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Optimal Model of Continuous Knowledge Transfer in the Big Data Environment

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Abstract: With market competition becoming fiercer, enterprises must update their products by constantly assimilating new big data knowledge and private knowledge to maintain their market shares at different time points in the big data environment. Typically, there is mutual influence between each knowledge transfer if the time interval is not too long. It is necessary to study the problem of continuous knowledge transfer in the big data environment. Based on research on one-time knowledge transfer, a model of continuous knowledge transfer is presented, which can consider the interaction between knowledge transfer and determine the optimal knowledge transfer time at different time points in the big data environment. Simulation experiments were performed by adjusting several parameters. The experimental results verified the model's validity and facilitated conclusions regarding their practical application values. The experimental results can provide more effective decisions for enterprises that must carry out continuous knowledge transfer in the big data environment.

Keywords: Big data, knowledge transfer, optimization model, simulation experiment, different time points.

1 Introduction

With the market competition becoming fiercer, enterprises must introduce new products based on technological innovation to maintain market share [Chatterjee and Eliashberg (1990)]. This need is more obvious for high-tech enterprises. To achieve technological innovation and launch multi-generation innovative products as well as to improve product performance, enterprises must constantly assimilate new knowledge. The process by which enterprises absorb and innovatively apply knowledge through various channels is termed knowledge transfer [Szulanski (2000)].

The rapid development of the Internet, networking, social networks, and cloud computing

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has culminated in the big data era. Various types of derivative information have been increasing exponentially. Daily, a flood of data is created by the interactions of billions of individuals using computers, Global Position System (GPS) devices, cellular telephones, and medical devices [Schwab (2012)]. These data are often referred to as 'big data', which are characterized by proliferation in the number of data sources and increasing data size. Practical discoveries through aggregation, statistical analysis and the creative combination of data in science, government and private industry indicated the future path of data-driven business [Sukumar and Kerrell (2013)]. Useful knowledge mined from big data by specialized agencies or personnel has become an important type of knowledge from which the individual enterprise can derive strategic advantage [Suchanek and Weikum (2013); Horst and Duboff (2015); Jun, Park and Jang (2015); Manyika, Chui, Brown et al. (2011)]. This type of knowledge can be termed the big data knowledge [Wu, Chen and Li (2016)].

In the big data environment, enterprises must update their products by constantly assimilating new big data knowledge and private knowledge to maintain their market shares at different time points. Big data knowledge can enhance productivity and create significant value for enterprises by guiding decisions, trimming cost and increasing the quality of products and services [McGuire, Manyika and Chui (2012); Lohr (2012)]. Private knowledge is usually the core patent knowledge, which sometimes cannot be obtained from big data, or mining from big data may involve violations of intellectual property rights and personal privacy [Wu, Zhu and Wu (2014)]. Typically, the two types of knowledge are not transferred simultaneously.

Scholars have studied the importance of knowledge transfer in the big data environment [Wu, Chen and Li (2016); Koman and Kundrikova (2016); Wu (2017)]. Several studies suggest that enterprises must transfer at least two types of knowledge in the big data environment. However, these studies only analyzed the simultaneous occurrence of two types of knowledge [Wu, Chen and Li (2016); Wu (2017); Wu, Zapevalova, Chen et al. (2018)]. There is no literature on continuous knowledge transfer in the big data environment. Although Wu et al [Wu, Zapevalova, Chen et al. (2018)] have studied multiple knowledge transfer in the big data environment, they just take the knowledge transfer at different time points as many times of independent knowledge transfer. However, the first knowledge transfer usually affects the second knowledge transfer in real-world circumstances if the time interval is not too long. It is necessary to study the problem of continuous knowledge transfer in the big data environment.

A number of scholars have analyzed multi-generation product or technology knowledge diffusion using Bass or Lotka-Voherra models [Kim, Shin, Park et al. (2009); Barkoczi, Lobonţiu and Bacali (2015); Ganguly (2015)]. These models are primarily concerned with technical knowledge diffusion in the entire market and scarcely address the change in continuous knowledge transfer efficiency of each enterprise. Some scholars suggest that artificial neural network (ANN) learning model be applied for user recommendation and prediction from the big data [Jung, Kim and Sim (2016)]. Although ANN modeling procedure consists of learning, validation and prediction steps, the efficiency of knowledge transfer is seldom considered. Some scholars believe that the selection of the optimal time is one of the most important factors to improve the efficiency of knowledge transfer [Farzin (1996); Doraszelski (2004); Wu and Zeng (2009); Szulanski, Ringov and Jensen (2016); Wu, Chen and Li (2016); Liu, Zhang and Xia (2017); Shinde and Ashtankar (2017); Wu, Zapevalova, Chen et al. (2018)].

This paper proposes a time optimization model for continuous knowledge transfer. This model can consider the interaction between each knowledge transfer and determine the optimal knowledge transfer time at different time points in the big data environment. The experimental results can provide more effective decisions for enterprises that must carry out continuous knowledge transfer in the big data environment. In the first section, the importance of continuous knowledge transfer in the big data environment and the necessity of analyzing continuous knowledge transfers are considered. Model hypotheses and the modeling method are presented in Section 2. A time optimization model of continuous knowledge transfer is presented in Section 3. The simulation experiments and the analysis of the model results are described in Section 4. Conclusions are drawn in Section 5.

2 Hypotheses and modeling method

Assume that an enterprise must transfer only two types of knowledge in the big data environment. One type of knowledge is big data knowledge provided by a big data knowledge provider. The other type is private knowledge provided by another enterprise. The two types of knowledge are not transferred simultaneously. Rather, the private knowledge is transferred soon after the big data knowledge.

2.1 Quantitative expression of knowledge transfer in the big data environment

An innovation network is a social context of enterprises and research institutes that are linked to one another to share resources and knowledge to gain critical competencies that contribute to their competitiveness in the marketplace [Zuech, Khoshgoftaar and Wald (2015)]. In the big data environment, knowledge resources associate with one another through the Internet. The scale of the innovation network becomes large, the connections between the knowledge storage units are complex, and the knowledge storage units have heterogeneity. Enterprises in innovation networks can directly share resources and knowledge with one another. In addition, they can obtain knowledge of other knowledge storage units from big data knowledge providers. It is difficult to fully characterize an innovation network in the big data environment using a general binary network.

