Tacit Knowledge Spreading Based on Knowledge Spreading Model on Networks with Consideration of Intention Mechanism

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Journal of Digital Information Management

ABSTRACT: *At present, knowledge management (KM) is critical to the success of a firm in digital information era. KM effectiveness and competitive advantages of a firm can be increased and sustained by effectively encouraging employees to propagate useful tacit knowledge across the organization. Tacit knowledge propagates through direct contact among individuals in an organization. Therefore, we consider employees and their contacts as an undirected network, which is also considered as a knowledge exchange network. We model the peculiarities of a tacit knowledge spreading in knowledge network with consideration of intention mechanism, and this model is compared with Susceptible-Infected-Susceptible (SIS) model. We provide simulation and numerical results to support our analyses and results. Results show that the degree distribution of knowledge exchange network and intention mechanism have great influence on tacit knowledge spreading. Our results show that a threshold that governs whether a tacit knowledge can spread across the organization exists. Analysis results can guide KM and digital information management in view of the theoretical and practical aspects.*

Subject Categories and Descriptors:
I.6.3 [Simulation and Modeling]: Applications

General Terms:
Management, Theory

Keywords: Knowledge management, Tacit knowledge spreading, Simulation Modelling, Intention mechanism, Degree distribution

Received: 2 March 2015, Revised 17 April 2015, Accepted 25 April 2015

1. Introduction

Given the importance of knowledge in digital information ear, knowledge management (KM) is critical to the success of a firm [1]. Competitive advantage in the future will be determined by knowledge and information resources, which are known as KM and digital information management [2]. As a necessary intangible asset for any organization, knowledge should be elaborately managed. On the basis of Polanyi's conceptualization [3], Nonaka suggested that knowledge can be classified as explicit and tacit [4]. Tacit knowledge is significant in the knowledge system of humans and is the core resource in human brains dominating their behaviors [4]. Tacit knowledge is naturally stickier than explicit knowledge. Therefore, transferring tacit knowledge to others is more difficult than transferring explicit knowledge [5]. The technological innovation capabilities and KM effectiveness of a firm can be increased by effectively encouraging employees to propagate useful tacit knowledge across the organization.

Numerous studies on KM have proved that employee knowledge spreading enhances firm performance, such as information absorptive capacity and information diffusion capability [6].

Employees worry that their job performance may be jeopardized, thus, they have no willingness to share useful knowledge with others [7]. Studies have shown that the largest challenge to KM and digital information management is whether individuals have intentions to propagate and share useful knowledge and information [8]. Therefore, the employees who have acquired a tacit knowledge are divided into employees with tacit knowledge sharing intentions and employees without tacit knowledge sharing intentions. Given that the knowledge sharing intentions of individuals are one of the strong factors of actual employee knowledge spreading behavior [9], many researchers have studied how the tacit knowledge sharing intentions of individuals affect tacit knowledge spreading among them. However, prior KM studies aimed at this research area are apparently limited in empirical and analytic research, which analyzes and predicts the existing and future phenomena, respectively [5-10]. The related theoretical and quantitative studies are not sufficient. Accordingly, this study performs some analysis by applying the method of transmission dynamics on networks combined with computer simulations from the perspective of theoretical and quantitative research to guide KM effectively.

The contact among employees cannot be a uniform collision, and the number of employees who are contacted by different employees may be different in unit time. Tacit knowledge spreading in an organization can be considered as the spreading and evolution of this knowledge in a specific knowledge network. The spreading of this knowledge depends not only on tacit knowledge characteristics, but also on the topological characteristics of a network. Therefore, employees of an organization and their contacts are considered as an undirected network, which is also considered as a knowledge exchange network. Similar to the characteristics of epidemic spreading, those of tacit knowledge spreading process in an organization can be simply summarized as follows: only a small number of spreaders exist at the initial stage, and the others are individuals who have acquired tacit knowledge without tacit knowledge sharing intentions and individuals without tacit knowledge. Tacit knowledge spreading shows great resemblance to spread of epidemic diseases, which is achieved through direct contact among individuals [11]. We model the characteristics of tacit knowledge spreading, and this model is compared with Susceptible–Infected–Susceptible (SIS) model. In Section 2, we describe the model and derive the threshold that governs whether a tacit knowledge can spread in an organization. In Section 3, numerical simulations and sensitivity analysis are presented to support the results. We study the effects of the degree distribution of knowledge exchange network and intention mechanism on tacit knowledge spreading. Finally, conclusions are drawn in Section 4.

