k,l)} = \sqrt{(i-k)^2 + (j-l)^2} \tag{3}$$

where, k and $l$ are respectively the coordinate value of $L(k,l)$ in $L$.

#### 3.3.2. *State space Ω*

Based on the classification and definition of the knowledge status, we set $S_{L(i,j)}^t = \{0,1,2,3,4\} \in \Omega$ as the state space. The value of $S_{L(i,j)}^t$ represents the state of cell $L(i,j)$ at time $t$. Specifically, $S_{L(i,j)}^t = 0$ denotes the state of knowledge susceptible (S), $S_{L(i,j)}^t = 1$ denotes the state of knowledge contactor (E), $S_{L(i,j)}^t = 2$ denotes the state of knowledge disseminator (I), $S_{L(i,j)}^t = 3$ denotes the state of knowledge forgetter (R) and $S_{L(i,j)}^t = 4$ denotes the state of knowledge quitter (Q).

#### 3.3.3. *Neighbourhood V*

In this paper, the neighbourhood determines whether there is knowledge exchange relationship among individuals or not. The traditional CA models define two classic neighbourhood modes, which are the Von Neumann neighbourhood and the Moore neighbourhood. In order to better reflect the knowledge availability among individuals, this paper extends the above classic neighbourhoods (see Figure 2).

Based on the above analysis, this work further proposes a concept of knowledge availability. The knowledge availability among individuals depends on the two factors of neighbourhood type and cell distance. Specifically, the neighbourhood type determines the knowledge exchange scope of individuals, and the cell distance determines the knowledge exchange relationship strength among individuals. Both of the above factors jointly determine the value of knowledge availability among individuals.

#### 3.3.4. *Transition function F*

The successful transition from knowledge susceptible to knowledge contactor via knowledge exchange depends on the knowledge acquisition rate between them. In this work, we suppose that the knowledge acquisition rate is mainly codetermined by the knowledge learning capability of knowledge susceptible, and the transfer capability of its neighbour knowledge disseminator, and the cell distance between them. The knowledge acquisition rate is positive with the knowledge learning capability of knowledge susceptible and the transfer capability of the neighbour knowledge disseminator. Meanwhile, the shorter the cell distance is, the stronger the knowledge exchange relationship is. Therefore, there is a negative relationship between the knowledge acquisition rate and cell distance. Furthermore, the knowledge acquisition rate can be obtained according to the knowledge exchange strategy among individuals.

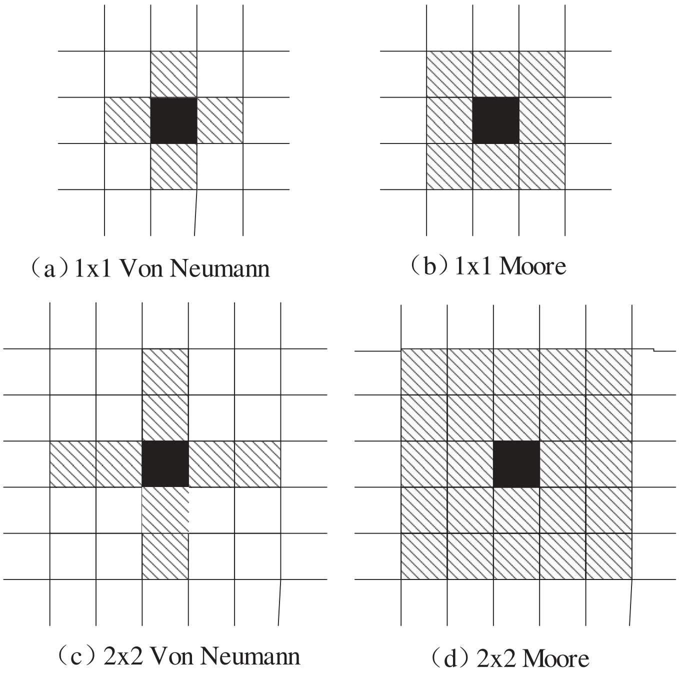



**Figure 2.** The extended cellular neighbourhood.

From the view of epistemology, combining the subjective and objective factors of individuals, we suppose that the individuals involved in knowledge diffusion are the rational people, thus they will chose the best strategy that comprehensively consider the knowledge learning capability, the knowledge transfer capability and the cell distance to get the best knowledge acquisition rate. Based on the above analysis, the knowledge acquisition rate $P^tL(i,j)\cdot L(k,l)$ between $L(i,j)$ and $L(k,l)$ at time $t$ can be obtained by the following function:

$$P^tL(i,j)\cdot L(k,l) = \max_{L(k,l)\in V_{L(i,j)}}\left\{\frac{1}{\mathrm{d}_{L(i,j)}^{L(k,l)}}\sqrt{fL(i,j)\cdot gL(k,l)}\right\} \quad (4)$$

where, $V_{L(i,j)}$ is the neighbourhood set of $L(i,j)$. $f_L(i,j)$ and $g_L(k,l)$ are respectively the knowledge learning capability of knowledge susceptible $L(i,j)$ and the knowledge transfer capability of knowledge disseminator $L(k,l)$. In order to reflect the individual heterogeneity, we that suppose $f_L(i,j)$ and $g_L(i,j)$ are in accord with $N(0,1)$, thus the individuals have different knowledge learning capability and transfer capability.

