Knowledge Structure and Its Impact on Knowledge Transfer in the Big Data Environment

Chuanrong Wu[1], Evgeniya Zapevalova[1], Feng Li[2], Deming Zeng[3]

[1] School of Economy and Management, Changsha University of Science & Technology, China
[2] School of Computer & Communication Engineering, Changsha University of Science & Technology, China
[3] School of Business Administration, Hunan University, China
wuchuanrong01@126.com, evgeniyaaya@qq.com,lif@csust.edu.cn,deming@hnu.edu.cn

Abstract

With the advent of the big data era, big data knowledge and private knowledge have become two dominant types of knowledge that an enterprise needs for product innovation. Based on the analysis of the relationships and the mutual influence between big data knowledge and private knowledge, a decision model of knowledge transfer that can take into consideration the influence of various knowledge structures on the efficiency of knowledge transfer is presented. Simulation experiments have been developed for different influence coefficients and knowledge weights. The experimental results are consistent with previous studies and the actual economic situation, suggesting that the model is valid. The model can provide decision-making support for enterprises to determine the allocation of a knowledge structure in the big data environment.

Keywords: Big data, Knowledge transfer, Knowledge structure, Efficiency, Decision model

1 Introduction

With the rapid development of the Internet, networking, social networks, and cloud computing, the era of big data has been ushered in. The date properties of integrity and availability become more and more important in many commercial applications [1]. The use of big data has become the basis of competition and growth for individual enterprises. It can enhance productivity and create significant value for enterprises by guiding decisions, trimming costs and increasing the quality of products and services [2]. For example, McGuire et al. assert that enterprises can mine customer behaviors (such as preferences, needs and feedback) by analyzing and processing big data to implement iterative development [3]. Bughin et al. suggest that the integration of massive amounts of data into research and development in the manufacturing industry is conducive to shortening the required time of parallel engineering, and to improving product quality [4]. Statsoft has noted that enterprises can improve the efficiency of their business operations and promote their own development by collecting data, analyzing data and publishing data in the process of the evolution of information technology [5]. Therefore, big data has become one of the most important elements for enterprises, and the useful knowledge mined from big data by some specialized agencies and personnel has become an important type of knowledge that enterprises need for innovation. This type of knowledge can be called big data knowledge [6-10].

In the big data environment, enterprises usually try their best to acquire new knowledge to carry out product innovation by transferring big data knowledge from big data knowledge providers [11-12]. Enterprises do so for two reasons. First, transferring big data knowledge from specialized big data knowledge providers can help reduce the costs and improve the performance of enterprises [13-14]. Second, although big data is widely available, some enterprises can not obtain knowledge directly from big data due to their own technological limitations [15-21]. Therefore, knowledge transfer is very important for enterprises in the big data environment; almost every enterprise needs to transfer big data knowledge from big data knowledge providers [6-10]. However, over mining from big data may violate intellectual property rights and personal privacy [22]. Enterprises need to transfer private knowledge from other organizations while transferring big data knowledge from big data knowledge providers.

A new product of an enterprise often includes not only big data knowledge but also private knowledge. Scholars have carried out numerous studies on knowledge transfer of one type of knowledge from different perspectives [23-32]. Some researchers have studied knowledge transfer of two types of knowledge in the big data environment [10, 12, 33]. However, thus far, few studies have taken into consideration the relationship between different types of knowledge and

*Corresponding Author: Chuanrong Wu; E-mail: wuchuanrong01@126.com
DOI: 10.3966/160792642018031902026

their influence on knowledge transfer efficiency. Different relationships and knowledge weights have different effects on the efficiency of knowledge transfer. It is necessary to analyze the knowledge structure and identify the impact of different knowledge structures on the efficiency of knowledge transfer when an enterprise not only needs to transfer big data knowledge but also needs to transfer private knowledge in the big data environment.

This paper is organized as follows: Section 1 introduces the background of knowledge transfer in the big data environment and the necessity of analyzing the relationship and mutual influence between big data knowledge and private knowledge. The knowledge structure in the big data environment is analyzed in Section 2. In Section 3, the modeling method and hypotheses are put forward. The optimization model is presented in Section 4. The validation and simulation experiments of the model are conducted in Section 5. The conclusions are drawn in Section 6.

2 Knowledge Structure in the Big Data Environment

The knowledge structure includes two aspects: one is the types and proportion of knowledge, and the other is the relationships and mutual influence between different types of knowledge. Product innovation often needs many types of knowledge in actual economic situations. The mode of big data knowledge transfer is different from the mode of private knowledge transfer. Big data knowledge and private knowledge are the two main types of knowledge that an enterprise needs for product innovation in the big data environment [10]. The proportion of knowledge can be determined by weighing the contribution of these two types of knowledge to product innovation.

Knowledge is a special type of product. According to the degree of correlation, the relationships between big data knowledge and private knowledge can be divided into independence, complementarity, alternativity, and competition. When two types of knowledge are independent, there is no mutual influence between them. If two types of knowledge are complementary, they are interdependent, and the transfer of one type of knowledge must be matched with another type of knowledge. Complementary knowledge types will promote each other in the process of knowledge transfer. Alternativity refers to the relationship in which the use of any separate types of knowledge can achieve the same goal. For example, software used for the same computer operating platform are alternatives. Alternative knowledge will have a negative effect on each other in the process of knowledge transfer. Competitive knowledge refers to two types of similar knowledge with a competitive relationship. Competitive knowledge will hinder the knowledge transfer of both types of knowledge. The relationships and mutual influence between big data knowledge and private knowledge are shown in Table 1.

Table 1. The relationships between and mutual influence of two types of knowledge

	Big data knowledge	
Private knowledge	Independent relationship (No effect)	Complementary relationship (Positive effect)
	Competitive relationship (Negative effect)	Alternative relationship (Negative effect)

3 Methodology of Modeling

3.1 Modeling Idea and Method

Suppose that an enterprise only needs to transfer two types of knowledge in the big data environment, where one type of knowledge is private knowledge from another enterprise and the other type of knowledge is big data knowledge from a big data knowledge provider. There is a mutual influence between these two types of knowledge. To analyze the impact of the knowledge structure on the efficiency of knowledge transfer, an optimization model of knowledge transfer can be established based on the maximization of the discount expected profit (DEP) of an enterprise in the context of the big data environment. The total DEP includes the DEP before knowledge transfer, the DEP after knowledge transfer and the transfer cost. The weights and the mutual influence between two types of knowledge will have effect on the DEP after knowledge transfer and on the knowledge transfer cost. The method of modeling is shown in Figure 1.