2. Analysis of Tacit Knowledge Spreading

The employees of the organization and their contacts are considered as a knowledge exchange network to study the dynamic evolution of tacit knowledge spreading. Each employee is regarded as a node, and each contact between two employees is represented as an edge connecting their nodes in the knowledge network. The degree distribution of the network is presented by $p(k)$, which is time-independent. We divide the employees of the organization into three classes: employees without tacit knowledge, employees with tacit knowledge but without tacit knowledge sharing intentions, and employees with tacit knowledge and tacit knowledge sharing intentions. Let N be the total number of employees, and let $N_k(t)$ be the total number of the employees whose contact number is k in unit time. The number of the nodes of degree k without tacit knowledge, the nodes of degree k with tacit knowledge but without tacit knowledge sharing intentions, and the nodes of degree with tacit knowledge and tacit knowledge sharing intentions can be described in terms of $S_k(t)$, $E_k(t)$, $T_k(t)$ and, respectively, as a function of time. Moreover, $N_k(t) = S_k(t) + E_k(t) + T_k(t)$ and $N = \Sigma_k N_k(t)$.

At present, most firms have a stable scale. Thus, we consider that the total number N remains constant. In tacit knowledge spreading progress, a contact between an employee who has acquired a tacit knowledge with tacit knowledge sharing intentions and an employee without tacit knowledge can lead to the spread of this knowledge. $p(l|k)$ is the probability that a node of degree is contacted to a node of degree l. $T_l(t)/N_l(t)$ is the probability that a node of degree l is a node with tacit knowledge and tacit knowledge sharing intentions. Accordingly, θ is the probability that a node of degree k without tacit knowledge is contacted by the nodes with tacit knowledge and tacit knowledge sharing intentions per contact.

$$\theta = \sum_{l=1}^{n} p(l|k)\, T_l(t)/N_l(t)$$

We consider that an employee without tacit knowledge can acquire this knowledge through a contact with an employee who has this knowledge and tacit knowledge sharing intentions at a rate of β. We suppose that a newly-born employee with tacit knowledge is an employee with tacit knowledge and tacit knowledge sharing intentions at a rate of λ. Therefore, the number of newly-born nodes of degree k with tacit knowledge and tacit knowledge sharing intentions is $\lambda\beta k S_k(t)\theta$ and $(1-\lambda)\,\beta k S_k(t)\theta$ is the number of newly-born nodes of degree k with tacit knowledge but without tacit knowledge sharing intensions in unit time. Employees with tacit knowledge forget this knowledge and become employees without tacit knowledge at a rate of γ. We suppose that an employee with tacit knowledge but without tacit knowledge sharing intentions becomes an employee with tacit knowledge and tacit

knowledge sharing intentions after enhancing their knowledge sharing intentions at a rate of μ. This kind of tacit knowledge spreading process is shown in Figure 1.

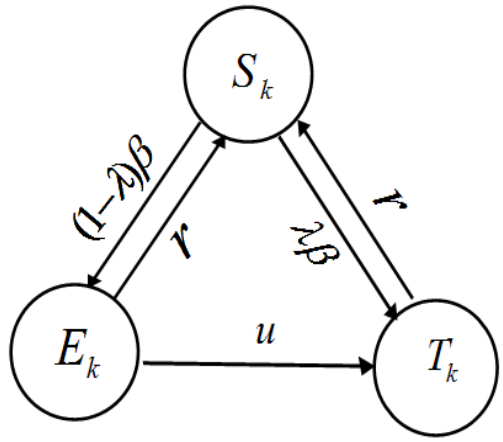

Figure 1. Flow chart of the state progression of individuals among different classes