### 3.3.5. *The individual heterogeneity*

The individual heterogeneity is reflected in that individuals have different knowledge learning capability, transfer capability, forgetting rate and quitting rate. After the knowledge susceptible becoming the knowledge contactor, they may further turn into the knowledge forgetter and knowledge quitter according to the knowledge forgetting rate and quitting rate. Especially, the knowledge forgetter will still seek knowledge exchange with knowledge disseminator, and then they can turn into the knowledge contactor again with certain probabilities. Meanwhile, because that the knowledge forgetter has contacted with the knowledge disseminator before, the knowledge forgetter has some foundation for the certain knowledge. Therefore, the learning capability of knowledge forgetter should be higher than its former status as a knowledge susceptible. Suppose the learning capability of knowledge forgetter $L(i,j)$ is $f^RL(i,j) = \sqrt[D+1]{fL(i,j)}$, where D is the times of $L(i,j)$ turning into knowledge contactor before. The above definition shows that with the times that knowledge forgetter becomes knowledge contactor increasing, its learning capability will subsequently increase. On the other hand, the transfer capability of knowledge disseminator may increase in the practice of exchanging knowledge. However, the growth of transfer capability is always very slow in reality. Hence, we suppose that the transfer capability of knowledge disseminator remains unchanged during the knowledge diffusion process.

Due to the different knowledge learning and absorption capability of individuals and the different value, complexity and learning cost of knowledge, the knowledge contactor will become the knowledge disseminator, knowledge forgetter or knowledge quitter with certain probabilities at the next moment. The transition possibilities into different knowledge status are denoted by the knowledge absorption rate $I_L(i,j)$, forgetting rate $R_L(i,j)$ and quitting rate $Q_L(i,j)$, which are in accord with $N(0,1)$, and there is $I_L(i,j)+R_L(i,j)+Q_L(i,j)=1$. Furthermore, when an individual turns into knowledge contactor repeatedly, due to the learning reinforcement effect, we suppose its knowledge forgetting rate and quitting rate will decrease accordingly with the transition times increasing. In this paper, we set the knowledge forgetting rate as $R'_L(i,j) = R_L(i,j)^{D+1}$, and set the knowledge quitting rate as $Q'_L(i,j) = Q_L(i,j)^{D+1}$, thus the knowledge absorption rate can be obtained as $I'_L(i,j) = 1 - R'_L(i,j)^{D+1} - Q'_L(i,j)^{D+1} > I_L(i,j)$.

#### 3.3.6. *The individual mobility*

In this paper, we adopt the thought of random walk CA to describe the individual mobility (Eloranta, 1993; Tan et al., 2013). The proportion of mobile individuals and the distance of movement in random walk are the two most important parameters, which should be taken into consideration. The rules of random walk CA are similar with the traditional CA. But it needs a random walk during every evolution time. The proportion of mobile individuals is taken to be $\psi$, while the maximum distance of movement is taken to be $MD$. The individuals involved in the movement are chosen with the help of a pseudorandom number generator (Knuth & Plass, 1981). For the selected individual $L(i,j)$, two independent random numbers, $md_i$ and $md_j$ ($|md_i|, |md_j| \le MD$), are generated. Then, the individual $L(i,j)$ and $L(i+md_i, j+md_j)$ are mutual interchanged, and a time of random walk is done.

## 4. Simulations

### 4.1. *The simulation hypotheses and parameters*

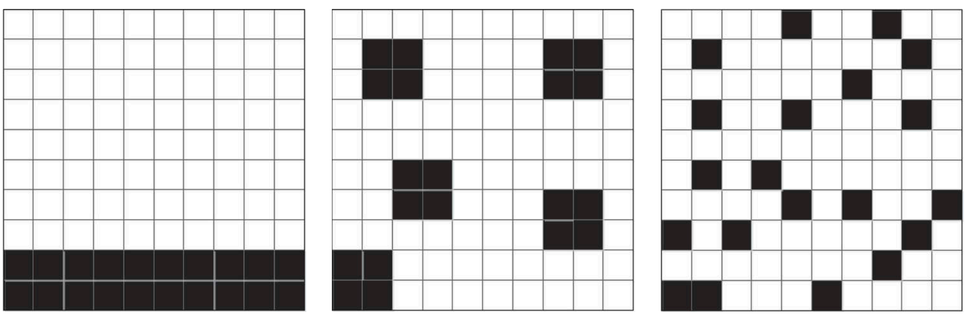
Based on the improved CA model of knowledge diffusion in KCOs, this work mainly studies the influences of the distribution pattern of initial knowledge disseminators, knowledge availability among individuals, knowledge quitting rate of individuals, maximum distance of movement, and the proportion of mobile individuals on the knowledge diffusion performance. For the simulation, this paper makes the following simulation hypotheses considering the key factors.

(1) This paper focuses on the introduction and diffusion of the certain knowledge in KCOs.
(2) Suppose that the KCOs have stable organisational structure and constant members. Thus, there are no changes of organisational structure and members during the knowledge diffusion process.
(3) Because of the heterogeneity and mobility of individuals, for the certain knowledge, knowledge susceptibles have different learning capabilities, knowledge disseminators have different disseminative capabilities, and knowledge contactors have different forgetting rates and quitting rates due to the different knowledge value, complexity and learning cost.
(4) For the certain knowledge, there are few knowledge innovators to obtain knowledge by independent innovation. Thus, we assume that individuals can only obtain knowledge by mutual knowledge exchange and transfer with the knowledge disseminators.