3.2 Model Hypotheses

In order to compare the current model with previous models, the same assumptions and variables remain unchanged. The assumptions and variables are as follows, the expression of an innovation network in the big data environment is $G=(V,E,BD)$; V_i and V_j are two enterprises in $G=(V,E,BD)$; V_i produces only one product; V_i transfers one type of private knowledge from V_j, and one type of big data knowledge from BD_k; $\omega_1,\omega_2 (0<\omega_1,\omega_2<1, \omega_1+\omega_2=1)$ represents the weights of private knowledge and big data knowledge; the update rate of private knowledge is β_1, the update rate of big data knowledge is β_2, and

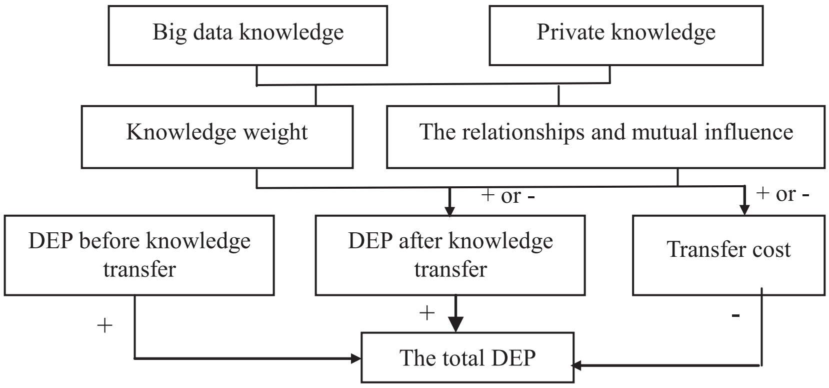

Figure 1. Model method

the total update rate of external knowledge after knowledge transfer is β; the total market volume of the product is Q; the price of the product is p; the discount rate is r; the marginal cost in the starting period is MC; the absorption capacity is α ($0<\alpha<1$); the market share of each enterprise in the starting period is ϕ; the total market volume increases at a rate of $\theta_1(0<\theta_1<1)$ in the first L_1 periods and decreases at a rate of $\theta(0<\theta<1)$ in other periods; $\rho_1(0<\theta_1<\rho_1<1)$ is the growth rate of the market share of V_i in the first L periods when V_i only transfers private knowledge; $\rho_2(0<\theta_1<\rho_2<1)$ is the growth rate of market share of V_i in the first L periods when V_i only transfers big data knowledge; $\rho(0<\theta_1<\rho<1)$ is the growth rate of the market share of V_i in the first L_1 periods immediately after knowledge transfer; the fixed transfer cost of private knowledge is k_1 and the fixed transfer cost of big data knowledge is k_2; and the life cycle of the product is N. The detailed assumptions refer to the Ref. [10] and [34]. Additionally, two new hypotheses are posited:

Hypothesis 1. V_i will transfer big data knowledge and private knowledge simultaneously in time period T. These two types of knowledge can be independent, complementary, alternative, or competitive.

Hypothesis 2. There is mutual influence between big data knowledge and private knowledge if they are not independent, and the influence coefficient of these two types of knowledge is σ.

4 Optimization Model

According to hypothesis 1, V_i wants to transfer one type of big data knowledge and one type of private knowledge simultaneously in time period T. $\xi(T)$ is the DEP before the knowledge transfer of V_i, $\xi(T)$ is the DEP after the knowledge transfer of V_i, and $K(T)$ is the knowledge transfer cost. The total DEP of V_i can be denoted $\psi(T)$, where $\psi(T)=\zeta(T)+\xi(T)-K(T)$.

4.1 The Mutual Influence between Two Types of Knowledge

When an enterprise produces a product using prior knowledge, the marginal cost in the starting period is MC. The enterprise will accumulate knowledge stock according to the knowledge absorption capacity $\alpha(0<\alpha<1)$. The marginal cost will decline at a rate of $(1-\alpha)$, and the marginal cost in a time period will reduce to $MC\alpha^n(n<T)$. When the enterprise adopts new knowledge in time period T, the marginal cost changes from $MC\alpha^T$ to $MC\beta^T$. The marginal cost in period n will reduce to $MC\beta^T\alpha^n(n\geq T)$.

According to previous hypotheses, the update rate of private knowledge is β_1, and the update rate of big data knowledge is β_2. When an enterprise adopts new knowledge in time period T, the update rate of external private knowledge evolves to β_1^T and the update rate of external big data knowledge evolves to β_2^T. The mutual influence depends on the knowledge distance between two types of knowledge. Suppose the mutual influence between private knowledge and big data knowledge is linear and within a certain potential threshold value. According to hypothesis 2, the influence coefficient is σ and the mutual influence can be expressed as $\sigma\left|\beta_1^T-\beta_2^T\right|$. It can be assumed that the enterprise will accumulate production experience with the new efficiency after knowledge transfer, therefore, the update rate of the enterprise in period T can be expressed as Eq. (1).

$$\beta=\omega_1\beta_1^T+\omega_2\beta_2^T+\sigma\left|\beta_1^T-\beta_2^T\right| \quad (0\leq\omega_1,\omega_2\leq 1,\omega_1+\omega_2=1) \tag{1}$$

The enterprise will accumulate production experience based on the efficiency of external knowledge. Therefore, when $\sigma>0$, the mutual influence is negative and the relationship between big data knowledge and private knowledge is either competitive or alternative. When $\sigma<0$, the mutual influence is positive and the relationship between big data knowledge and private knowledge is complementary. When $\sigma=0$, the two types of knowledge are independent.