In summary, we propose a tacit knowledge spreading model on networks. The dynamic model can be described as follows:

$$\begin{cases} \dfrac{dS_k(t)}{dt} = -\beta k S_k(t)\sum_{l=1}^{n} p(l\,|\,k)\dfrac{T_l(t)}{N_l(t)} + \gamma\left(E_k(t)+T_k(t)\right), \\ \dfrac{dE_k(t)}{dt} = (1-\lambda)\beta k S_k(t)\sum_{l=1}^{n} p(l\,|\,k)\dfrac{T_l(t)}{N_l(t)} - (\gamma+\mu)E_k(t), \\ \dfrac{dT_k(t)}{dt} = \lambda\beta k S_k(t)\sum_{l=1}^{n} p(l\,|\,k)\dfrac{T_l(t)}{N_l(t)} + \mu E_k(t) - \gamma T_k(t). \end{cases} \quad (1)$$

If the degree of the nodes in the knowledge exchange network is uncorrelated, then $p(l\,|\,k) = lp(l)/\langle k\rangle$.

Then (1) is rephrased as:

$$\begin{cases} \dfrac{dS_k(t)}{dt} = -\dfrac{\beta k S_k(t)}{N\langle k\rangle}\sum_{l=1}^{n} l\cdot T_l(t) + \gamma\left(E_k(t)+T_k(t)\right), \\ \dfrac{dE_k(t)}{dt} = \dfrac{(1-\lambda)\beta k S_k(t)}{N\langle k\rangle}\sum_{l=1}^{n} l\cdot T_l(t) - (\gamma+\mu)E_k(t), \\ \dfrac{dT_k(t)}{dt} = \dfrac{\lambda\beta k S_k(t)}{N\langle k\rangle}\sum_{l=1}^{n} l\cdot T_l(t) + \mu E_k(t) - \gamma T_k(t). \end{cases} \quad (2)$$

We calculated the expression of the threshold by applying the next-generation method [12]. Similar to the basic reproductive number [13], the number of secondary cases generated by a primary spreader is considered as the threshold, which is a measure of the power of spreaders to attack an organization completely without tacit knowledge. Moreover, the equilibrium without tacit knowledge of the system (2) is $P_0 = (0, 0, ..., 0, 0, 0, .., 0, N_0, N_1, ..., N_k)^t$, where $k = 0, 1, .. n$. Through calculation, we identified that $R_0 = \rho(FV^{-1})$, where $\rho(FV^{-1})$ represents the spectral radius of the matrix FV^{-1}. We can obtain,