As for the simulation parameters, we set the cellular space as a two-dimensional array with $20 \times 20$ cells, which means that the KCO has 400 individuals. At the initial time of knowledge diffusion, there only are the knowledge disseminators and knowledge susceptibles. In this work, we suppose that the distribution patterns of initial knowledge disseminators mainly include the monopolistic distribution, the small-group distribution and the random distribution (Figure 3). The neighbourhood types are the four types proposed in section 3.3.3. The simulation time unit is week, and the total simulation time is $T = 50$. For each situation, we simulate 50 times to calculate the average value as the final result. The proportion of knowledge disseminators $r_t$ and the knowledge diffusion speed $v_t$ are introduced as the indexes to measure the performance of knowledge diffusion, and their definitions are shown as follows:

$$r_t = \frac{\textit{The quantity of knowledge disseminators at time } t}{\textit{The total quantity of individuals}} \tag{5}$$

$$v_t = \textit{The quantity of knowledge disseminators at time } t \tag{6}$$



(a) The monopolistic distribution (b) The small group distribution (c) The random distribution

**Figure 3.** The distribution patterns of initial knowledge disseminators.

### 4.2. The impact of the distribution pattern of initial knowledge disseminators on knowledge diffusion

As stated in Section 4.1, the distribution patterns of initial knowledge disseminators are respectively the monopolistic distribution, the small-group distribution and the random distribution. Suppose that the proportion of initial knowledge disseminators is 5%, and the neighbourhood type is 1 × 1 Moore. In this situation, the individual mobility is not taken into consideration. The impact of the distribution pattern of initial knowledge disseminators on knowledge diffusion is shown in Figure 4.

In Figure 4, the proportion of knowledge disseminators $r_t$ shows an overall increasing trend over time. Stepping into the later stage of knowledge diffusion process, the proportion of knowledge disseminators $r_t$ gradually presents an equilibrium status, and this equilibrium status will remain sustained and stable over time. Meanwhile, the knowledge diffusion speed $v_t$ gradually increases at the early stage of knowledge diffusion process, then it has a shift from high to low. The shift point appears after the knowledge going through the whole KCO. At this moment, the most non-knowledge disseminators have contacted the certain knowledge, and then may become the knowledge disseminators or knowledge quitters with certain probabilities, whose status will remain unchanged. The results are consistent with the conclusions of the literature (Kim & Park, 2009; Meng et al., 2003), and they also confirm the theory of knowledge value augmentation (Demarest, 1997), that is, the knowledge diffusion and sharing will increase the total amount of knowledge in organisations. Moreover, the above results reflect the following reality of knowledge diffusion in KCO: For the specific knowledge introduced by KCO, the individuals are in a state of demand for the knowledge at the early stage of knowledge diffusion. With the advancement of knowledge collaboration, a large amount of knowledge exchange and cooperation activities are carried out among individuals. Then, increasing individuals become the knowledge disseminators via the effective knowledge exchange and absorption. Stepping into the later stage of knowledge diffusion, along with the gradual completion of knowledge collaboration work, there are a sufficient number of individuals becoming the knowledge disseminators, and the knowledge demand of other individuals have progressively decreased. Thus, the occurrence of knowledge diffusion and the knowledge growth are becoming increasingly less, which finally leads to the slowdown of knowledge diffusion speed.

Meanwhile, we can draw a conclusion from the simulation result in Figure 4: the distribution patterns of initial knowledge disseminators have a significant influence on the knowledge diffusion performance. Specifically, the random distribution has the highest knowledge diffusion performance, the monopolistic distribution has the lowest knowledge diffusion performance, and the small-group distribution lies somewhere in between. The literature (Meng et.al, 2004; Zhu et al., 2006) applied the CA model and multi-agent model to study the influence of knowledge source distribution patterns on the diffusion performance of knowledge or innovation, and obtained the similar conclusions. However, this work has an improvement compared to the above studies, which clearly contrasts the pros and cons of the three typical certain distribution patterns of the knowledge sources, so as to make this study more practical. Due to the knowledge privilege and knowledge conservatism of the monopolistic distribution and small-group distribution patterns, the knowledge disseminators are confined to a narrow hierarchy or a small group in KCO, which limits the sufficient knowledge contact and exchange among the knowledge disseminators and other individuals. Obviously, it goes against knowledge diffusion. Moreover, it also explains why the hierarchy and small group of organisations are not beneficial to the efficient knowledge diffusion and sharing among organisation members.

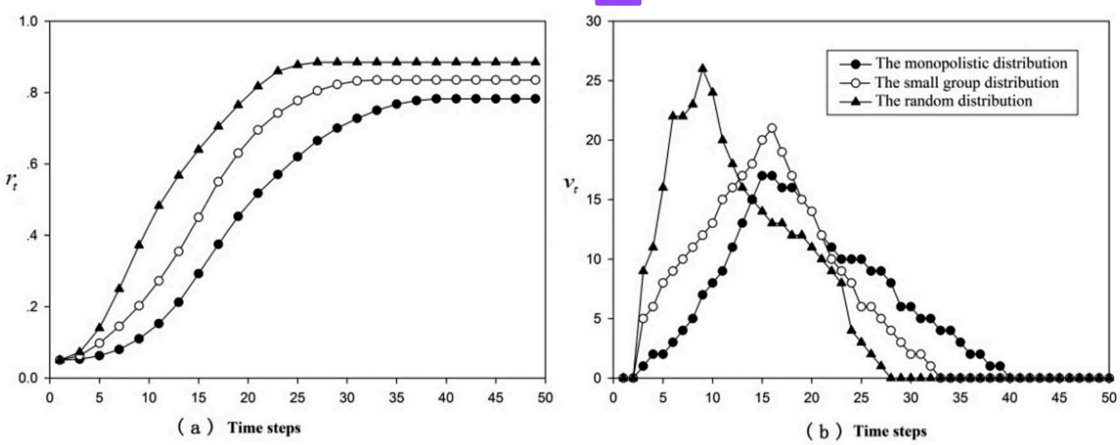



Figure 4. The impact of the distribution of initial knowledge disseminators on knowledge diffusion.

