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...
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 \( V = \{V_j\} \) is the set of nodes and \( V_j \) 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 \( \phi \), 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 $\beta_1$, and the update rate of private knowledge at the time period $n = 0$ is $\beta_2$ ($0 < \beta_1, \beta_2 < 1$).

Hypothesis 6. $\zeta_i(T)$ 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 $T_2$. $\zeta_i(T_1)$ 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 $K_2(T)$ 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, $\Psi(T_1, T_2) = \zeta_i(T_1) + \xi_1(T_1) - K_1(T_1) + \xi_2(T_2) - K_2(T_2)$. The conceptual model is as shown in Fig. 1.
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)].

$$
\zeta_1(T_1) = \begin{cases} 
  pQ\phi\sum_{n=1}^{\gamma_1} (1 + \theta_1)^n r^n - Q\phi MC\sum_{n=1}^{\gamma_1} (1 + \theta_1)^n \alpha^n r^n & T_1 \leq L_1 \\
  pQ\phi\sum_{n=1}^{\gamma_1} (1 + \theta_1)^n r^n - Q\phi MC\sum_{n=1}^{\gamma_1} (1 + \theta_1)^n \alpha^n r^n + pQ\phi(1 + \theta_1)^{L_1}\sum_{n=L_1+1}^{\gamma_1} (1 - \theta)^{n-L_1} r^n & T_1 > L_1 \\
  -Q\phi MC(1 + \theta_1)^{L_1}\sum_{n=L_1+1}^{\gamma_1} (1 - \theta)^{n-L_1} \alpha^n r^n & T_1 > L_1 
\end{cases}
$$

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 $\alpha^{T_1}$. The update rate of external big data knowledge in time period
$T_1$ is $\beta^{T_1}_{\ast}$. Therefore, the knowledge potential difference can be expressed as 
$(\alpha^{T_1}_{\ast} - \beta^{T_1}_{\ast})$. The variable cost can be computed by $F_1(\alpha^{T_1}_{\ast} - \beta^{T_1}_{\ast})$, 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).

$$K_i(T_1) = [k_i + F_1(\alpha^{T_1}_{\ast} - \beta^{T_1}_{\ast})]r^{T_1}$$

(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 $\rho_i$ 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 $\theta$. Therefore, the market share of $V_i$ in period $n$ after the big data knowledge transfer can be denoted as in Eq. (3).

$$\lambda(n,T_1) = \begin{cases} 
\phi(1+\theta_1)^{T_1}(1+\rho_i)^n & n \leq L_2, \ T_1 \leq L_1 \\
\phi(1+\theta_1)^{T_1}(1-\theta)^{v-L_1}(1+\rho_i)^n & n \leq L_2, \ T_1 \geq L_1 \\
\phi(1+\theta_1)^{T_1}(1+\rho_i)^n(1-\theta)^{v-L_1} & n > L_2, \ T_1 \geq L_1 \\
\phi(1+\theta_1)^{T_1}(1-\theta)^{v-L_1}(1+\rho_i)^n(1-\theta)^{v-L_1} & n > L_2, \ T_1 > L_1 
\end{cases}$$

(3)

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

$$\Pi^* = pQ\lambda(n,T_1) - Q\lambda(n,T_1)MC\beta^{T_1}_{\ast}\alpha^n$$

(4)

If we discount the profits in period $n$ to the starting point by multiplying Eq. (4) by $r^{T_1}\rho^n$ 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).

$$\xi_i(T_1) = \sum_{n=1}^{T_1} (pQ\lambda(n,T_1) - Q\lambda(n,T_1)MC\beta^{T_1}_{\ast}\alpha^n)r^n r^{T_1}$$

(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: $T_2 \leq L_2$. 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 $T_2 \leq L_2$,

$$
\xi_i(T_2) = \begin{cases} 
 pQ\phi(1+\theta_j)^{T_2}r^n \sum_{i=1}^{T_2} (1+\rho_j)^n r^n - MCQ\phi(1+\theta_j)^{T_2} r^n \sum_{i=1}^{T_2} (1+\rho_j)^n a^n r^n & T_1 \leq T_2 \leq L_1 \\
 pQ\phi(1+\theta_j)^{T_2} r^n \sum_{i=1}^{T_2} (1+\rho_j)^n r^n - MCQ\phi(1+\theta_j)^{T_2} r^n \sum_{i=1}^{T_2} (1+\rho_j)^n a^n r^n & T_2 < T_1, T_1 \leq L_1 \\
 -MCQ(1+\theta_j)^{T_2} r^n \sum_{i=1}^{T_2} (1+\rho_j)^n a^n r^n & L_1 < T_1, T_2 \leq L_1 \\
 -MCQ(1+\theta_j)^{T_2} r^n \sum_{i=1}^{T_2} (1+\rho_j)^n a^n r^n & L_1 < T_1, T_2 \leq L_1 \\
 \end{cases}
$$