$$F = \begin{bmatrix} \frac{\mu(1-\lambda)\beta S_1^0}{(\mu+\gamma)\gamma N\langle k\rangle} & \frac{2\mu(1-\lambda)\beta S_1^0}{(\mu+\gamma)\gamma N\langle k\rangle} & \cdots & \frac{n\mu(1-\lambda)\beta S_1^0}{(\mu+\gamma)\gamma N\langle k\rangle} & \frac{(1-\lambda)\beta S_1^0}{\gamma N\langle k\rangle} & \cdots & \frac{n(1-\lambda)\beta S_1^0}{\gamma N\langle k\rangle} \\ \frac{2\mu(1-\lambda)\beta S_2^0}{(\mu+\gamma)\gamma N\langle k\rangle} & \frac{2^2\mu(1-\lambda)\beta S_2^0}{(\mu+\gamma)\gamma N\langle k\rangle} & \cdots & \frac{2n\mu(1-\lambda)\beta S_2^0}{(\mu+\gamma)\gamma N\langle k\rangle} & \frac{2(1-\lambda)\beta S_2^0}{\gamma N\langle k\rangle} & \cdots & \frac{2n(1-\lambda)\beta S_2^0}{\gamma N\langle k\rangle} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ \frac{n\mu(1-\lambda)\beta S_n^0}{(\mu+\gamma)\gamma N\langle k\rangle} & \frac{2n\mu(1-\lambda)\beta S_n^0}{(\mu+\gamma)\gamma N\langle k\rangle} & \cdots & \frac{n^2\mu(1-\lambda)\beta S_n^0}{(\mu+\gamma)\gamma N\langle k\rangle} & \frac{n(1-\lambda)\beta S_n^0}{\gamma N\langle k\rangle} & \cdots & \frac{n^2(1-\lambda)\beta S_n^0}{\gamma N\langle k\rangle} \\ \frac{\mu\lambda\beta S_1^0}{(\mu+\gamma)\gamma N\langle k\rangle} & \frac{2\mu\lambda\beta S_1^0}{(\mu+\gamma)\gamma N\langle k\rangle} & \cdots & \frac{n\mu\lambda\beta S_1^0}{(\mu+\gamma)\gamma N\langle k\rangle} & \frac{\lambda\beta S_1^0}{\gamma N\langle k\rangle} & \cdots & \frac{n\lambda\beta S_1^0}{\gamma N\langle k\rangle} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ \frac{n\mu\lambda\beta S_n^0}{(\mu+\gamma)\gamma N\langle k\rangle} & \frac{2n\mu\lambda\beta S_n^0}{(\mu+\gamma)\gamma N\langle k\rangle} & \cdots & \frac{n^2\mu\lambda\beta S_n^0}{(\mu+\gamma)\gamma N\langle k\rangle} & \frac{n\lambda\beta S_n^0}{\gamma N\langle k\rangle} & \cdots & \frac{n^2\lambda\beta S_n^0}{\gamma N\langle k\rangle} \end{bmatrix},$$

where $k = 0, 1, ... n$,

$$V = \begin{bmatrix} \mu+\gamma & 0 & \cdots & 0 & 0 & 0 & \cdots & 0 \\ 0 & \mu+\gamma & \cdots & 0 & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \mu+\gamma & 0 & 0 & \cdots & 0 \\ -\mu & 0 & \cdots & 0 & \gamma & 0 & \cdots & 0 \\ 0 & -\mu & \cdots & 0 & 0 & \gamma & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & -\mu & 0 & 0 & \cdots & \gamma \end{bmatrix}_{2n\times 2n}.$$

Hence, the threshold is

$$R_0 = \frac{\mu(1-\lambda)\beta\langle k^2\rangle}{(\mu+\gamma)\gamma\langle k\rangle} + \frac{\lambda\beta\langle k^2\rangle}{\gamma\langle k\rangle} \quad (3)$$

If $R_0 < 1$, then the equilibrium P_0 is asymptotically stable. Otherwise, P_0 is unstable [13]. Accordingly, the value of $R_0 = 1$ is the threshold that governs whether a tacit knowledge can spread in an organization. If $R_0 < 1$, then knowledge spreading is terminated, and this knowledge gradually disappears in an organization. If $R_0 > 1$, then this knowledge can spread across an organization. The value of $R_0 = 1$ is the threshold, and it indicates that if the number of employees without tacit knowledge is less than 1, to whom tacit knowledge is spread by an employee with tacit knowledge and tacit knowledge sharing intentions before the employee with tacit knowledge forgets this knowledge, then tacit knowledge gradually disappears. On the contrary, this knowledge can spread.

If $\lambda = 0$, then

$$R_0 = \frac{\beta\langle k^2\rangle}{\gamma\langle k\rangle\left(1-\gamma/\left(\mu+\gamma\right)\right)}$$

At this time, R_0 is an increasing function on parameter μ if $\lambda = 1$, namely, $1-\lambda = 0$, then

$$R_0 = \frac{\beta\ \langle k^2\rangle}{\gamma <k>}$$

At this time, the value of R_0 has nothing to do with the value of parameter μ.

Similarly, if $\mu = 0$, then

$$R_0 = \frac{\lambda\beta\ \langle k^2\rangle}{\gamma <k>}$$

At this time, R_0 is an increasing function on parameter λ. In summary, the value of the threshold relates to the value of parameter λ in any case. This observation shows that we should make a sufficient number of employees without tacit knowledge directly become employees with tacit knowledge and tacit knowledge sharing intentions to contribute to tacit knowledge spreading and to increase KM effectiveness.