On the other hand, with the less hierarchy and more authorisation, the random distribution pattern, which reflects the flat organisational structure, makes every individual in KCO representing the centricity and exchanging knowledge more openly and effectively. Therefore, the random distribution pattern is conducive to the introduction and diffusion of new knowledge. For the management practice of knowledge diffusion in KCO, the above results give us the following management highlights: first, the hierarchy and small group of KCO goes against knowledge diffusion, thus the managers of KCO should break the hierarchy barriers in organisation and the small group among its members to lower the difficulties of knowledge exchange, by improving the mutual trust and collaboration among KCO members and encouraging the knowledge exchange and sharing willingness of members. Second, considering the advantage of the random distribution pattern, it is an effective way to improving knowledge diffusion performance, by strengthening the flat management of KCO, enhancing the openness of knowledge resources within KCO, and giving its members more equal chances and knowledge authorisation to exchange knowledge openly and effectively.

### 4.2. *The impact of the knowledge availability among individuals on knowledge diffusion*

Suppose that the neighbourhood types are respectively 1 × 1 Von Neumann, 1 × 1 Moore, 2 × 2 Von Neumann and 2 × 2 Moore. The proportion of initial knowledge disseminators is 5%, and the distribution pattern is the random distribution pattern. Same as the Section 4.2, the individual mobility is not taken into consideration. The impact of the knowledge availability among individuals on knowledge diffusion is shown in Figure 5.

As seen in Figure 5, when the neighbourhood type is 2 × 2 Moore, there are the highest knowledge diffusion performance in KCO, and when the neighbourhood type is 1 × 1 Moore, 2 × 2 Von Neumann, or 1 × 1 Von Neumann, the knowledge diffusion performance declines in turn. The simulation results indicate that the knowledge accessibility among individuals has a positive influence on the knowledge diffusion performance. The above four neighbourhood types have different size of neighbourhood space. The bigger the neighbourhood space is, the more individuals are involved in knowledge exchange, and the higher the knowledge accessibility is. Thus, the successful probability of knowledge diffusion subsequently increases with the knowledge accessibility getting higher. It should be noted that 1 × 1 Moore and 2 × 2 Von Neumann both contain 8 neighbour cells, that is, each individual can exchange knowledge with 8 neighbour individuals in the two neighbourhood types. However, as mentioned in section 3.3.3, the knowledge accessibilities are not only determined by the neighbourhood type, but also by the cell distance among individuals. The shorter the cell distance reflects the higher strength knowledge exchange relationship among individuals, which improves the knowledge accessibility among individuals. As for this simulation scenario, the maximum cell distance among individuals in 1 × 1 Moore is $\sqrt{2}$, while maximum cell distance among individuals in 2 × 2 Von Neumann is 2. Hence, the knowledge accessibility of 1 × 1 Moore is higher than 2 × 2 Von Neumann, which explains why the knowledge diffusion performance of 1 × 1 Moore is higher than 2 × 2 Von Neumann. Some researches (Fritsch & Kauffeld-Monz, 2010; Reagans & McEvily, 2003; Yu, Xiao, & Gong, 2009) have used the empirical research and complex network methods to investigate and verify the positive effects of the knowledge exchange relationships and relationship strengths among individuals on the knowledge diffusion performance. Furthermore, this paper applies the concepts of neighbourhood and cell distance to comprehensively study the influence of the above factors on knowledge diffusion performance, and gets the similar conclusions. The simulation results reveals that in the knowledge management of KCO, from the perspective of

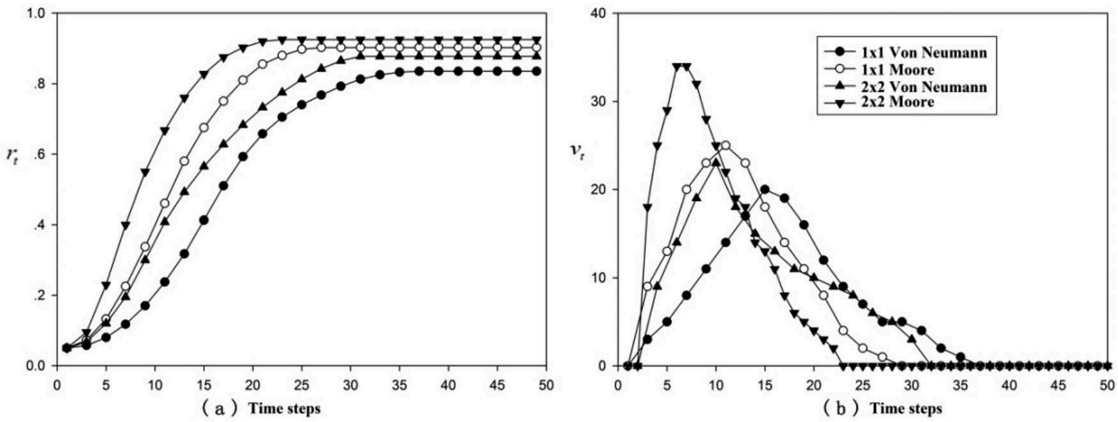



**Figure 5.** The impact of the knowledge accessibility among individuals on knowledge diffusion.

improving the knowledge accessibility among KCO members, the managers of KCO can strengthen the formal and informal knowledge exchange and cooperation relationships among KCO members to encourage more members to join into the knowledge diffusion activities, through the targeted performance evaluation and incentive systems. Meanwhile, the managers of KCO should also make full use of the knowledge exchange network among the KOC members to enrich and expand the channels knowledge exchange and diffusion between KCO members, and improve the knowledge exchange relationship strength among members.