(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).

$$
\xi_i(T_2) = \begin{cases} 
 pQ\phi(1+\theta_j)^{T_2}r^n \sum_{i=1}^{T_2} (1+\rho_j)^n r^n - MCQ\phi(1+\theta_j)^{T_2} r^n \sum_{i=1}^{T_2} (1+\rho_j)^n a^n r^n & T_1 \leq L_1, T_2 > L_1 \\
 pQ\phi(1+\theta_j)^{T_2} r^n \sum_{i=1}^{T_2} (1+\rho_j)^n r^n - MCQ\phi(1+\theta_j)^{T_2} r^n \sum_{i=1}^{T_2} (1+\rho_j)^n a^n r^n & T_1 < L_1, T_2 > L_1 \\
 -MCQ(1+\theta_j)^{T_2} r^n \sum_{i=1}^{T_2} (1+\rho_j)^n a^n r^n & L_1 < T_1, T_2 > L_1 \\
 \end{cases}
$$

(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 $\alpha$, 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 $\beta_{2}^{T_1} \alpha^{T_2}$. Therefore, the knowledge potential difference can be expressed as $(\beta_{1}^{T_1} \alpha^{T_2} - \beta_{2}^{T_1} \alpha^{T_2})$. The variable cost can be computed by $F_2(\beta_{1}^{T_1} \alpha^{T_2} - \beta_{2}^{T_1} \alpha^{T_2})$, 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).

$$K_{2}(T_2) = [k_2 + F_2(\beta_{1}^{T_1} \alpha^{T_2} - \beta_{2}^{T_1} \alpha^{T_2})] \tau^{T_1+T_2} \quad (0 < T_2 \leq N) \tag{8}$$

### 3.5 DEP after the private knowledge transfer

From Hypotheses 3 and 4, the market share of $V_i$ increases at the rate of $\rho_2$ 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 $\theta$. 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).

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

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

(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).

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

(11)

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

When \( T_2 \leq L_2 \),

\[
\xi_2(T_2) = \begin{cases} 
\frac{pQ\phi(1+\theta_1)\gamma(T_1+T_2)\sum_{i=1}^{i_1}(1+\rho_2)^i}{r(T_1+T_2)} \left(1 + (1+\rho_2)^{i_1} \right) & T_1 \leq L_1, \ T_2 \leq L_1 \\
\frac{-QMC\phi(1+\theta_1)\gamma(T_1+T_2)\beta_2^{(T_1+T_2)}\sum_{i=1}^{i_2}(1+\rho_2)^i a^i r^n}{r(T_1+T_2)} & T_1 \leq L_1, \ T_2 > L_1 \\
\frac{+pQ\phi(1+\theta_1)\gamma(T_1+T_2)\beta_2^{(T_1+T_2)}\sum_{i=1}^{i_3}(1-\theta)^{i_3-i_2} a^i r^n}{r(T_1+T_2)} & T_1 \leq L_1, \ T_2 > L_1
\end{cases}
\]

When \( T_2 > L_2 \),
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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).

\[
\max \Psi(T_1, T_2) = \max(\zeta(T_1) + \zeta(T_2) - K(T_1) + \zeta_2(T_2) - K_2(T_2))
\]  

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 \( 0 \leq T_1, T_2 \leq N \), 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.

| Parameter | \( Q \) | \( p \) | \( MC \) | \( \theta_1 \) | \( \theta \) | \( \phi \) | \( k_1 \) | \( k_2 \) | \( \alpha \) | \( N \) | \( r \) |
|-----------|---------|---------|---------|------------|---------|---------|---------|---------|---------|-------|-------|
| 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 | $L_1$ | $L_2$ | $L_3$ | $\rho_1$ | $\rho_2$ | $\beta_1$ | $\beta_2$ | $F_1$ | $F_2$ |
|-----------|-------|-------|-------|-----------|-----------|-----------|-----------|-------|-------|
| 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 | 24183 | 24193 | 24118 | 24014 | $T_1=1$ |
|       | DEP 22431 | 24272 | 24845 | 25208 | 25417 | 25537 | 25503 | 25431 | 25334 | $T_1=2$ |
|       | DEP 23961 | 25640 | 26107 | 26400 | 26566 | 26648 | 26611 | 26543 | 26454 | $T_1=3$ |
|       | DEP 25249 | 26785 | 27168 | 27406 | 27538 | 27593 | 27556 | 27492 | 27411 | $T_1=4$ |
|       | DEP 31027 | 32355 | 32443 | 32457 | 32358 | 32277 | 32188 | 32098 | 32011 | $T_1=5$ |
|       | DEP 29468 | 30619 | 30665 | 30658 | 30616 | 30554 | 30481 | 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 $\alpha$ as a variable.