Let $G=(V,E,BD)$ be an expression of an innovation network in the big data environment, where $V=\{V_i\}$ is the set of nodes and V_i represents a knowledge transfer organization, which can be an enterprise, research institute or other knowledge storage unit except the big data knowledge providers in the network. $E=\{e_{i,j}\}$ is the set of edges, and $e_{i,j}$ represents the knowledge transfer between nodes. $BD=\{BD_k\}$ is the set of big data knowledge providers in and innovation network, and BD_k provides the big data knowledge for other nodes (particularly for enterprises and research institutes). If V_i transfers one type of private knowledge from V_j, $e_{j,i}=1$. If V_i does not transfer private knowledge from V_j, $e_{j,i}=0$. If V_j transfers one type of private knowledge from V_i, $e_{i,j}=1$. If V_j does not transfer private knowledge from V_i, $e_{i,j}=0$. If V_i transfers one type of big data knowledge from BD_k, $e_{k,i}=1$. If V_i does not transfer big data knowledge from BD_k, $e_{k,i}=0$. However, if the knowledge that BD_k transferred from many nodes $V=\{V_i\}$ is common knowledge, then we suppose $e_{i,k}=0$.

2.2 Model hypotheses

This paper is based on previous research on one-time knowledge transfer. The same assumptions and variables remain unchanged as follows: 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 $\alpha(0<\alpha<1)$, the market share of V_i in the starting period is ϕ, and the life cycle of the product is N. For details on assumptions, see models of Wu et al. [Wu, Chen and Li (2016); Wu and Zeng (2009)]. In addition, eight new hypotheses are proposed:

Hypothesis 1. V_i and V_j are two enterprises in $G=(V,E,BD)$, BD_k is a big data knowledge provider in $G=(V,E,BD)$, and V_i produces only one product.

Hypothesis 2. V_i transfers one type of big data knowledge from BD_k firstly at time period T_1. After time period T_2, V_i transfers the private knowledge from V_j ($0<T_1,T_2<N$). The time interval T_2 is not too long, and there is mutual influence between two knowledge transfers.

Hypothesis 3. The market share of V_i 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.

Hypothesis 4. $\rho_1(0<\theta_1<\rho_1<1)$ is the growth rate of the market share of V_i in the first L_2 periods immediately after V_i transfers big data knowledge at the time period T_1. $\rho_2(0<\theta_1<\rho_2<1)$ is the growth rate of the market share of V_i in the first L_3 periods immediately after V_i transfers the private knowledge at time period T_2.

Hypothesis 5. The update rate of the big data knowledge at time period $n=0$ is β_1, and the update rate of private knowledge at the time period $n=0$ is β_2 $(0<\beta_1,\beta_2<1)$.

Hypothesis 6. $\zeta_1(T)$ is the discount expectation of profits (DEP) of V_i received before transferring the big data knowledge, $\xi_1(T)$ is the DEP of V_i received after transferring the big data knowledge and before transferring the private knowledge, and $\xi_2(T)$ is the DEP of V_i received after transferring the private knowledge at time period T_2.

Hypothesis 7. $K_1(T)$ is the knowledge transfer cost of the big data knowledge, $K_2(T)$ is the knowledge transfer cost of the private knowledge.

Hypothesis 8. The life cycle of product N is renumbered after each knowledge transfer.

2.3 Conceptual model of continuous knowledge transfer

Based on Hypotheses 2, 6 and 7, V_i wants to transfer one type of big data knowledge at time period T_1 and one type of private knowledge at time period T_2. $\zeta_1(T_1)$ is the DEP of V_i received before transferring the big data knowledge, $\xi_1(T_1)$ is the DEP of V_i received after transferring the big data knowledge, and $\xi_2(T_2)$ is the DEP of V_i received after transferring the private knowledge. $K_1(T)$ is the knowledge transfer cost of the big data knowledge, and $K_2(T_2)$ is the knowledge transfer cost of the private knowledge. The total DEP of V_i can be denoted as $\Psi(T_1,T_2)$. Therefore, $\Psi(T_1,T_2)=\zeta_1(T_1)+\xi_1(T_1)-K_1(T_1)+\xi_2(T_2)-K_2(T_2)$. The conceptual model is as shown in Fig. 1.

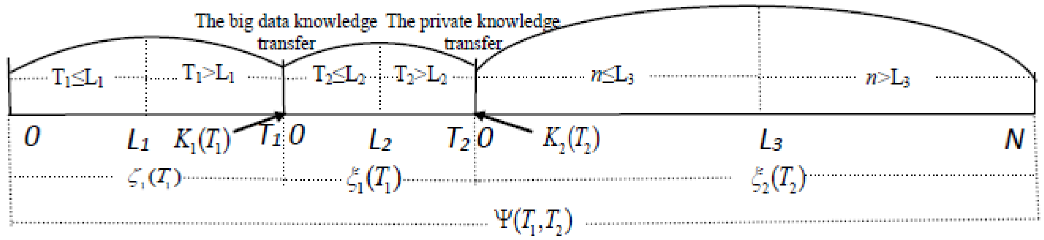

Figure 1: Conceptual model of continuous knowledge transfer

3 Optimization model of continuous knowledge transfer

3.1 DEP before the big data knowledge transfer

Because no new knowledge transfer occurs during this period, the enterprise produces new products using prior knowledge. The market share changes from growth to decay in time period $T = L_1$. Thus, the entire life cycle can be divided into two phases. The net profit of the enterprise can be calculated by subtracting the total cost from the total sales revenue. Then, the total DEP before knowledge transfer can be obtained by discounting the profit of each phase to the starting point $n = 0$. The DEP before knowledge transfer is shown as Eq. (1). The detailed calculation is introduced by Wu et al. [Wu and Zeng (2009)].