### 4.3. *The impact of the individual mobility on knowledge diffusion*

In this work, the individual mobility mainly shows in the proportion of mobile individuals and the distance of movement. First, we investigate the impact of the proportion of mobile individuals on knowledge diffusion. Suppose that the proportions of mobile individuals $\psi$ respectively are 0, 20%, 50%, and 100%. The maximum distance of movement MDis 5. The proportion of initial knowledge disseminators is 5%, the distribution pattern is random pattern, and the neighbourhood type is 1 × 1 Von Neumann. The impact of the proportion of mobile individuals on knowledge diffusion is shown in Figure 6.

Figure 6 shows the proportion of mobile individuals has a positive influence on the knowledge diffusion performance. Tracing back to the simulation process, we can easily see that the bigger the proportion of mobile individuals is, the more the active individuals who will be involved in a broader range of knowledge exchange, and the more effectively the individuals can exchange knowledge within the whole cellular space. Reflecting into the reality of KCO management, with the more proportion of mobile individuals, the members in KCO have more intention and initiative to exchange knowledge, and they can more proactively exchange knowledge with a broader range of people by breaking through the organisational hierarchy or knowledge conservatism in KCO. Therefore, the managers of KCO should encourage more members and promote their initiative to actively exchange knowledge in an open and free communication environment, by weakening the knowledge diffusion barriers among members from the different hierarchies, departments, and even different cultures. In this way, KCOs will inject more vitality into knowledge sharing with more and more members' involvement, and the knowledge diffusion performance will get an effective improvement.

Secondly, the maximum distance of movement is studied to comprehensively reflect the impact of individual mobility on knowledge diffusion. Suppose that the maximum distances of movement MD respectively are 0, 5, 10, and 20. In particular, the maximum distance of movement 0 means there is no mobility of individuals, and the maximum distance of movement 20 means that the mobile individuals can freely move within the whole cellular space. The proportion of mobile individuals is 20%, and the other parameter settings are same with the scenario of the proportion of mobile individuals. The simulation result is shown in Figure 7.

As seen in Figure 6, there is a positive correlation between the maximum distances of movement and the knowledge diffusion performance. In the simulation process, we can iconically get that the bigger the maximum distances of movement is, the broader the range of individuals' knowledge exchange is, and the higher possibility for individuals in every position of KCO to contact and obtain the knowledge. In practice, the simulation results imply that the open knowledge communication environment can make members with more knowledge exchange vitality to promote the knowledge diffusion performance within KCO. It explains the reason why the enterprises with creative and open culture, such as Google, Facebook and Xiaomi, etc. have more efficient knowledge

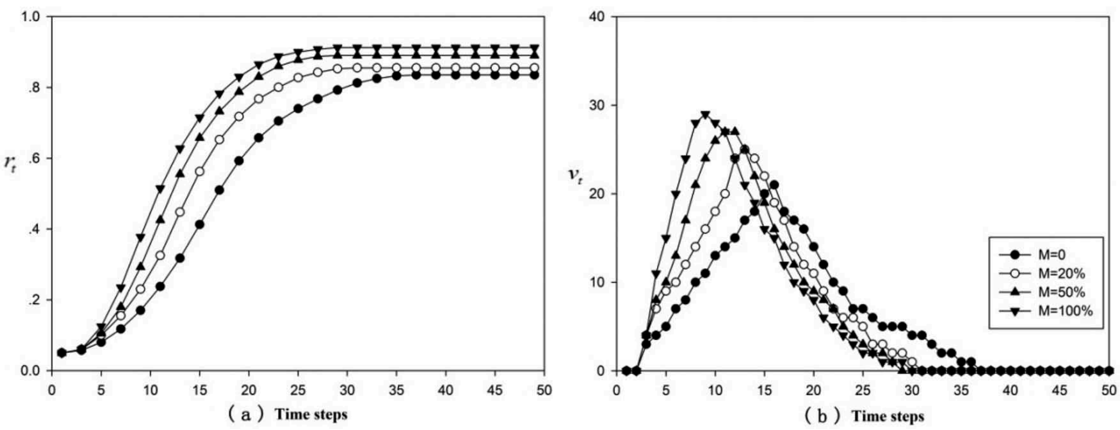



Figure 6. The impact of the proportion of mobile individuals on knowledge diffusion.