4.2 DEP before Knowledge Transfer

Because there is no new knowledge transfer during this period, the DEP before knowledge transfer can be calculated by subtracting the total cost from the total sales revenue and then discounting the profit of each phase to the starting point $n=0$ .The DEP before knowledge transfer is as determined according to Eq. (2), which can also be found in Ref. [10].

$$\zeta(T)=\begin{cases} pQ\phi\sum_{n=1}^{T}(1+\theta_1)^n r^n - Q\phi MC\sum_{n=1}^{T}(1+\theta_1)^n\alpha^n r^n & T\le L_1 \\ pQ\phi\sum_{n=1}^{L_1}(1+\theta_1)^n r^n - Q\phi MC\sum_{n=1}^{L_1}(1+\theta_1)^n\alpha^n r^n & \\ +\,pQ\phi(1+\theta_1)^{L_1}\sum_{n=L_1+1}^{T}(1-\theta)^{n-L_1}r^n & \\ -\,Q\phi MC(1+\theta_1)^{L_1}\sum_{n=L_1+1}^{T}(1-\theta)^{n-L_1}\alpha^n r^n & T>L_1 \end{cases} \tag{2}$$

4.3 Transfer Cost

Enterprises have to pay a certain amount of knowledge transfer cost when absorbing private knowledge and big data knowledge. Knowledge transfer cost K can be divided into the fixed cost and the variable cost. The fixed transfer cost k includes the fixed transfer cost of private knowledge k_1 and the fixed transfer cost of big data knowledge k_2. Because $\omega_1,\omega_2(0\le\omega_1,\omega_2\le 1;\omega_1+\omega_2=1)$ is used to denote the weight of private knowledge and big data knowledge, $k=\omega_1 k_1+\omega_2 k_2$, where k_1,k_2 are constants.

Variable cost is related to the potential difference between external knowledge and internal knowledge. The potential energy of the internal knowledge is related to the absorption capacity α. The potential energy of the external knowledge is determined by the update rates of private knowledge, big data knowledge and the interaction between them. The update rate of external knowledge in time period T is shown in Eq. (1); therefore, the knowledge potential difference can be expressed as Eq. (3).

$$\alpha^T-(\omega_1\beta_1^T+\omega_2\beta_2^T+\sigma\left|\beta_1^T-\beta_2^T\right|) \tag{3}$$

The variable cost can be computed by $F(\alpha^T-(\omega_1\beta_1^T+\omega_2\beta_2^T+\sigma\left|\beta_1^T-\beta_2^T\right|))$, where F is a constant. By discounting the transfer cost to the starting point after adding the fixed cost and variable cost, the present value of the knowledge transfer cost can be expressed as Eq. (4).

$$K(T)=\left[\omega_1k_1+\omega_2k_2+F(\alpha^T-(\omega_1\beta_1^T+\omega_2\beta_2^T+\sigma\left|\beta_1^T-\beta_2^T\right|))\right]r^T \quad (0\le\omega_1,\omega_2\le 1;\omega_1+\omega_2=1) \tag{4}$$

4.4 DEP after transferring

Suppose that there is no influence on the growth rate of the market share and that ω_1,ω_2 are the weights of private knowledge and big data knowledge to the growth rate of market share; the growth rate of total market share ρ can be calculated using Eq. (5).

$$\rho=\omega_1\rho_1+\omega_2\rho_2(0\le\omega_1,\omega_2\le 1;\omega_1+\omega_2=1) \tag{5}$$

From previous hypotheses, the market share of V_i will increase at a rate of ρ in the first L periods immediately after time period T and then decay at a rate of θ. Hence, the market share of V_i in period n can be expressed as Eq. (6).

$$\lambda(n,T)=\begin{cases}\phi(1+\theta_1)^T(1+\omega_1\rho_1+\omega_2\rho_2)^n & n\le L,\ T\le L_1\\ \phi(1+\theta_1)^{L_1}(1-\theta)^{T-L_1}(1+\omega_1\rho_1+\omega_2\rho_2)^n & n\le L,\ T>L_1\\ \phi(1+\theta_1)^T(1+\omega_1\rho_1+\omega_2\rho_2)^n(1-\theta)^{n-L} & n>L,\ T\le L_1\\ \phi(1+\theta_1)^{L_1}(1-\theta)^{T-L_1}(1+\omega_1\rho_1+\omega_2\rho_2)^L(1-\theta)^{n-L} & n>L,\ T>L_1\end{cases} \tag{6}$$

The knowledge adopted by V_i in time period T was updated by β^T, which reduced the marginal cost in time period T to $MC\beta^T$. As shown in Eq. (1), $MC\beta^T$ can be expressed as $MC(\omega_1\beta_1^T+\omega_2\beta_2^T+\sigma\left|\beta_1^T-\beta_2^T\right|)$. Renumbering the periods after knowledge transfer as n starting from 1 to N, the marginal cost in period n becomes $MC(\omega_1\beta_1^T+\omega_2\beta_2^T+\sigma\left|\beta_1^T-\beta_2^T\right|)\alpha^n$. Hence, the total production cost in period n after knowledge transfer is $Q\lambda(n,T)MC(\omega_1\beta_1^T+\omega_2\beta_2^T+\sigma\left|\beta_1^T-\beta_2^T\right|)\alpha^n$. By subtracting the total production cost from the sales revenue $pQ\lambda(n,T)$, the profit in time period n after knowledge transfer is expressed as Eq. (7).

$$\Pi^*=pQ\lambda(n,T)-Q\lambda(n,T)MC(\omega_1\beta_1^T+\omega_2\beta_2^T+\sigma\left|\beta_1^T-\beta_2^T\right|)\alpha^n \tag{7}$$

After discounting the profits in time period n to the starting point by multiplying Eq. (7) with $r^T r^n$ and summing all the discounted profits in period N, the DEP after knowledge transfer becomes

$$\xi(T)=r^T\sum_{n=1}^{N}(pQ\lambda(n,T)-Q\lambda(n,T)\,MC(\omega_1\beta_1^T+\omega_2\beta_2^T+\sigma\left|\beta_1^T-\beta_2^T\right|)\alpha^n)r^n \tag{8}$$

Using Eqs. (6) and (8), the expected profits after knowledge transfer can be expressed as Eq. (9).