$$\zeta_1(T_1) = \begin{cases} pQ\phi\sum_{n=1}^{T_1}(1+\theta_1)^n r^n - Q\phi MC\sum_{n=1}^{T_1}(1+\theta_1)^n \alpha^n r^n & T_1 \le L_1 \\ pQ\phi\sum_{n=1}^{L_1}(1+\theta_1)^n r^n - Q\phi MC\sum_{n=1}^{L_1}(1+\theta_1)^n \alpha^n r^n + pQ\phi(1+\theta_1)^{L_1}\sum_{n=L_1+1}^{T_1}(1-\theta)^{n-L_1} r^n & \\ -Q\phi MC(1+\theta_1)^{L_1}\sum_{n=L_1+1}^{T_1}(1-\theta)^{n-L_1}\alpha^n r^n & T_1 > L_1 \end{cases} \tag{1}$$

3.2 Transfer cost of the big data knowledge

The cost of knowledge transfer consists of fixed cost and variable cost. In the big data environment, enterprises must pay a fixed data-processing fee k_1 when transferring big data knowledge from the big data knowledge provider. Thus, the fixed transfer cost of the big data knowledge is k_1, which is a constant.

The variable cost is related to the potential difference between the external knowledge and the internal knowledge. The enterprise accumulates its knowledge stock according to the knowledge absorption capacity $\alpha\ (0 < \alpha < 1)$, and the internal knowledge in time period T_1 is α^{T_1}. The update rate of external big data knowledge in time period

T_1 is $\beta_1^{T_1}$. Therefore, the knowledge potential difference can be expressed as $(\alpha^{T_1}-\beta_1^{T_1})$. The variable cost can be computed by $F_1(\alpha^{T_1}-\beta_1^{T_1})$, where F_1 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 big data knowledge transfer cost in the big data environment can be expressed as Eq. (2).

$$K_1(T_1)=[k_1+F_1(\alpha^{T_1}-\beta_1^{T_1})]r^{T_1} \tag{2}$$

3.3 DEP after the big data knowledge transfer

From Hypotheses 3 and 4, the market share of V_i increases at the rate of ρ_1 in the first L_2 periods immediately after V_i transfers the big data knowledge at time period T_1. Then, it decays at a rate of θ. Therefore, the market share of V_i in period n after the big data knowledge transfer can be denoted as in Eq. (3).

$$\lambda(n,T_1)=\begin{cases}\phi(1+\theta_1)^{T_1}(1+\rho_1)^n & n\le L_2,\ T_1\le L_1\\ \phi(1+\theta_1)^{L_1}(1-\theta)^{T_1-L_1}(1+\rho_1)^n & n\le L_2,\ T_1> L_1\\ \phi(1+\theta_1)^{T_1}(1+\rho_1)^n(1-\theta)^{n-L_2} & n> L_2,\ T_1\le L_1\\ \phi(1+\theta_1)^{L_1}(1-\theta)^{T_1-L_1}(1+\rho_1)^{L_2}(1-\theta)^{n-L_2} & n> L_2,\ T_1> L_1\end{cases} \tag{3}$$

The knowledge adopted by V_i in time period T_1 has been updated by $\beta_1^{T_1}$, which cause the marginal cost in time period T_1 to decrease to $MC\beta_1^{T_1}$. If we renumber the periods after knowledge transfer as n starting from 1 to T_2, the marginal cost in period n becomes $MC\beta_1^{T_1}\alpha^n$. Therefore, the total production cost in period n after knowledge transfer is $Q\lambda(n,T_1)MC\beta_1^{T_1}\alpha^n$. By subtracting the total production cost $Q\lambda(n,T_1)MC\beta_1^{T_1}\alpha^n$ from the sales revenue $pQ\lambda(n,T_1)$, the profit in period n after knowledge transfer is as in Eq. (4).

$$\Pi^*=pQ\lambda(n,T_1)-Q\lambda(n,T_1)MC\beta_1^{T_1}\alpha^n \tag{4}$$

If we discount the profits in period n to the starting point by multiplying Eq. (4) by $r^{T_1}r^n$ and sum up all the discount profits in period T_1, the DEP after the big data knowledge transfer and before the private knowledge transfer is as in Eq. (5).

$$\xi_1(T_1)=\sum_{n=1}^{T_2}(pQ\lambda(n,T_1)-Q\lambda(n,T_1)MC\beta_1^{T_1}\alpha^n)r^nr^{T_1} \tag{5}$$

When transferring big data knowledge from a big data knowledge provider, the enterprise often finds that certain core patent knowledge cannot be acquired. Thus, the enterprise transfers private knowledge from another enterprise or research institute. Typically, the time between the big data knowledge transfer and the private knowledge transfer is not long. Therefore, we assume that the private knowledge transfer occurs during the growth stage of the market share, as presented in Hypothesis 4: $T_2 \le L_2$. Based on Eqs. (3) and (5), the expected profits after the big data knowledge transfer and before the private knowledge transfer can be expressed as Eq. (6).

When $T_2 \le L_2$,

$$\xi_1(T_1)=\begin{cases} pQ\phi(1+\theta_1)^{T_1} r^{T_1}\sum_{n=1}^{T_2}(1+\rho_1)^n r^n - MCQ\phi(1+\theta_1)^{T_1} r^{T_1}\beta_1^{T_1}\sum_{n=1}^{T_2}(1+\rho_1)^n \alpha^n r^n & T_1 \le L_1, T_2 \le L_2 \\ pQ\phi(1+\theta_1)^{L_1}(1-\theta)^{T_1-L_1} r^{T_1}\sum_{n=1}^{T_2}(1+\rho_1)^n r^n & \\ -MCQ\phi(1+\theta_1)^{L_1}(1-\theta)^{T_1-L_1}\beta^{T_1} r^{T_1}\sum_{n=1}^{T_2}(1+\rho_1)^n \alpha^n r^n & L_1 < T_1, T_2 \le L_2 \end{cases} \tag{6}$$