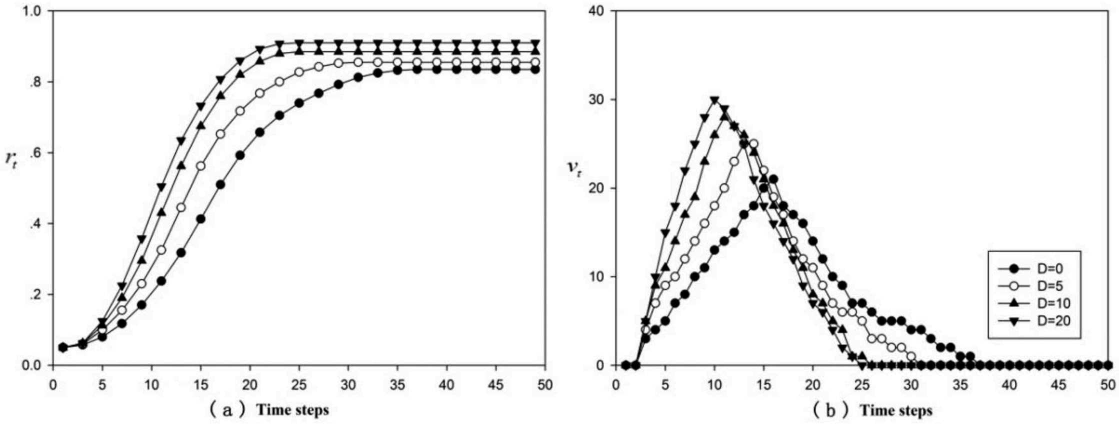



**Figure 7.** The impact of the maximum distances of movement on knowledge diffusion.

sharing and innovation ability than the traditional hierarchy organisations. These enterprises provide their employee a more open knowledge exchange environment, and encourage them to express and share their ideas in a wider space with bolder initiatives (Zhang, 2013; Zhao & Feng, 2016). Therefore, in these enterprises, the employee can easily and actively exchange knowledge with people in every position, which is proven to be conducive to knowledge diffusion. In practice, the above simulation conclusion should be taken seriously by the managers and decision-makers in order to promote the knowledge diffusion performance of KCOs.

### 4.4. *The impact of knowledge quitting on knowledge diffusion*

In this work, the individual knowledge quitting rate mainly depends on the knowledge value, complexity, and learning cost. The different knowledge has different value, complexity, and learning cost, which are summarised and defined as the knowledge characteristic to reflect the knowledge heterogeneity. Suppose the knowledge quitting rate respectively obey $N(0,0.25)$, $N(0.25,0.50)$, $N(0.50,0.75)$, and $N(0.75,0.10)$. The proportion of initial knowledge disseminators is 5%, the distribution pattern is random pattern, and the neighbourhood type is $1 \times 1$ Moore. The impact of the knowledge quitting rate on knowledge diffusion is shown in Figure 8.

As seen in Figure 8, there is a negative correlation between the knowledge quitting rate and the knowledge diffusion performance. Specifically, the higher the knowledge quitting is, the less knowledge disseminators in the final state of knowledge diffusion, and the slow the knowledge diffusion speed is. Observing the entire simulation process, the higher knowledge quitting rate brings more knowledge quitters in the cellular space. Because of the knowledge quitters remaining unchanged, the appearance of increasing knowledge quitters generates lots of knowledge vacuum zone, which will impede or even cut off the knowledge exchange among the knowledge disseminators and the other individuals, thus reduce the success probability of knowledge diffusion. In practice, the higher knowledge quitting rate reflects that the knowledge value and learning cost can meet the member expectations of knowledge exchange and absorption, which makes members more inclined to choose to become knowledge quitter. To sum up, the increasing of knowledge quitting rate and continuous production of knowledge quitter decrease the success probability of knowledge exchange and diffusion, and ultimately reduce the

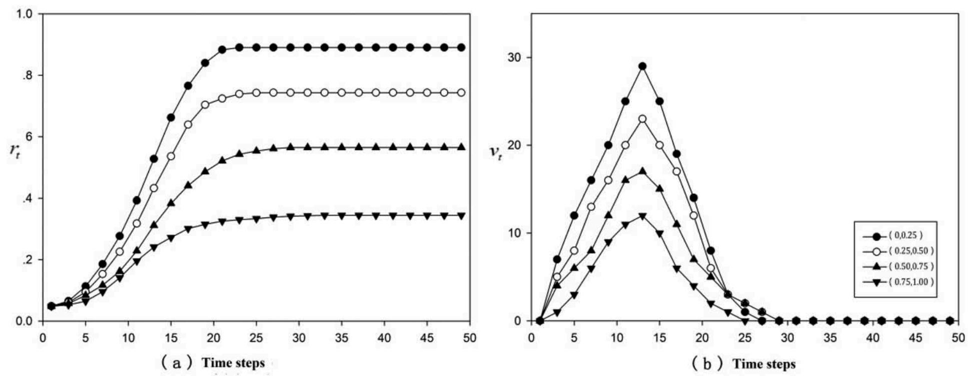



**Figure 8.** The impact of knowledge quitting rate on knowledge diffusion

overall performance of knowledge diffusion. The results enlighten us that in the knowledge diffusion process of KCO, the knowledge characteristic and heterogeneity do significantly affect the knowledge diffusion performance due to its influence on knowledge quitting rate. Therefore, from the perspective of optimising knowledge characteristic and knowledge quitting rate, the managers of KCO should strictly check and manage the value of quasi-introduced knowledge to avoid the organisation resource wasting or even misguiding caused by worthless knowledge. For the introduced valuable knowledge, the KCO should adopt the ways such as propagandising and training to increase members' recognition of the value of introducing knowledge and enhance their willingness to learn knowledge. On the other hand, for complex and high learning cost knowledge, the step-level training, stage training, and standardisation courses can be taken to reduce the knowledge learning cost, thereby adjusting the members' expectations of knowledge value and learning costs, and eventually decreasing the knowledge quitting rate and improving the knowledge diffusion performance.