$$\xi(T)=\begin{cases} pQ\phi(1+\theta_1)^T r^T \sum_{n=1}^{L}(1+\omega_1\rho_1+\omega_2\rho_2)^n r^n \\ \quad -MCQ\phi(1+\theta_1)^T r^T(\omega_1\beta_1^T+\omega_2\beta_2^T+\sigma\left|\beta_1^T-\beta_2^T\right|)\sum_{n=1}^{L}(1+\omega_1\rho_1+\omega_2\rho_2)^n\alpha^n r^n \\ \quad +pQ\phi(1+\theta_1)^T(1+\omega_1\rho_1+\omega_2\rho_2)^L r^T\sum_{n=L+1}^{N}(1-\theta)^{n-L}r^n \\ \quad -MCQ\phi(1+\theta_1)^T r^T(\omega_1\beta_1^T+\omega_2\beta_2^T+\sigma\left|\beta_1^T-\beta_2^T\right|)(1+\omega_1\rho_1+\omega_2\rho_2)^L\sum_{n=L+1}^{N}(1-\theta)^{n-L}\alpha^n r^n & T\le L_1 \\ pQ\phi(1+\theta_1)^{L_1}(1-\theta)^{T-L_1} r^T \sum_{n=1}^{L}(1+\omega_1\rho_1+\omega_2\rho_2)^n r^n \\ \quad -MCQ\phi(1+\theta_1)^{L_1}(1-\theta)^{T-L_1}(\omega_1\beta_1^T+\omega_2\beta_2^T+\sigma\left|\beta_1^T-\beta_2^T\right|)r^T\sum_{n=1}^{L}(1+\omega_1\rho_1+\omega_2\rho_2)^n\alpha^n r^n \\ \quad +pQ\phi(1+\theta_1)^{L_1}(1-\theta)^{T-L_1}(1+\omega_1\rho_1+\omega_2\rho_2)^L r^T\sum_{n=L+1}^{N}(1-\theta)^{n-L}r^n \\ \quad -MCQ\phi(1+\theta_1)^{L_1}(1-\theta)^{T-L_1} r^T(\omega_1\beta_1^T+\omega_2\beta_2^T+\sigma\left|\beta_1^T-\beta_2^T\right|)(1+\omega_1\rho_1+\omega_2\rho_2)^L\sum_{n=L+1}^{N}(1-\theta)^{n-L}\alpha^n r^n & T>L_1 \end{cases} \quad \textbf{(9)}$$

4.5 Total DEP Model

The optimization problem will be to find the maximum of $\zeta(T)+\xi(T)-K(T)$ to the given parameters. Therefore, the optimization model of different knowledge structures can be expressed as Eq.(10).

$$\max\psi(T)=\max(\zeta(T)+\xi(T)-K(T)) \quad \textbf{(10)}$$

5 Simulation Experiments and Results

5.1 Model Solution and Parameter Setting

Eq. (10) shows that $\psi(T)$ is a piecewise continuous differential function of T. Therefore, $\psi(T)$ can reach its maximum in a closed interval $1\le T\le N$, and the maximum profit in the life cycle of the product can be found. Matlab 7.0 is used to compile a program, and simulation experiments can be conducted by adjusting the model's parameters.

To simulate knowledge transfer in the big data environment, some parameters are chosen for testing. To compare the simulation results in Ref. [10], the values of the same parameters are the same while the new parameters are set to new values. The parameters are set as follows: the total product sales $Q=1000$; the relative value of price per unit product $p=60$; the market share of V_i in the starting period $\phi=8\%$; the growth rates of total market volume in the first $L_1(L_1=3)$ periods $\theta_1=3\%$; the natural attenuation rate of market volume in the other periods $\theta=3\%$; the growth rate of two types of knowledge to the market share in the first $L=5$ periods immediately after knowledge transfer $\rho_1=6\%,\rho_2=8\%$; the marginal cost in the starting period $MC=40$; the fixed transfer cost of private knowledge $k_1=300$; the fixed transfer cost of big data knowledge $k_2=80$; the coefficient of the variable cost $F=1000$; the knowledge absorption capacity $\alpha=95\%$; the update rate of private knowledge $\beta_1=88\%$; the update rate of big data knowledge $\beta_2=84\%$; and the life cycle of the product $N=10$. Assuming the market is risk-neutral and the discount rate is 10%, then $r=1/(1+10\%)\approx 0.9$.

5.2 Simulation and Validation When the Influence Coefficient $\sigma=0$

(1) When $\sigma=0$, private knowledge and big data knowledge are independent. Under this circumstance, there is no mutual influence between the two types of knowledge, and only the weights will affect the knowledge structure and the efficiency of knowledge transfer. To compare with previous research, let $\beta_2=88\%$ and set all the other parameters except ω_1,ω_2 to the same values as described in the previous section. The experimental results are the same as in Ref. [10], which suggested that the model is valid.

(2) Let $\sigma=0$ and $\beta_2=84\%$; this indicates that the update rate of big data knowledge is enhanced. Table 2, Table 3, Figure 2 and Figure 3 show the changes of total DEP and transfer cost for various levels of ω_1,ω_2 when $\sigma=0$, $\beta_2=84\%$. $\omega_2=0$ is used to express $\omega_1=1,\omega_2=0$, $\omega_2=0.1$ to express $\omega_1=0.9,\omega_2=0.1$, and so on. When enhancing the update rate of big data knowledge, the total DEP increases with the weight of big data knowledge, and the transfer cost decline with the weight of big data knowledge. Because the greater proportion of higher-efficiency knowledge can help enterprises to increase sales and trim costs. The experimental results of the simulation are in accordance with the actual economic situation, which suggests that the model is valid.

Table 2. Total DEP with different weights of two types of knowledge when $\sigma=0,\beta=84\%$

Period	1	2	3	4	5	6	7	8	9	10	weight	
DEP	18048	20070	21775	22136	22304	22341	22294	22196	22068	21927	ω_1=1	ω_2=0
DEP	18253	20313	22035	22386	22535	22551	22481	22359	22211	22051	ω_1=0.9	ω_2=0.1
DEP	18460	20558	22298	22638	22769	22762	22669	22525	22355	22176	ω_1=0.8	ω_2=0.2
DEP	18669	20805	22563	22893	23005	22975	22859	22692	22501	22302	ω_1=0.7	ω_2=0.3
DEP	18879	21054	22831	23150	23243	23191	23050	22861	22648	22429	ω_1=0.6	ω_2=0.4
DEP	19091	21305	23102	23409	23483	23408	23244	23031	22796	22558	ω_1=0.5	ω_2=0.5
DEP	19305	21559	23375	23671	23726	23628	23439	23203	22946	22688	ω_1=0.4	ω_2=0.6
DEP	19520	21815	23650	23936	23971	23850	23637	23376	23097	22819	ω_1=0.3	ω_2=0.7
DEP	19737	22074	23928	24203	24219	24074	23836	23551	23250	22951	ω_1=0.2	ω_2=0.8
DEP	19956	22334	24209	24473	24468	24300	24037	23728	23404	23084	ω_1=0	ω_2=1

Table 3. Transfer cost with different weights of two types of knowledge when $\sigma = 0, \beta = 84\%$