To determine the influence degree of the knowledge absorption capacity $\alpha$ on the DEP and the optimal time of knowledge transfer in the big data environment, all the
parameters except $\alpha$ are set with the same values as in section (1). Changing $\alpha$ from 95% to 90% means that the knowledge absorption capacity is enhanced. Tab. 4 and Fig. 3 show the DEP varying with $\alpha$. 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 $\alpha$

| $T_1$ | 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 | 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 | 30075 | 30049 | 30026 | $T_1=8$ |
| DEP   | 27971 | 28710 | 28678 | 28646 | 28614 | 28584 | 28555 | 28530 | 28507 | $T_1=9$ |
| DEP   | 26659 | 27307 | 27274 | 27242 | 27212 | 27183 | 27158 | 27135 | 27114 | $T_1=10$ |

Figure 3: Changes in total DEP with $\alpha$

(3) Simulation with $\beta_1, \beta_2$ as a variable. To determine the influence of the update rate
of big data knowledge $\beta_1$ on the DEP and the optimal time of knowledge transfer in the big data environment, all the parameter except $\beta_1$ are set with the same values as in section (1). Changing $\beta_1$ 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 $\beta_1$.

### Table 5: Total DEP with $\beta_1$

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

### Figure 4: Changes in total DEP with $\beta_1$

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 $\beta_2$ on the DEP and the optimal time of knowledge transfer in the big data environment, all the parameter except $\beta_2$ are set with the same values as in section (1). Changing $\beta_1$ 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 $\beta_2$.

Table 6: Total DEP with $\beta_2$

| $T_2$ | 1   | 2   | 3   | 4   | 5   | 6   | 7   | 8   | 9   | 10  |
|------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| DEP  | 21627 | 23870 | 24594 | 25146 | 25068 | 24917 | 24732 | 24528 | 24732 | 24528 |
| DEP  | 23662 | 25597 | 26104 | 26357 | 26438 | 26298 | 26146 | 25970 | 25783 | 25467 |
| DEP  | 25273 | 26963 | 27314 | 27498 | 27438 | 27324 | 27177 | 27013 | 26843 | 26573 |
| DEP  | 26559 | 28054 | 28293 | 28384 | 28376 | 28302 | 28188 | 28050 | 27900 | 27746 |
| DEP  | 32206 | 33466 | 33396 | 33261 | 33093 | 32912 | 32730 | 32557 | 32397 | 32251 |
| DEP  | 30500 | 31571 | 31469 | 31328 | 31170 | 31007 | 30850 | 30702 | 30567 | 30446 |
| DEP  | 28849 | 29769 | 29653 | 29372 | 29229 | 29094 | 28969 | 28856 | 28756 | 28602 |
| DEP  | 27290 | 28084 | 27967 | 27839 | 27710 | 27586 | 27471 | 27366 | 27173 | 27019 |
| DEP  | 25840 | 26530 | 26418 | 26302 | 26189 | 26083 | 25986 | 25899 | 25821 | 25752 |
| DEP  | 24509 | 25112 | 25008 | 24905 | 24808 | 24718 | 24636 | 24563 | 24499 | 24442 |

Figure 5: Changes in total DEP with $\beta_2$

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 $\alpha$, $\beta_1$, and $\rho_1$, 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 $L_1$](image)

![Figure 7: Changes in total DEP with $\rho_2$](image)

(5) Simulation with $\rho_2$ as a variable. To determine the influence of the market share of private knowledge $\rho_2$ on the DEP and the optimal time of private knowledge transfer $T_2$, all the parameters except $\rho_2$ are set with the same values as in Section (1).
Changing $\rho_2$ from 8% to 15% means that the market share of the private knowledge increases. Fig. 7 shows the DEP varying with $\rho_2$.

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.

Acknowledgments: This research was supported by the National Natural Science Foundation of China (Grant No. 71704016, 71331008), the Natural Science Foundation of Hunan Province (Grant No. 2017JJ2267), Key Projects of Chinese Ministry of Education (17JZD022); and the Project of China Scholarship Council for Overseas Studies (201208430233, 201508430121), which are acknowledged.

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