Additionally, it also should be noted that in the knowledge diffusion process, the individual heterogeneity of knowledge status have undergone a change from relatively homogeneous to highly heterogeneous, and finally to relatively homogeneous again. At the early stage of knowledge diffusion, there are only two types of knowledge status, that is, the knowledge disseminators and knowledge susceptibles in the KCO. Then, the other types of knowledge status are consecutively appearing and increasing, and the proportion of each type of knowledge status are gradually tends to balance over time. As stepping in to the later stage of knowledge diffusion, the distribution balance of different knowledge status is broken, and the individual heterogeneity of knowledge status returns to relatively homogeneous again. At this moment, there are only knowledge disseminators and knowledge quitter in the KCO. It indicates, once more, that the knowledge quitting rate is the key factor which affects the distribution of knowledge status and the final knowledge diffusion performance in KCO. Therefore, the management of knowledge quitting rate should be taken as the important knowledge management content, which deserves sufficient attention by managers.

## 5. Conclusion

The comprehensive and deep understanding of the knowledge diffusion process and rule are the important preconditions to effectively manage organisational knowledge resource. In this work, we investigate the knowledge diffusion process and rule in KCO by developing an improved CA model with heterogeneity and mobility. Learning from the SEIR epidemic model, this paper classifies the individuals of KCO involved in knowledge diffusion into different knowledge status, and re-describes the knowledge diffusion process from the perspective of epidemic spread. Regarding the influences of individuals' heterogeneity and mobility on knowledge diffusion, a knowledge diffusion model based on an improved CA with heterogeneity and mobility is developed to study the process and rule of knowledge diffusion from the perspective of micro-knowledge exchange among individuals. To analyse and reveal the influences of distribution pattern of initial knowledge disseminator, knowledge accessibility among individuals, individual mobility and knowledge quitting rate on knowledge diffusion, the simulation method are used with the proportion of knowledge disseminators and the knowledge diffusion speed as the measures of knowledge diffusion performance. The simulation results and implications provide a significant decision support for the managers of KOC to better understand the knowledge diffusion mechanism and effectively improve the knowledge diffusion performance.

To further deepen and enrich this research, the following three directions will be carried out in the future work. First, the heterogeneity of knowledge, such as the tacit characteristic of knowledge, knowledge complexity, knowledge stickiness and knowledge value, and its connections with knowledge diffusion will be empirically studied to deeper reveal the real-knowledge diffusion. Second, we are going to incorporate the knowledge creation activities into our model to discover more interesting achievements about the issue of knowledge diffusion. Lastly, we intend to develop a decision support system to monitor the introduction and diffusion of certain knowledge, in which the proposed model of this work is embedded, in order to provide more efficient decision support for the knowledge management in KCO.

## Disclosure statement

No potential conflict of interest was reported by the authors.

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## References

Balzter, H., Braun, P. W., & Köhler, W. (1998). Cellular automata models for vegetation dynamics. *Ecological Modelling*, *107*(2), 113–125.

Bass, F. M. (1969). A new product growth model for consumer durables. *Management Science*, *15*(5), 215–227.

Biswas, M. H. A., Paiva, L. T., & Pinho, M. D. R. D. (2014). A SEIR model for control of infectious diseases with constraints. *Mathematical Biosciences & Engineering*, *11* (4), 761–784.

Carneiro, A. (2013). How does knowledge management influence innovation and competitiveness? *Journal of Knowledge Management*, *4*(2), 87–98.

Cohen, W. M., & Levinthal, D. A. (1990). Adsorptive capacity: A new perspective on learning. *Administrative Science Quarterly*, *35*(1), 128–152.

Demarest, M. (1997). Understanding knowledge management. *Long Range Planning*, *30*(3), 374–384.

Eloranta, K. (1993). Random walks in cellular automata. *Nonlinearity*, *6*(6), 1025.

Eugster, P. T., Guerraoui, R., Kermarrec, A. M., & Massoulié, L. (2004). Epidemic information dissemination in distributed systems. *Computer*, *37*(5), 60–67.

Feng, B., & Fan, Z. P. (2012). A partner selection method for knowledge creation team based on collaborative effect. *Chinese Journal of Management*, *9*(2), 258–261.

Fritsch, M., & Kauffeld-Monz, M. (2010). The impact of network structure on knowledge transfer: An application of social network analysis in the context of regional innovation networks. *The Annals of Regional Science*, *44*(1), 21–38.

Gilmour, D. (2003). How to fix knowledge management. *Harvard Business Review*, *81*(10), 16–17.

Guseo, R., & Guidolin, M. (2009). Modelling a dynamic market potential: A class of automata networks for diffusion of innovations. *Technological Forecasting and Social Change*, *76*(6), 806–820.

Haldin-Herrgard, T. (2000). Difficulties in diffusion of tacit knowledge in organizations. *Journal of Intellectual Capital*, *1*(4), 357–365.

Hansen, M. T. (1999). The search-transfer problem: The role of weak ties in sharing knowledge across organization subunits. *Administrative Science Quarterly*, *44*(1), 82–111.

Iudin, D., Sergeyev, Y. D., & Hayakawa, M. (2015). Infinity computations in cellular automaton forest-fire model. *Communications in Nonlinear Science and Numerical Simulation*, *20*(3), 861–870.

Jeon, S., Kim, Y.-G., & Koh, J. (2011). An integrative model for knowledge sharing in communities-of-practice. *Journal of Knowledge Management*, *15*(2), 251–269.

Joia, L. A., & Lemos, B. (2010). Relevant factors for tacit knowledge transfer within organisations. *Journal of Knowledge Management*, *14*(3), 410–427.

Khabouze, M., Hattaf, K., & Yousfi, N. (2015). Three-dimensional cellular automaton for modeling the hepatitis B virus infection. *International Journal for Computational Biology*, *4*(1), 13–20.