Period	1	2	3	4	5	6	7	8	9	10	weight	
Cost	333	347	347	338	322	303	282	260	238	216	ω_1=1	ω_2=0
Cost	317	335	337	330	316	298	277	255	233	212	ω_1=0.9	ω_2=0.1
Cost	301	322	328	322	309	292	272	251	229	208	ω_1=0.8	ω_2=0.2
Cost	284	310	318	315	303	286	267	246	225	204	ω_1=0.7	ω_2=0.3
Cost	268	298	309	307	296	281	262	241	220	200	ω_1=0.6	ω_2=0.4
Cost	252	286	299	299	290	275	257	237	216	196	ω_1=0.5	ω_2=0.5
Cost	236	273	290	291	283	269	251	232	212	192	ω_1=0.4	ω_2=0.6
Cost	220	261	280	283	277	264	246	227	207	188	ω_1=0.3	ω_2=0.7
Cost	203	249	270	276	270	258	241	223	203	184	ω_1=0.2	ω_2=0.8
Cost	187	237	261	268	264	252	236	218	199	180	ω_1=0	ω_2=1

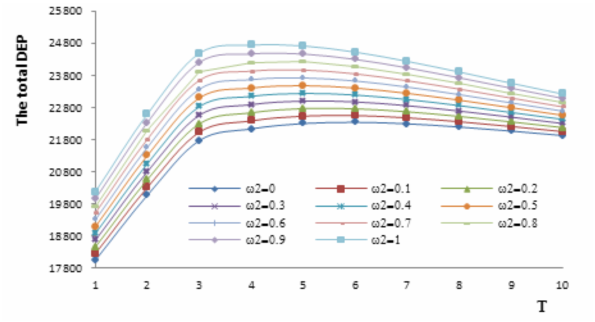

Figure 2. Changes of total DEP when $\sigma = 0, \beta = 84\%$

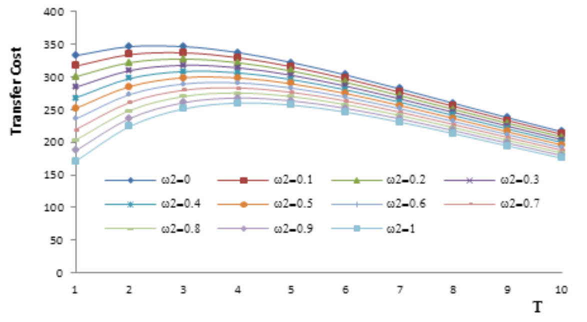

Figure 3. Changes of transfer cost when $\sigma = 0, \beta = 84\%$

5.3 Simulation When the Influence Coefficient $\sigma > 0$

(1) When $\sigma > 0$, the relationship between big data knowledge and private knowledge is either competitive or alternative. When $\sigma = 0.5$, there is negative influence between big data knowledge and private knowledge, and the influence coefficient is 0.5. To determine the effect of knowledge structure on the DEP and transfer cost, all the other parameters are set with the same values except for the weights of the two types of knowledge ω_1, ω_2, which vary from $\omega_1 = 0.9, \omega_2 = 0.1$ to $\omega_1 = 0.1, \omega_2 = 0.9$. Table 4, Table 5, Figure 4 and Figure 5 show the changes of total DEP and transfer cost with ω_1, ω_2 when $\sigma = 0.5$. Compared with an influence coefficient of $\sigma = 0$, total DEP and transfer cost decline. The reason is that the competition and alternativity between the two types of knowledge will hinder knowledge transfer for both types of knowledge. The greater the mutual influence between two types of competitive or alternative knowledge, the less knowledge is transferred, and the transfer costs decline with the profits.

(2) To find the influence of the knowledge structure on the efficiency of knowledge transfer when two types of knowledge are competitive or alternative, all the parameters are set with the same values except for the influence coefficient, which changes from $\sigma = 0.8$ to $\sigma = 1.5$. Figure 6 and Figure 7 show that total DEP changes with the influence coefficient and the weights of two types of knowledge. The results indicate that the greater the influence coefficient, the smaller the total DEP; however, the total DEP increase with the weight of big data knowledge at the same influence coefficient. The reason is that the greater the mutual influence between two types of competitive or alternative knowledge, the less knowledge is transferred. At the same degree of mutual influence, big data knowledge can help enterprises to guide decisions, trim costs, and increase sales. The profits will increase and the transfer cost will decline with the weight of the big data knowledge.

Additionally, Figure 7 shows that the influence coefficient can be greater than 1. If the influence coefficient of big data knowledge and private knowledge is greater than 1, the degree of influence between the two types of knowledge is above the average influence level.

5.4 Simulation and Validation When the Influence Coefficient $\sigma < 0$

When $\sigma < 0$, big data knowledge and private knowledge are complementary. When $\sigma = -0.8$, there is positive influence between big data knowledge and private knowledge, and the influence coefficient is 0.8. To determine the effect of the knowledge structure on

Table 4. Total DEP with different weights of two types of knowledge when $\sigma = 0.5$

Period	1	2	3	4	5	6	7	8	9	10	weight	
DEP	17939	19811	21434	21785	21972	22043	22037	21979	21890	21783	ω_1=0.9	ω_2=0.1
DEP	18144	20052	21693	22033	22201	22251	22222	22142	22032	21906	ω_1=0.8	ω_2=0.2
DEP	18350	20296	21954	22283	22433	22461	22409	22306	22175	22030	ω_1=0.7	ω_2=0.3
DEP	18558	20541	22217	22536	22667	22673	22597	22472	22320	22156	ω_1=0.6	ω_2=0.4
DEP	18768	20789	22483	22791	22904	22887	22788	22639	22466	22283	ω_1=0.5	ω_2=0.5
DEP	18979	21039	22752	23049	23142	23103	22980	22809	22613	22410	ω_1=0.4	ω_2=0.6
DEP	19192	21292	23023	23309	23383	23321	23174	22979	22762	22539	ω_1=0.3	ω_2=0.7
DEP	19407	21547	23297	23572	23627	23541	23370	23152	22912	22669	ω_1=0.2	ω_2=0.8
DEP	19624	21804	23573	23837	23873	23763	23568	23326	23064	22801	ω_1=0.1	ω_2=0.9

Table 5. Transfer cost with different weights of two types of knowledge when $\sigma = 0.5$