When $T_2 > L_2$, based on Eqs. (3) and (5), the expected profits after the big data knowledge transfer and before the private knowledge transfer can be expressed as Eq. (7).

$$\xi_1(T_1)=\begin{cases} pQ\phi(1+\theta_1)^{T_1} r^{T_1}\sum_{n=1}^{L_2}(1+\rho_1)^n r^n - MCQ\phi(1+\theta_1)^{T_1} r^{T_1}\beta_1^{T_1}\sum_{n=1}^{L_2}(1+\rho_1)^n \alpha^n r^n & \\ +pQ\phi(1+\theta_1)^{T_1}(1+\rho_1)^{L_2} r^{T_1}\sum_{n=L_2+1}^{T_2}(1-\theta)^{n-L_2} r^n & \\ -MCQ\phi(1+\theta_1)^{T_1} r^{T_1}\beta_1^{T_1}(1+\rho_1)^{L_2}\sum_{n=L_2+1}^{T_2}(1-\theta)^{n-L_2}\alpha^n r^n & T_1 \le L_1, T_2 > L_2 \\ pQ\phi(1+\theta_1)^{L_1}(1-\theta)^{T_1-L_1} r^{T_1}\sum_{n=1}^{L_2}(1+\rho_1)^n r^n - MCQ\phi(1+\theta_1)^{L_1}(1-\theta)^{T_1-L_1}\beta^{T_1} r^{T_1}\sum_{n=1}^{L_2}(1+\rho_1)^n \alpha^n r^n & \\ +pQ\phi(1+\theta_1)^{L_1}(1-\theta)^{T_1-L_1}(1+\rho_1)^{L_2} r^{T_1}\sum_{n=L_2+1}^{T_2}(1-\theta)^{n-L_2} r^n & \\ -MCQ\phi(1+\theta_1)^{L_1}(1-\theta)^{T_1-L_1} r^{T_1}\beta_1^{T_1}(1+\rho_1)^{L_2}\sum_{n=L_2+1}^{T_2}(1-\theta)^{n-L_2}\alpha^n r^n & L_1 < T_1, T_2 > L_2 \end{cases} \tag{7}$$

3.4 Transfer cost of the private knowledge

The private knowledge is the core patent knowledge. Therefore, V_i must pay a portion of the patent license fee as the fixed cost of the private knowledge when transferring such knowledge. Suppose k_2 is the fixed transfer cost of the private knowledge, which is a constant.

After time period T_1, V_i accumulates knowledge stock based on the efficiency of the big data knowledge. The knowledge absorption capacity is α, and the internal knowledge in time period T_2 is $\beta_1^{T_1}\alpha^{T_2}$. The update rate of external private knowledge in time period T_2 is $\beta_2^{(T_1+T_2)}$. Therefore, the knowledge potential difference can be expressed as $(\beta_1^{T_1}\alpha^{T_2}-\beta_2^{(T_1+T_2)})$. The variable cost can be computed by $F_2(\beta_1^{T_1}\alpha^{T_2}-\beta_2^{(T_1+T_2)})$, where F_2 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 private knowledge transfer cost can be expressed as Eq. (8).

$$K_2(T_2)=[k_2+F_2(\beta_1^{T_1}\alpha^{T_2}-\beta_2^{(T_1+T_2)})]r^{(T_1+T_2)} \quad (0<T_2\le N) \tag{8}$$

3.5 DEP after the private knowledge transfer

From Hypotheses 3 and 4, the market share of V_i increases at the rate of ρ_2 in the first L_3 periods immediately after V_i transfers the private knowledge at time period T_2. Subsequently, it decays at a rate of θ. Therefore, the market share of V_i in period n after the transfer of private knowledge at the time period T_2 can be denoted as in Eq. (9).

$$\lambda(n,T_2)=\begin{cases}\phi(1+\theta_1)^{T_1}(1+\rho_1)^{T_2}(1+\rho_2)^n & n\le L_3,\ T_2\le L_2,\ T_1\le L_1\\ \phi(1+\theta_1)^{L_1}(1-\theta)^{T_1-L_1}(1+\rho_1)^{T_2}(1+\rho_2)^n & n\le L_3,\ T_2\le L_2,\ T_1>L_1\\ \phi(1+\theta_1)^{T_1}(1+\rho_1)^{L_2}(1-\theta)^{T_2-L_2}(1+\rho_2)^n & n\le L_3,\ T_2>L_2,\ T_1\le L_1\\ \phi(1+\theta_1)^{L_1}(1-\theta)^{T_1+T_2-L_1-L_2}(1+\rho_1)^{L_2}(1+\rho_2)^n & n\le L_3,\ T_2>L_2,\ T_1>L_1\\ \phi(1+\theta_1)^{T_1}(1+\rho_1)^{T_2}\ (1+\rho_2)^{L_3}(1-\theta)^{n-L_3} & n>L_3,\ T_2\le L_2,\ T_1\le L_1\\ \phi(1+\theta_1)^{L_1}(1-\theta)^{T_1-L_1}(1+\rho_1)^{T_2}(1+\rho_2)^{L_3}(1-\theta)^{n-L_3} & n>L_3,\ T_2\le L_2,\ T_1>L_1\\ \phi(1+\theta_1)^{T_1}(1+\rho_1)^{L_2}(1-\theta)^{T_2-L_2}(1+\rho_2)^{L_3}(1-\theta)^{n-L_3} & n>L_3,\ T_2>L_2,\ T_1\le L_1\\ \phi(1+\theta_1)^{L_1}(1-\theta)^{T_1+T_2-L_1-L_2}(1+\rho_1)^{L_2}(1+\rho_2)^{L_3}(1-\theta)^{n-L_3} & n>L_3,\ T_2>L_2,\ T_1>L_1\end{cases} \tag{9}$$

The knowledge adopted by V_i at time period T_2 has been updated by $\beta_2^{(T_1+T_2)}$, which causes the marginal cost in time period T_2 to decrease to $MC\beta_2^{(T_1+T_2)}$. We renumber the periods after the private knowledge transfer as n starting from 1 to N, and the marginal cost in period n becomes $MC\beta_2^{(T_1+T_2)}\alpha^n$. Therefore, the total production cost in period n after the private knowledge transfer is $Q\lambda(n,T_2)MC\beta_2^{(T_1+T_2)}\alpha^n$. By subtracting the total production cost $Q\lambda(n,T_2)MC\beta_2^{(T_1+T_2)}\alpha^n$ from the sales revenue $pQ\lambda(n,T_2)$, the profit in period n after the private knowledge transfer is as in Eq.