Kim, H., & Park, Y. (2009). Structural effects of R&D collaboration network on knowledge diffusion performance. *Expert Systems with Applications*, *36*(5), 8986–8992.

Kiss, I. Z., Broom, M., Craze, P. G., & Rafols, I. (2010). Can epidemic models describe the diffusion of topics across disciplines? *Journal of Informetrics*, *4*(1), 74–82.

Knuth, D. E., & Plass, M. F. (1981). Breaking paragraphs into lines. *Software: Practice and Experience*, *11*(11), 1119–1184.

Lai, X. H., & Wang, W. P. (2006). Simulation of the spread knowledge inside knowledge-based organization based on cellular automata. *Chinese Journal of Management*, *3*(5), 514–518.

Lee, V. H., Foo, T. L., Leong, L. Y., & Ooi, K. B. (2016). Can competitive advantage be achieved through knowledge management? A case study on SMEs. *Expert Systems with Applications*, *65*(C), 136–151.

Meng, X. F., Liu, H., & Wu, H. M. (2003). Multi-agent model of knowledge diffusion in network space. *Studies in Science of Science*, *21*(6), 636–641.

Mu, J., Tang, F., & Maclachlan, D. L. (2010). Absorptive and disseminative capacity: Knowledge transfer in intra-organization networks. *Expert Systems with Applications*, *37*(1), 31–38.

Nieves, J., Quintana, A., & Osorio, J. (2016). Organizational knowledge and collaborative human resource practices as determinants of innovation. *Knowledge Management Research & Practice*, *14*(3), 237–245.

Ozel, B. (2012). Collaboration structure and knowledge diffusion in Turkish management academia. *Scientometrics*, *93*(1), 183–206.

Qi, L. Y., Wang, K. Y., Zhang, F. F., & Zhao X. Y. (2008). A research on the model of knowledge transfer based on system dynamics in the enterprise. *Journal of Management Science*, *21*(6), 9–20.

Reagans, R., & McEvily, B. (2003). Network structure and knowledge transfer: The effects of cohesion and range. *Administrative Science Quarterly*, *48*(2), 240–267.

Roper, S., Love, J. H., & Bonner, K. (2017). Firms' knowledge search and local knowledge externalities in innovation performance. *Research Policy*, *46*(1), 43–56.

Shi, Y., & Li, N. (2010). Impact factors of team knowledge diffusion based on social relationship network. *Science & Technology Progress & Policy*, *17*(14), 137–140.

Singh, J. (2005). Collaborative networks as determinants of knowledge diffusion patterns. *Management Science*, *51* (5), 756–770.

Su, J., Yang, Y., & Zhang, N. (2017). Measurement of knowledge diffusion efficiency for the weighted knowledge collaboration networks. *Kybernetes*, *46*(4), 672–692.

Su, J. F., Yang, Y., & Yang, T. (2015). Simulation of Conflict Contagion in Customer Collaborative Product Innovation. *International Journal of Simulation Modelling*, *14*(1), 134–144.

Tamjidyamcholo, A., Baba, M. S. B., Tamjid, H., & Gholipour, R. (2013). Information security–Professional perceptions of knowledge-sharing intention under self-efficacy, trust, reciprocity, and shared-language. *Computers & Education*, *68*, 223–232.

Tan, X. X., Dai, Q. W., Shi, P. Y., Wang, L. Y., & Gang, J. T. (2013). CA-based epidemic propagation model with inhomogeneity and mobility. *Journal of Dalian University of Technology*, *53*(6), 908–914.

Tsai, C. M. (2008). Integrating intra-firm and inter-firm knowledge diffusion into the knowledge diffusion model. *Expert Systems with Applications*, *34*(2), 1423–1433.

Wang, J.-P., Guo, Q., Yang, G.-Y., & Liu, J.-G. (2015). Improved knowledge diffusion model based on the collaboration hypernetwork. *Physica A: Statistical Mechanics and Its Applications*, *428*, 250–256.

Wensley, A. K. P., & Navarro, J. G. C. (2015). Overcoming knowledge loss through the utilization of an unlearning context. *Journal of Business Research*, *68*(7), 1563–1569.

Wolfram, S. (1984). Cellular automata as models of complexity. *Nature*, *311*(5985), 419–424.

Wu, Y., & Zhu, W. (2012). An integrated theoretical model for determinants of knowledge sharing behaviours. *Kybernetes*, *41*(10), 1462–1482.

Yu, T. Y., Xiao, R. B., & Gong, X. G. (2009). Tacit knowledge diffusion in organizational networks and the analysis of learning strategies. *Journal of Management Science*, *22*(6), 21–28.

Zahra, S. A., & George, G. (2002). Absorptive Capacity: A Review, Reconceptualization, and Extension. *Academy of Management Review*, *27*(2), 185–203.

Zhang, S., Qiao, K., & Wang, K. Y. (2008). An empirical study on knowledge sharing and its influencing factors. *Information Studies: Theory & Application*, *31*(4), 502–506.

Zhang, X. (2013). Open access, open knowledge, and open innovation pushes for open knowledge services—3O convergence and a new paradigmatic shift for research libraries. *New Technology of Library & Information Service*, *29*, 1–10.

Zhao, F., & Feng, Z. (2016). The effect of social media on firms' knowledge-based competitiveness: A case study of Xiaomi. *Science of Science & Management of S & T*, *37*, 33–42.

Zhu, J. S., Lai, M. Y., & Nie, P. Y. (2006). Study on technology spillovers and absorptive capability based on cellular automata model. *Systems Engineering-Theory & Practice*, *26*(8), 63–80.