Period	1	2	3	4	5	6	7	8	9	10	weight	
Cost	299	307	305	297	284	268	250	231	212	194	ω_1=0.9	ω_2=0.1
Cost	283	294	295	289	277	262	245	227	208	190	ω_1=0.8	ω_2=0.2
Cost	266	282	286	281	271	256	240	222	204	186	ω_1=0.7	ω_2=0.3
Cost	250	270	276	273	264	251	235	217	200	182	ω_1=0.6	ω_2=0.4
Cost	234	258	267	266	257	245	229	213	195	178	ω_1=0.5	ω_2=0.5
Cost	218	245	257	258	251	239	224	208	191	174	ω_1=0.4	ω_2=0.6
Cost	202	233	248	250	244	233	219	203	187	170	ω_1=0.3	ω_2=0.7
Cost	185	221	238	242	238	228	214	199	182	166	ω_1=0.2	ω_2=0.8
Cost	169	209	228	235	231	222	209	194	178	162	ω_1=0.1	ω_2=0.9

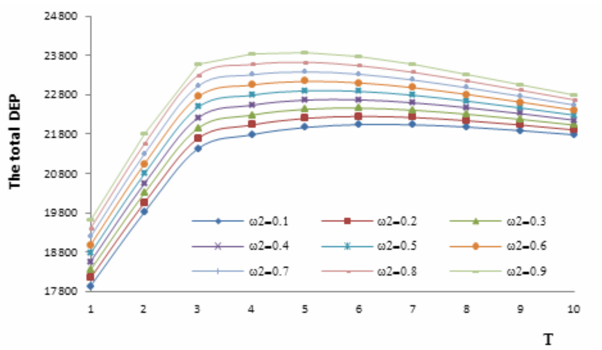

Figure 4. Changes of total DEP when $\omega_1, \omega_2, \sigma = 0.5$

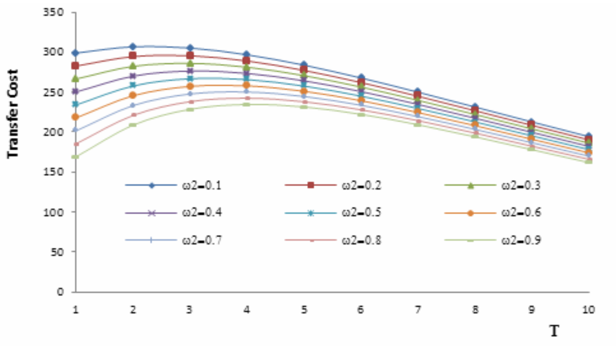

Figure 5. Changes of transfer cost when $\omega_1, \omega_2, \sigma = 0.5$

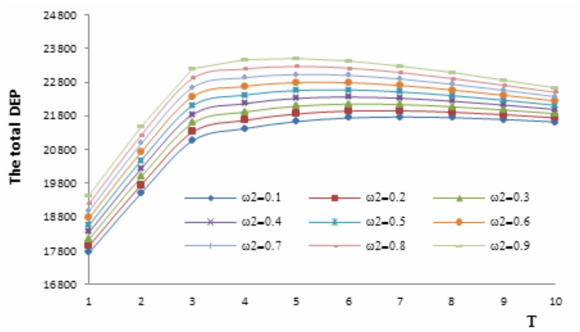

Figure 6. Changes of total DEP when $\omega_1, \omega_2, \sigma = 0.8$

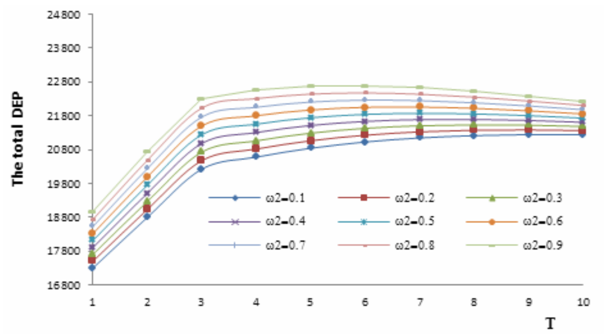

Figure 7. Changes of total DEP when $\omega_1, \omega_2, \sigma = 1.5$

the DEP and transfer cost, all the other parameters are set with the same values except the weights of the two types of knowledge ω_1, ω_2, which vary from $\omega_1 = 0.9, \omega_2 = 0.1$ to $\omega_1 = 0.1, \omega_2 = 0.9$, and so on. Table 6, Table 7, Figure 8 and Figure 9 show the changes of total DEP and transfer cost with ω_1, ω_2 when $\sigma = -0.8$.

Compared to the influence coefficient $\sigma = 0$, total DEP and transfer cost are higher. The reason is that the complementary relationship between the two types of knowledge is conducive to knowledge transfer. The greater the mutual influence between two types of complementary knowledge, the more knowledge is transferred, and the transfer costs increase with the profits.

Compared to the influence coefficient $\sigma < 0$, the growth of total DEP when $\sigma = -0.8$ is much greater than the absolute value of the decline of the total DEP when $\sigma = 0.5$. That means the degree of influence of the knowledge structure is only related to the absolute value of the influence coefficient. By enhancing the weight of big data knowledge, the total DEP will increase, and the transfer cost will decline. The experimental results of the simulation are in accordance with the actual economic situation.

Table 6. Total DEP with different weights of two types of knowledge when $\sigma = -0.8$

Period	1	2	3	4	5	6	7	8	9	10	weight	
DEP	18756	21116	22997	23348	23437	23362	23191	22968	22725	22479	ω_1=0.9	ω_2=0.1
DEP	18967	21366	23267	23607	23677	23579	23384	23138	22873	22607	ω_1=0.8	ω_2=0.2
DEP	19179	21619	23539	23868	23919	23798	23579	23309	23022	22737	ω_1=0.7	ω_2=0.3
DEP	19393	21874	23814	24132	24164	24019	23776	23482	23173	22867	ω_1=0.6	ω_2=0.4
DEP	19608	22131	24091	24399	24410	24243	23974	23657	23325	22999	ω_1=0.5	ω_2=0.5
DEP	19826	22391	24371	24667	24660	24468	24175	23833	23478	23131	ω_1=0.4	ω_2=0.6
DEP	20045	22653	24653	24939	24911	24696	24377	24011	23633	23266	ω_1=0.3	ω_2=0.7
DEP	20265	22917	24938	25213	25165	24926	24582	24191	23790	23401	ω_1=0.2	ω_2=0.8
DEP	20488	23184	25226	25490	25422	25158	24788	24372	23947	23537	ω_1=0.1	ω_2=0.9