(10).

$$\Pi^{*} = pQ\lambda(n,T_2) - Q\lambda(n,T_2)MC\beta_2^{(T_1+T_2)}\alpha^n \tag{10}$$

We discount the profits in period n to the starting point by multiplying Eq. (10) by $r^{(T_1+T_2)}r^n$ and sum all the discount profits in period N. Thus, the DEP after the private knowledge transfer is as in Eq. (11).

$$\xi_2(T_2) = \sum_{n=1}^{N}(pQ\lambda(n,T_2) - Q\lambda(n,T_2)MC\beta_2^{(T_1+T_2)}\alpha^n)r^n r^{(T_1+T_2)} \tag{11}$$

Based on Eqs. (9) and (11), the expected profits after the private knowledge transfer can be expressed as Eqs. (12) and (13).

When $T_2 \le L_2$,

$$\xi_2(T_2) = \begin{cases} pQ\phi(1+\theta_1)^{T_1}(1+\rho_1)^{T_2} r^{(T_1+T_2)} \sum_{n=1}^{L_3}(1+\rho_2)^n r^n & \\ -QMC\phi(1+\theta_1)^{T_1}(1+\rho_1)^{T_2} r^{(T_1+T_2)} \beta_2^{(T_1+T_2)} \sum_{n=1}^{L_3}(1+\rho_2)^n \alpha^n r^n & \\ +pQ\phi(1+\theta_1)^{T_1}(1+\rho_1)^{T_2} r^{(T_1+T_2)} (1+\rho_2)^{L_3} \sum_{n=L_3+1}^{N}(1-\theta)^{n-L_3} r^n & \\ -QMC\phi(1+\theta_1)^{T_1}(1+\rho_1)^{T_2} r^{(T_1+T_2)} (1+\rho_2)^{L_3} \beta_2^{(T_1+T_2)} \sum_{n=L_3+1}^{N}(1-\theta)^{n-L_3}\alpha^n r^n & T_2 \le L_2, T_1 \le L_1 \\ pQ\phi(1+\theta_1)^{L_1}(1-\theta)^{T_1-L_1}(1+\rho_1)^{T_2} r^{(T_1+T_2)} \sum_{n=1}^{L_3}(1+\rho_2)^n r^n & \\ -QMC\phi(1+\theta_1)^{L_1}(1-\theta)^{T_1-L_1}(1+\rho_1)^{T_2} r^{(T_1+T_2)} \beta_2 r^{(T_1+T_2)} \sum_{n=1}^{L_3}(1+\rho_2)^n \alpha^n r^n & \\ +pQ\phi(1+\theta_1)^{L_1}(1-\theta)^{T_1-L_1}(1+\rho_1)^{T_2} r^{(T_1+T_2)} (1+\rho_2)^{L_3} \sum_{n=L_3+1}^{N}(1-\theta)^{n-L_3} r^n & \\ -MCQ\phi(1+\theta_1)^{L_1}(1-\theta)^{T_1-L_1}(1+\rho_1)^{T_2} r^{(T_1+T_2)} (1+\rho_2)^{L_3} \beta_2^{(T_1+T_2)} \sum_{n=L_3+1}^{N}(1-\theta)^{n-L_3}\alpha^n r^n & T_2 \le L_2, T_1 > L_1 \end{cases} \tag{12}$$

When $T_2 > L_2$,

$$\xi_2(T_2)=\begin{cases} pQ\phi(1+\theta_1)^{T_1}(1+\rho_1)^{L_2}(1-\theta)^{T_2-L_2}r^{(T_1+T_2)}\sum_{n=1}^{L_3}(1+\rho_2)^n r^n \\ -QMC\phi(1+\theta_1)^{T_1}(1+\rho_1)^{L_2}(1-\theta)^{T_2-L_2}r^{(T_1+T_2)}\beta_2^{(T_1+T_2)}\sum_{n=1}^{L_3}(1+\rho_2)^n\alpha^n r^n \\ +pQ\phi(1+\theta_1)^{T_1}(1+\rho_1)^{L_2}(1-\theta)^{T_2-L_2}r^{(T_1+T_2)}(1+\rho_2)^{L_3}\sum_{n=L_3+1}^{N}(1-\theta)^{n-L_3}r^n \\ -QMC\phi(1+\theta_1)^{T_1}(1+\rho_1)^{L_2}(1-\theta)^{T_2-L_2}r^{(T_1+T_2)}(1+\rho_2)^{L_3}\beta_2^{(T_1+T_2)}\sum_{n=L_3+1}^{N}(1-\theta)^{n-L_3}\alpha^n r^n & T_2>L_2, T_1\le L_1 \\ pQ\phi(1+\theta_1)^{L_1}(1-\theta)^{T_1+T_2-L_1-L_2}(1+\rho_1)^{L_2}r^{(T_1+T_2)}\sum_{n=1}^{L_3}(1+\rho_2)^n r^n \\ -QMC\phi(1+\theta_1)^{L_1}(1-\theta)^{T_1+T_2-L_1-L_2}(1+\rho_1)^{L_2}r^{(T_1+T_2)}\beta_2^{(T_1+T_2)}\sum_{n=1}^{L_3}(1+\rho_2)^n\alpha^n r^n \\ +pQ\phi(1+\theta_1)^{L_1}(1-\theta)^{T_1+T_2-L_1-L_2}(1+\rho_1)^{L_2}r^{(T_1+T_2)}(1+\rho_2)^{L_3}\sum_{n=L_3+1}^{N}(1-\theta)^{n-L_3}r^n \\ -MCQ\phi(1+\theta_1)^{L_1}(1-\theta)^{T_1+T_2-L_1-L_2}(1+\rho_1)^{L_2}r^{(T_1+T_2)}(1+\rho_2)^{L_3}\beta_2^{(T_1+T_2)}\sum_{n=L_3+1}^{N}(1-\theta)^{n-L_3}\alpha^n r^n & T_2>L_2, T_1>L_1 \end{cases} \tag{13}$$