Many social networks, which include online social networks, have scale-free topology and follow power law degree distributions [14]. In this study, if the knowledge network has a scale-free degree distribution, then $p(k) \propto k^{-\nu}$. If $\nu > 3$, then the second moment of the degree distribution of nodes is finite. According to Equation (3), R_0 is finite. If $\nu < 3$, then the second moment of the degree distribution of nodes diverges. According to Equation (3), R_0 also diverges ($R_0 \to \infty$). Therefore, for sufficiently high heterogeneity, even infinitesimally small spreading rates can make a tacit knowledge exist and propagate among employees continually. In summary, the degree distribution of the knowledge network has a significant effect on tacit knowledge spreading.

3. Numerical Simulations

We currently present numerical simulations to support the aforementioned obtained theoretical results. According to the rule of 150, an organization must ensure that the total number of employees is less than 150 if doing so results in efficient operation and becomes the incubator of information and knowledge transmission in digital information era [15,16]. Once the number of individuals is more than 150, organizations are divided to contribute to KM effectively. Therefore, if 150 is the total number of employees in the organization, then, $N = 150$. The most useful knowledge is in the grasp of few people in an organization, and knowledge spreading activities are uncommon [17]. Thus, more than half of the knowledge assets are wasted because this knowledge is not shared fully, which is very common in small- and medium-sized firms [17]. Accordingly, 5 is assumed the initial number of employees who have acquired tacit knowledge.

Moreover, 4 is assumed the number of the employees without tacit knowledge sharing intentions, and 1 is the number of the employees with tacit knowledge sharing intentions. The previously selected number of employees with tacit knowledge and the number of employees without this knowledge at the initial time vary in a reasonable range, which is not dependent on the results we obtained. In this study, we use "day" as the unit of time if, the maximum number of contacts of an employee is 60 in a day, i.e., $n = 60$.Barabási's team determined that many social networks are scale-free, which follow the power-law degree distributions [18]. The number of contacts each individual has is generally very uneven. That is to say, most employees have a very small number of contacts, and few individuals have exceedingly large number of contacts (i.e., hubs) [19]. Therefore, we assume that the network follows power-law degree distribution, and the probability takes the form：

$$p\left(k\right) \propto k^{-\nu} / \sum_{k=0}^{n} k^{-\nu} .$$

Based on the aforementioned results, if $\nu < 3$, the second moment of the nodes' degree distribution diverges $\langle k^2\rangle \to \infty$), i.e., R_0 also diverges ($R_0 \to \infty$). In particular, no threshold exists. Accordingly, we assume $\nu = 3.2$ that and $\beta = 0.001, \gamma = 0.01$.

First, we choose $\mu = 1, \lambda = 0.0001$. Then, $R_0 = 0.8545 < 1$.

Figure 2 shows that the number of the employees who have acquired tacit knowledge changes with time. The number of the employees with tacit knowledge decreases gradually to 0, and this knowledge gradually disappears in an organization. The results of the numerical simulations obviously coincide with the value of threshold.

Then, we choose $\mu = 0, \lambda = 0.001$ and $R_0 = 1.0365 > 1$.
We choose $\mu = 0, \lambda = 0.01$ and then $R_0 = 1.1357 > 1$.
We choose $\mu = 0, \lambda = 0.1$ and then $R_0 = 1.3731 > 1$.

Figure 3 clearly shows that the density of employees with tacit knowledge first increases sharply over time steps and finally reaches a peak value of approximately 0.6. This observation indicates that the maximum fraction of individuals spreading the knowledge is approximately 60%. The observations are as follows: Figure 3 reveals that intension mechanism has a significant influence on tacit knowledge spreading. The greater parameter λ is, the larger the threshold and the final size of the employees with tacit knowledge are. The results of the numerical simulations obviously coincide with threshold value. The numerical simulations confirm the validity of the theoretical results.