Table 7. Transfer cost with different weights of two types of knowledge when $\sigma = -0.8$

Period	1	2	3	4	5	6	7	8	9	10	weight	
Cost	346	379	389	383	368	346	320	294	267	241	ω_1=0.9	ω_2=0.1
Cost	329	367	380	376	361	340	315	289	263	237	ω_1=0.8	ω_2=0.2
Cost	313	355	370	368	355	334	310	284	258	233	ω_1=0.7	ω_2=0.3
Cost	297	342	360	360	348	329	305	280	254	229	ω_1=0.6	ω_2=0.4
Cost	281	330	351	352	342	323	300	275	250	225	ω_1=0.5	ω_2=0.5
Cost	265	318	341	345	335	317	295	270	245	221	ω_1=0.4	ω_2=0.6
Cost	248	306	332	337	329	312	290	266	241	217	ω_1=0.3	ω_2=0.7
Cost	232	293	322	329	322	306	285	261	237	213	ω_1=0.2	ω_2=0.8
Cost	216	281	313	321	315	300	280	256	232	209	ω_1=0.1	ω_2=0.9

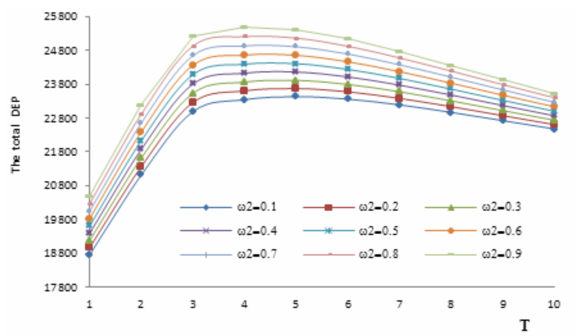

Figure 8. Changes of total DEP when $\omega_1, \omega_2, \sigma = -0.8$

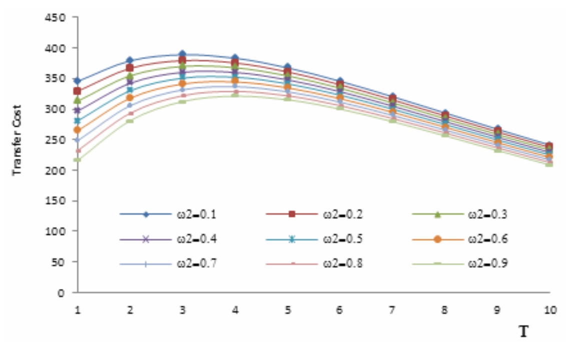

Figure 9. Changes of transfer cost when $\omega_1, \omega_2, \sigma = -0.8$

6 Conclusion

This paper analyzes the knowledge structure and its impact on knowledge transfer in the big data environment. With the advent of the big data era, big data knowledge and private knowledge have become two dominant types of knowledge that an enterprise needs for product innovation. Based on the analysis of the relationships and the mutual influence between big data knowledge and private knowledge, a decision model of knowledge transfer that can take into consideration the influence of various knowledge structures on the efficiency of knowledge transfer is presented. Simulation experiments have been developed for different influence coefficients and knowledge weights. The experimental results are consistent with those of previous studies and the actual economic situation, which suggests that the model is valid. It can provide decision-making support for enterprises to determine the allocation of knowledge structures in the big data environment.

Acknowledgements

This work was supported by the National Natural Science Foundation of China (Grant No. 71704016, 71233002, 71402010); the Natural Science Foundation of Hunan Province (Grant No. 2017JJ2267, 12JJ4073); the Scientific Research Fund of Hunan Provincial Education Department (Grant No. 11C0029); the Educational Economy and Financial Research Base of Hunan Province(Grant No. 13JCJA2); and the Project of China Scholarship Council for Overseas Studies (201208430233, 201508430121).

References

[1] Y. J. Ren, J. Shen, J. Wang, J. Han, S. Y. Lee, Mutual Verifiable Provable Data Auditing in Public Cloud Storage, *Journal of Internet Technology*, Vol. 16, No. 2, pp. 317-323, March, 2015.

[2] S. Lohr, *The Age of Big Data*, http://www.fsb.muohio.edu/lij14/311_read.pdf.

[3] T. McGuire, J. Manyika, M. Chui, Why Big Data is the New Competitive Advantage, *Ivey Business Journal*, Vol. 76, No. 4, pp. 1-4, July, 2012.

[4] J. Bughin, M. Chui, J. Manyika, Clouds, Big Data, and Smart Assets: Ten Tech-enabled Business Trends to Watch, *McKinsey Quarterly*, Vol. 56, No. 1, pp. 75-86, January, 2010.

[5] B. Statsoft, G. S. Gmbh, P. Statsoft, I. L. Statsoft, I. Lda, *The Big Data Revolution*, http://www.buyukverienstitusu.com/s/1870/i/The_Bi g_Data_Revolution.pdf.

[6] F. Suchanek, G. Weikum, Knowledge Harvesting in the Big-Data Era, *The 2013 ACM SIGMOD International Conference on Management of Data*, New York, NY, 2013, pp. 933-938.

[7] P. Horst, R. Duboff, Don't Let Big Data Bury Your Brand, *Harvard Business Review*, Vol. 93, No. 11, pp. 78-86, November, 2015.

[8] S. Jun, S. Park, D. Jang, A Technology Valuation Model Using Quantitative Patent Analysis: A Case Study of Technology Transfer in Big Data Marketing, *Emerging Markets Finance and Trade*, Vol. 51, No. 5, pp. 963-974, September, 2015.

[9] J. Manyika, M. Chui, B. Brown, J. Bughin, R. Dobbs, C. Roxburgh, A. H. Byers, *Big Data: The Next Frontier for Innovation, Competition, and Productivity*, https://www.mckinsey.com/business-functions/digital-mckinsey/our-insights/big-data-the-next-frontier-for-innovation

[10] C. R. Wu, Y. W. Chen, F. Li, Decision Model of Knowledge Transfer in Big Data Environment, *China Communications*, Vol. 13, No. 7, pp. 100-107, July, 2016.

[11] J. A. Norton, F. M. Bass, A Diffusion Theory Model of Adoption and Substitution for Successive Generations of High-Technology Products, *Management Science*, Vol. 33, No. 9, pp. 1069-1086, September, 1987.

[12] C. R. Wu, Models of Dualistic Complementary Knowledge Transfer in Big-data Environments, *Information Technology Journal*, Vol. 16, No. 1, pp. 17-26, January, 2017.