3.6 Total DEP model of continuous knowledge transfer

The optimization problem of two-times knowledge transfer at different time points is to find the maximum of $\Psi(T_1,T_2)$ for the given parameters. Therefore, the optimization model of knowledge transfer can be expressed as Eq. (14).

$$\max\Psi(T_1,T_2)=\max(\zeta_1(T_1)+\xi_1(T_1)-K_1(T_1)+\xi_2(T_2)-K_2(T_2)) \tag{14}$$

4 Simulation and results of continuous knowledge transfer

4.1 Model solution

Eq. (14) indicates that $\Psi(T_1,T_2)$ is a piecewise continuous differential function of T. Therefore, $\Psi(T_1,T_2)$ can reach its maximum in a closed interval $0\le T_1,T_2\le N$, and the maximum profit in the life cycle of the product can be found. Considering the power of the numerical calculation and simulation functions, Matlab 7.0 can be used to compile a program. Numerous experiments could be conducted by adjusting model's parameters.

4.2 Simulation experiments

(1) Parameter setting and simulation. To simulate the actual situation of knowledge transfer in the big data environment, several parameters are chosen for testing. The values of the parameters used by Wu et al. [Wu, Chen and Li (2016)] are presented in Tab. 1.

Table 1: Parameter values

Parameter	Q	p	MC	θ_1	θ	ϕ	k_1	k_2	α	N	r
Value	1000	60	40	3%	3%	8%	80	300	95%	10	0.9

The values of several new parameters are presented in Tab. 2.

Table 2: Parameter values

Parameter	L_1	L_2	L_3	ρ_1	ρ_2	β_1	β_2	F_1	F_2
Value	4	2	4	4%	8%	90%	88%	250	1000

From the experimental results in Tab. 3 and Fig. 2, the optimal time of the big data knowledge transfer T_1 is 5, and the optimal time of the private knowledge transfer T_2 is 4.

Table 3: Total DEP with T_1 and T_2

T_2	1	2	3	4	5	6	7	8	9	10	
DEP	20598	22626	23333	23785	24052	24185	24222	24193	24118	24014	T_1=1
DEP	22431	24272	24845	25208	25418	25517	25537	25503	25431	25334	T_1=2
DEP	23961	25640	26107	26400	26566	26640	26648	26611	26543	26454	T_1=3
DEP	25249	26785	27168	27406	27538	27593	27594	27556	27492	27411	T_1=4
DEP	31027	32355	32443	32457	32422	32358	32277	32188	32098	32011	T_1=5
DEP	29468	30619	30665	30658	30616	30554	30481	30404	30327	30254	T_1=6
DEP	27964	28965	28982	28962	28918	28860	28795	28729	28664	28602	T_1=7
DEP	26542	27413	27413	27385	27341	27288	27231	27174	27119	27067	T_1=8
DEP	25217	25976	25964	25933	25891	25843	25794	25745	25698	25655	T_1=9
DEP	23995	24658	24639	24607	24568	24525	24483	24441	24402	24366	T_1=10

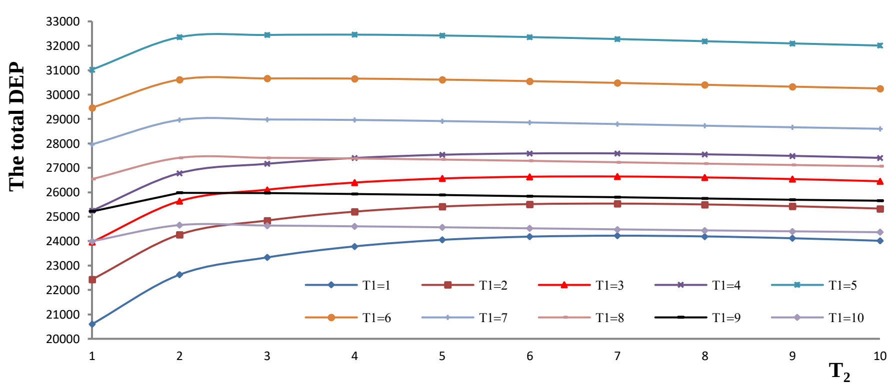

Figure 2: Changes in total DEP with T_1 and T_2

(2) Simulation with α as a variable.

To determine the influence degree of the knowledge absorption capacity α on the DEP and the optimal time of knowledge transfer in the big data environment, all the parameters except α are set with the same values as in section (1). Changing α from 95% to 90% means that the knowledge absorption capacity is enhanced. Tab. 4 and Fig. 3 show the DEP varying with α. From the experimental results in Tab. 4 and Fig. 3, the optimal knowledge transfer time of the big data knowledge T_1 remains 5. However, the optimal knowledge transfer time of the private knowledge T_2 changes from 4 to 3. Therefore, when the knowledge absorption capacity increases, the optimal knowledge transfer time of big data knowledge T_1 remains the same. However, the optimal knowledge transfer time of private knowledge T_2 will be earlier. The reason is that the big data knowledge is precisely like common knowledge. The knowledge absorptive capacity has little effect on the optimal knowledge transfer time of the big data knowledge. However, the optimal knowledge transfer time of the private knowledge transfer is advanced.