Figures 2 and 3 indicate that, if we can ensure that a sufficient number of employees without tacit knowledge

directly become employees with tacit knowledge and tacit knowledge sharing intentions, then the matter on whether this knowledge can spread across the organization does not consider the matter on whether the tacit knowledge sharing intentions of employees with tacit knowledge but without tacit knowledge sharing intentions can be improved. In summary, intention mechanism has a significant effect on tacit knowledge spreading and KM effectiveness.

Finally, we perform the sensitivity analysis of the threshold in terms of parameter λ and μ to illustrate further the effects of intension mechanism on tacit knowledge spreading and KM.

Figure 4 clearly shows that R_0 increases as each parameter (λ or μ) increases, whereas the influence of λ is greater on R_0 than μ. In Figure 4, the other parameter values are the same as those in Figure 2, except λ and μ. If we change the parameter values or the initial conditional values in a reasonable range, the conclusions of the sensitivity analysis are roughly the same.

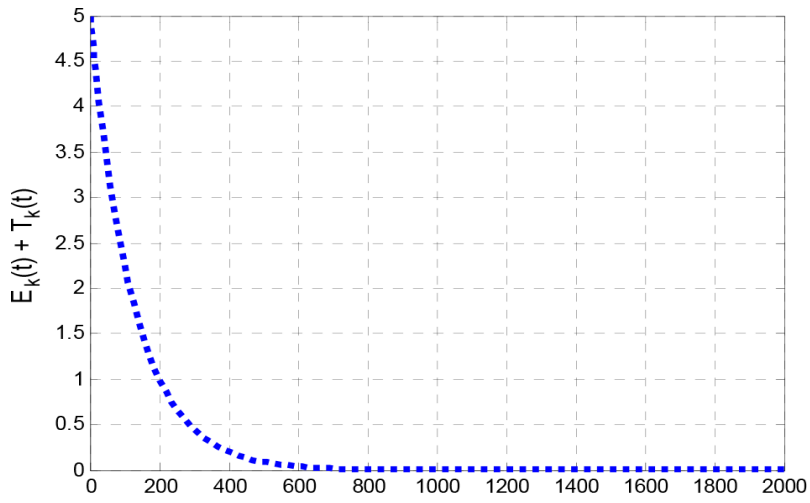

Figure 2. The total number of employees with tacit knowledge changes over time t with $\mu = 1$, $\lambda = 0.0001$

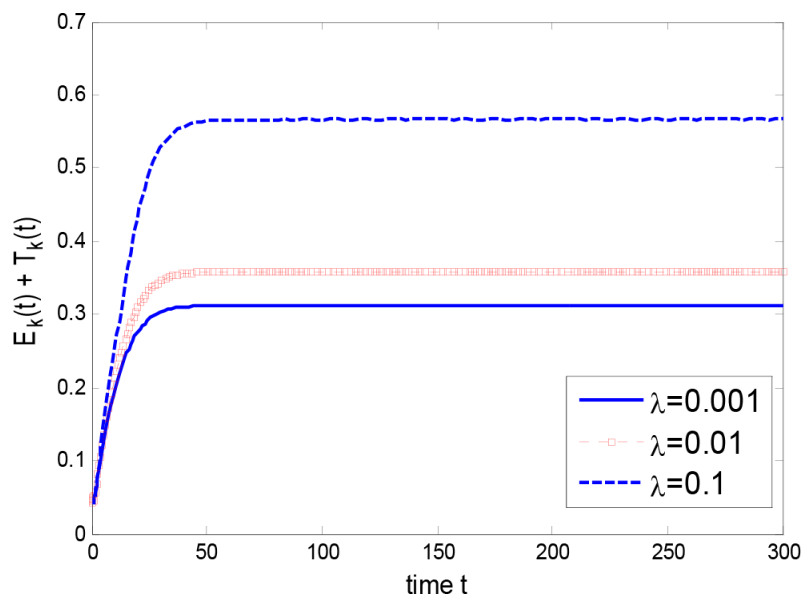

Figure 3. The total number of employees with tacit knowledge changes over time t with $\mu = 0$