[13] J. Alcacer, J. Oxley, Learning by Supplying, *Strategic Management Journal*, Vol. 35, No. 2, pp. 204-223, February, 2014.

[14] J. Barthélemy, D. Adsit, The Seven Deadly Sins of Outsourcing, *The Academy of Management Executive*, Vol. 17, No. 2, pp. 87-98, May, 2003.

[15] Y. Kong, M. J. Zhang, D. Y. Ye, A Belief Propagation-based Method for Task Allocation in Open and Dynamic Cloud Environments, *Knowledge-based Systems*, Vol. 115, pp. 123-132, January, 2017.

[16] Z. J. Fu, X. M. Sun, Q. Liu, L. Zhou, J. G. Shu, Achieving Efficient Cloud Search Services: Multi-keyword Ranked Search over Encrypted Cloud Data Supporting Parallel Computing, *IEICE Transactions on Communications*, Vol. E98-B, No. 1, pp. 190-200, January, 2015.

[17] Z. J. Fu, K. Ren, J. G. Shu, X. M. Sun, F. X. Huang, Enabling Personalized Search over Encrypted Outsourced Data with Efficiency Improvement, *IEEE Transactions on Parallel and Distributed Systems*, Vol. 27, No. 9, pp. 2546-2559, September, 2016.

[18] Z. G. Qu, J. Keeney, S. Robitzsch, F. Zaman, X. J. Wang, Multilevel Pattern Mining Architecture for Automatic Network Monitoring in Heterogeneous Wireless Communication Networks, *China Communications*, Vol. 13, No. 7, pp. 108-116, July, 2016.

[19] Z. H. Xia, X. H. Wang, X. M. Sun, B. W. Wang, Steganalysis of Least Significant Bit Matching Using Multi-order Differences, *Security and Communication Networks*, Vol. 7, No. 8, pp. 1283-1291, August, 2014.

[20] A. Labrinidis, H. V. Jagadish, Challenges and Opportunities with Big Data, *Proceedings of the Vldb Endowment*, Vol. 5, No. 12, pp. 2032-2033, August, 2012.

[21] E. Begoli, J. Horey, Design Principles for Effective Knowledge Discovery from Big Data, *The Joint 10th Working IEEE/IFIP Conference on Software Architecture and 6th European Conference on Software Architecture*, Helsinki, Finland, 2012, pp. 215-218.

[22] X. D. Wu, X. Q. Zhu, G. Q. Wu, W. Ding, Data Mining with Big Data, *IEEE Transactions on Knowledge & Data Engineering*, Vol. 26, No. 1, pp. 97-107, January, 2014.

[23] H. M. Khamseh, D. Jolly, Knowledge Transfer in Alliances: The Moderating Role of the Alliance Type, *Knowledge Management Research & Practice*, Vol. 12, No. 4, pp. 409-420, November, 2014.

[24] J. Song, Subsidiary Absorptive Capacity and Knowledge Transfer within Multinational Corporations, *Journal of International Business Studies*, Vol. 45, No. 1, pp. 73-84, January, 2014.

[25] L. Argote, E. Fahrenkopf, Knowledge Transfer in Organizations: The Roles of Members, Tasks, Tools, and Networks, *Organizational Behavior & Human Decision Processes*, Vol. 136, pp. 146-159, September, 2016.

[26] W. L. Wu, Y. C. Lee, Knowledge Transfer and Creation in International Strategic Alliances: A Multi-level Perspective, *International Journal of Knowledge Management Studies*, Vol. 6, No. 1, pp. 1-15, January, 2015.

[27] M. D. Arteche, M. Santucci, S. V. Welsh, Clusters and Networks for Innovation and Knowledge Transfer. Impacton Argentinean Regional Growth, *Estudios Gerenciales*, Vol. 29, No. 127, pp. 127-138, June, 2013.
[28] V. Ratten, International Collaboration and Knowledge Transfer among Universities and Firms Affecting Regional Competitiveness, *Thunderbird International Business Review*, Vol. 58, No. 1, pp. 91-93, January/February, 2016.
[29] C. Pirnau, Databases Role Correlated with Knowledge Transfer between Entities of a Cluster, *"Mircea cel Batran" Naval Academy Scientific Bulletin*, Vol. 19, No. 1, July, 2016.
[30] J. A. Belso-Martinez, Resources, Governance, and Knowledge Transfer in Spanish Footwear Clusters: Can Local Firms be Locked Out by Their Crucial Partner? *International Regional Science Review*, Vol. 38, No. 2, pp. 202-231, April, 2015.
[31] C. R. Wu, Y. W. Chen, Time Optimization of Knowledge Transfer in High-tech Enterprises Innovation Networks, *System Engineering Theory and Practice*, Vol. 33, No. 4, pp. 955-962, April, 2013.
[32] S. Bagheri, R. J. Kusters, J. J. M. Trienekens, An Integrated Framework of Knowledge Transfer and ICT Issues in Co-creation Value Networks, *Procedia Computer Science*, Vol. 100, pp. 677-685, December, 2016.
[33] G. Koman, J. Kundrikova, Application of Big Data Technology in Knowledge Transfer Process between Business and Academia, *Procedia Economics & Finance*, Vol. 39, pp. 605-611, December, 2016.
[34] C. R. Wu, D. M. Zeng, Knowledge Transfer Optimization Simulation for Innovation Networks, *Information Technology Journal*, Vol. 8, No. 4, pp. 589-594, April, 2009.

Biographies

Chuanrong Wu received Ph.D. in Business Administration from Hunan University, China, in 2009. She works as a lecturer in College of Economy and Management, Changsha University of Science & Technology. Her research interests include big data management, knowledge management and computational experiments.

Evgeniya Zapevalova received her Bachelor's Degree from Tomsk State University, Russian Federation. She is currently on the second year of a Master's Degree program in Business Management in Changsha University of Science & Technology(China). Her interested areas include: big data, knowledge management and computational experiments.

Feng Li received his Ph.D. in computing science from Sun Yat-sen University, China, in 2001. He is currently a professor in School of Computer & Communication Engineering, Changsha University of Science & Technology, China. His research interests include network and information security, pattern identification.

Deming Zeng is a professor of School of Business Administration at Hunan University and Dean of Distance Learning and Continuing Education college of Hunan University. He received his Doctor's degree from University of Twente in Holland. His research interest is in big data, knowledge management, and technological innovation management.