Table 4: Total DEP with α

T_2	1	2	3	4	5	6	7	8	9	10	
DEP	23364	25201	25750	26152	26440	26640	26772	26852	26891	26899	T_1=1
DEP	24980	26670	27118	27446	27678	27838	27940	27999	28023	28022	T_1=2
DEP	26452	28010	28380	28648	28837	28964	29044	29086	29100	29093	T_1=3
DEP	27799	29239	29545	29766	29921	30023	30085	30116	30122	30110	T_1=4
DEP	34494	35751	35770	35767	35749	35723	35692	35660	35628	35597	T_1=5
DEP	32683	33782	33777	33760	33733	33702	33670	33638	33608	33579	T_1=6
DEP	30985	31947	31928	31901	31871	31838	31806	31776	31748	31722	T_1=7
DEP	29413	30256	30228	30197	30165	30133	30103	30075	30049	30026	T_1=8
DEP	27971	28710	28678	28646	28614	28584	28555	28530	28507	28486	T_1=9
DEP	26659	27307	27274	27242	27212	27183	27158	27135	27114	27096	T_1=10

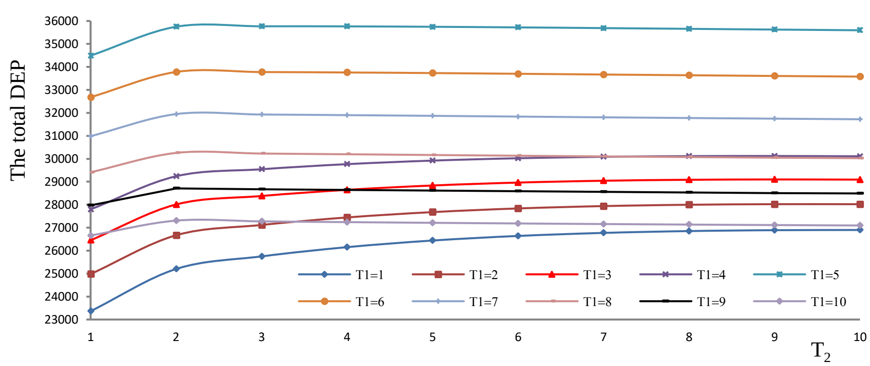

Figure 3: Changes in total DEP with α

(3) Simulation with β_1, β_2 as a variable. To determine the influence of the update rate

of big data knowledge β_1 on the DEP and the optimal time of knowledge transfer in the big data environment, all the parameter except β_1 are set with the same values as in section (1). Changing β_1 from 90% to 88% means that the update rate of the big data knowledge increases, and now, the efficiency of the big data knowledge is the same as that of the private knowledge. Tab. 5 and Fig. 4 show the DEP varying with β_1.

Table 5: Total DEP with β_1

T_2	1	2	3	4	5	6	7	8	9	10	
DEP	20662	22734	23478	23961	24253	24407	24462	24447	24384	24290	T_1=1
DEP	22535	24450	25084	25498	25750	25884	25933	25922	25870	25789	T_1=2
DEP	24090	25860	26403	26758	26976	27093	27137	27130	27086	27017	T_1=3
DEP	25390	27027	27493	27800	27989	28092	28132	28126	28089	28031	T_1=4
DEP	31165	32591	32760	32840	32861	32843	32800	32743	32679	32613	T_1=5
DEP	29597	30839	30960	31016	31025	31006	30969	30921	30869	30815	T_1=6
DEP	28082	29165	29251	29287	29289	29270	29237	29197	29154	29111	T_1=7
DEP	26647	27591	27651	27674	27671	27652	27624	27590	27555	27519	T_1=8
DEP	25309	26132	26173	26186	26180	26162	26137	26109	26080	26050	T_1=9
DEP	24075	24793	24819	24825	24817	24801	24779	24755	24731	24707	T_1=10

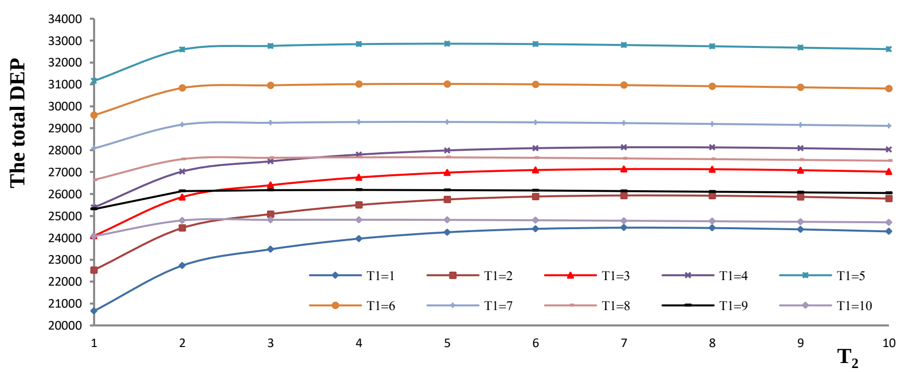

Figure 4: Changes in total DEP with β_1

Based on the experimental results in Tab. 5 and Fig. 4, the optimal knowledge transfer time of private knowledge T_2 changes from 4 to 5. It can be concluded that when the update rate of the big data knowledge increases, the optimal time of private knowledge T_2 becomes later. The reason is that if the data knowledge is more efficient, enterprise V_i will postpone the transfer of private knowledge.

To determine the influence of the update rate of private knowledge β_2 on the DEP and the optimal time of knowledge transfer in the big data environment, all the parameter except β_2 are set with the same values as in section (1). Changing β_2 from 88% to 84% means that the update rate of the private knowledge is increased. Tab. 6 and Fig. 5 show the DEP varying with β_2.