4. Conclusions

Knowledge spreading practices in firms are suggested to contribute to KM and digital information management. The information absorptive capacity and KM effectiveness of a firm can be increased by effectively encouraging employees to propagate useful tacit knowledge across the organization. The purpose of this study is to model and simulate tacit knowledge spreading process. The contributions of this study are threefold. First, the tacit knowledge spreading model investigated in this study has major practical importance, given that intention mechanism is a necessary factor that should be included. The spreading process. The contributions of this study are threefold. First, the tacit knowledge spreading model investigated in this study has major practical importance, given that intention mechanism is a necessary factor that should be included. The findings show that improving the potential tacit knowledge sharing intentions of employees

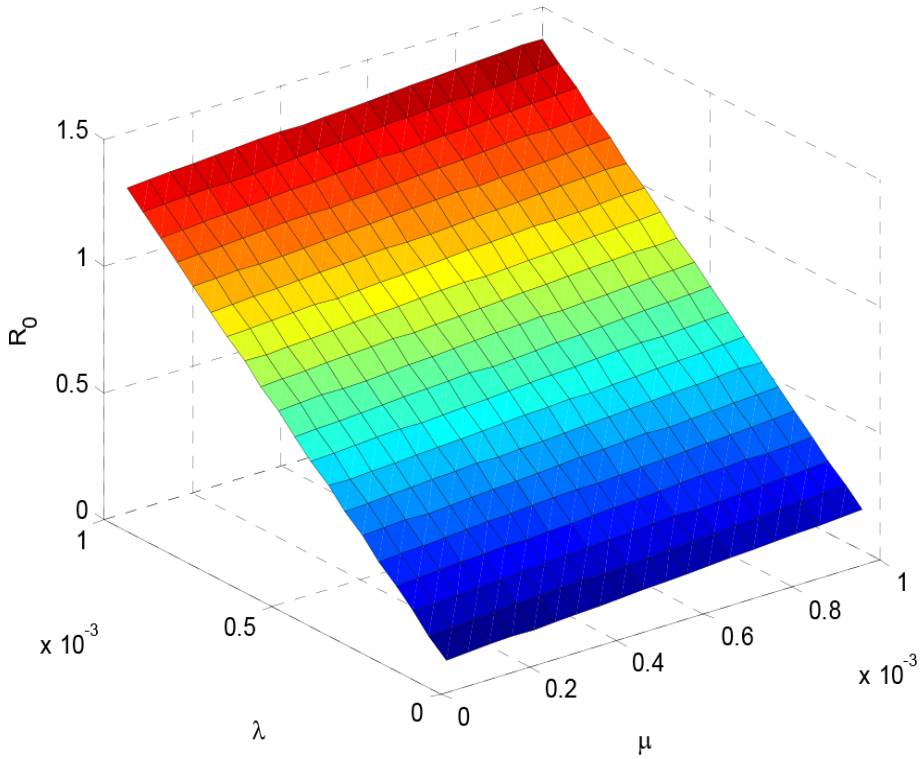

Figure 4. The threshold R_0 in terms of parameters λ and μ. In this paper, $\beta = 0.001, \gamma = 0.01$

without tacit knowledge and making a sufficient number of these employees directly become employees with tacit knowledge and tacit knowledge sharing intentions efficiently contribute to tacit knowledge spreading and KM effectiveness.

The second contribution of this study involves considering the employees of an organization and their contacts as a knowledge exchange network and analyzing the effects of knowledge network topology on tacit knowledge spreading. If the knowledge network follows power-law degree distributions and if this network has sufficiently high heterogeneity, even infinitesimally small knowledge transmission rates can make tacit knowledge exist and spread continually in the organization.

The third contribution is proposing tacit knowledge spreading model on networks enlightened by the SIS model and deriving the threshold that governs whether a tacit knowledge can be spread across an organization. Numerical simulations are presented to support the theoretical results. The results can guide KM and digital information management from the perspective of theoretical and quantitative research with regard to theoretical and practical aspects.

Acknowledgements

The work was supportsed by the National Natural Science Foundation of China (No. 71271032) and National Soft Science Plan funded project (2011GXS5K089).

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