Table 6: Total DEP with β_2

T_2	1	2	3	4	5	6	7	8	9	10	
DEP	21627	23870	24594	24984	25146	25156	25068	24917	24732	24528	T_1=1
DEP	23662	25597	26104	26357	26438	26405	26298	26146	25970	25783	T_1=2
DEP	25273	26963	27314	27471	27498	27438	27324	27177	27013	26843	T_1=3
DEP	26559	28054	28293	28384	28376	28302	28188	28050	27900	27746	T_1=4
DEP	32206	33466	33396	33261	33093	32912	32730	32557	32397	32251	T_1=5
DEP	30500	31571	31469	31328	31170	31007	30850	30702	30567	30446	T_1=6
DEP	28849	29769	29653	29516	29372	29229	29094	28969	28856	28756	T_1=7
DEP	27290	28084	27967	27839	27710	27586	27471	27366	27273	27190	T_1=8
DEP	25840	26530	26418	26302	26189	26083	25986	25899	25821	25752	T_1=9
DEP	24509	25112	25008	24905	24808	24718	24636	24563	24499	24442	T_1=10

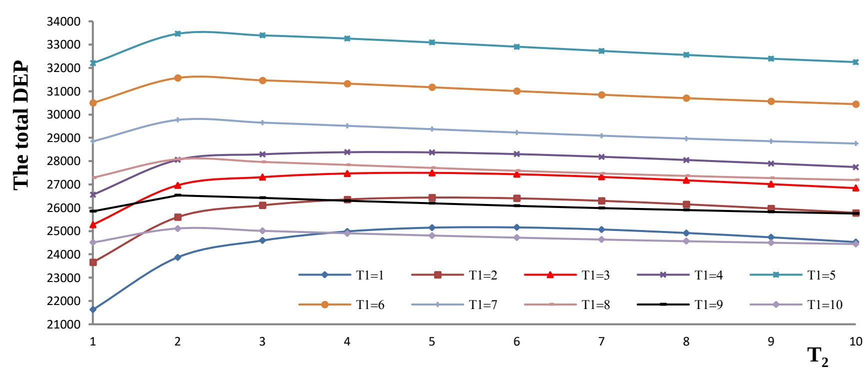

Figure 5: Changes in total DEP with β_2

Based on the experimental results in Tab. 6 and Fig. 5, the optimal knowledge transfer time of private knowledge T_2 changes from 4 to 2. Therefore, when the update rate of private knowledge increases, the optimal knowledge transfer time of private knowledge T_2 is earlier. The reason is that the higher the efficiency of the private knowledge, the earlier enterprise V_i will transfer the private knowledge.

(4) Simulation with L_1 as a variable.

To determine the influence of the parameters on the optimal knowledge transfer time of the big data knowledge transfer, several parameters, such as α, β_1, and ρ_1, are adjusted separately. However, the optimal knowledge transfer time of the big data knowledge remains unchanged. Only when L_1 is adjusted from 4 to 3 does, the optimal knowledge transfer time of big data knowledge T_1 change from 5 to 4 (Fig. 6). This outcome means that when the market share knowledge begins to decrease, enterprise V_i transfers the big data knowledge from the big data knowledge provider BD_k.

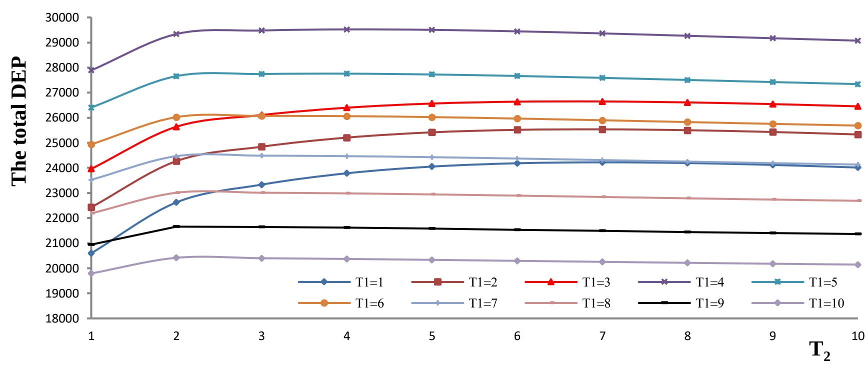

Figure 6: Changes in total DEP with L_1

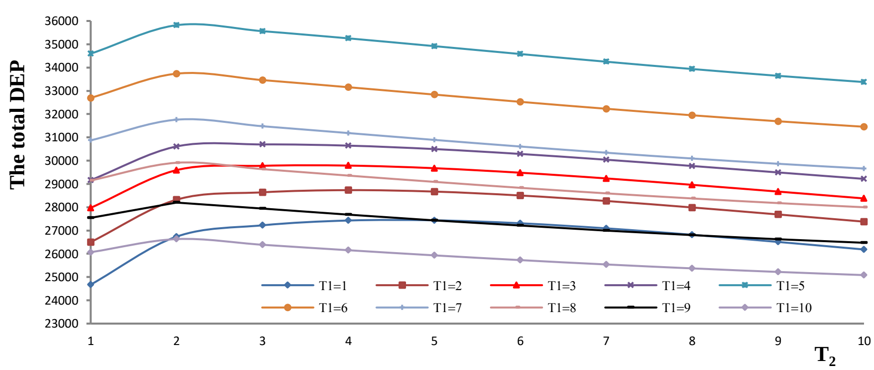

Figure 7: Changes in total DEP with ρ_2

(5) Simulation with ρ_2 as a variable. To determine the influence of the market share of private knowledge ρ_2 on the DEP and the optimal time of private knowledge transfer T_2, all the parameters except ρ_2 are set with the same values as in Section (1).

Changing ρ_2 from 8% to 15% means that the market share of the private knowledge increases. Fig. 7 shows the DEP varying with ρ_2.

Based on the experimental results in Fig. 2 and 7, the optimal knowledge transfer time of private knowledge T_2 changes from 4 to 2. This outcome implies that if the market share of the private knowledge becomes larger after knowledge transfer, the optimal knowledge transfer time of the private knowledge T_2 advances. The reason for enterprise V_i to adopt the private knowledge earlier is that the core patent knowledge can help enterprise obtain a larger market share. Therefore, the simulation results of the model are consistent with the practical situation.

5 Conclusion

This paper analyzed the time optimization problem of continuous knowledge transfer of two types of knowledge in the big data environment. Based on an analysis of the importance of continuous knowledge transfer in the big data environment and the mutual influence of each knowledge transfer, a time optimization model of continuous knowledge transfer was established. Several simulation experiments were performed on typical parameters. The experimental results verified the model's validity and facilitated conclusions regarding their practical application values. The experimental results can provide more effective decisions for enterprises that must carry out continuous knowledge transfer in the big data environment.

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