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Research Article
Models of Dualistic Complementary Knowledge Transfer in Big-data Environments

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Abstract

Background: With the advent of the big-data era, it is widely accepted that enterprises need to transfer private knowledge and big-data knowledge at the same time. These two types of knowledge are usually complementary and it is necessary to consider their mutual influence on the efficiency of knowledge transfer. **Materials and Methods:** Based on studies of independent knowledge transfer, models of dualistic complementary knowledge-transfer are presented to determine the maximum profits of knowledge transfer. **Results:** The results were the same as those of previous studies in which the mutual influence of private and big-data knowledge was not considered and the model used in the present study is found to be valid. Forecasts were developed for different influence coefficients and dualistic complementary knowledge weights. Profits and transfer costs increased with the influence coefficient of dualistic complementary knowledge. When the weight of big-data knowledge was enhanced, profits increased but transfer costs declined. The results of the simulation experiment used in the present study are consistent with an actual economic situation. **Conclusion:** It is suggested that enterprises should take into consideration the mutual influence of dualistic complementary knowledge and determine the appropriate proportion of dualistic complementary knowledge according to the degree of mutual influence and discounted profits when transferring knowledge in a big-data environment.

Key words: Big data, knowledge transfer, complementary knowledge, efficiency, optimization model

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INTRODUCTION

Knowledge is one of the most important elements of core competence in today's economy and firms try to transfer and absorb it in each interaction within their environments[1,2]. The process of enterprises absorbing, applying and creating knowledge through various channels is called knowledge transfer[3]. Scholars have conducted numerous studies on knowledge transfer from different perspectives. Research has shown that inter-firm cooperative agreements provide opportunities for knowledge transfer and firm's partners in their cooperative actions are primary environmental or external sources of knowledge[4-6]. Previous studies have focused on such external environment characteristics of knowledge transfer as knowledge transfer in strategic alliances, industrial clusters and innovation networks[7-19].

With the rapid development of the internet, networking, social networks and cloud computing, the era of the big data has begun. 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 decision-making, trimming costs and increasing the quality of products and services[20,21]. Useful knowledge mined by agencies and personnel specializing in big-data is an important part of the knowledge that enterprises need for innovation[22-26] and this type of knowledge can be called big-data knowledge.

In a big-data environment, enterprises need to transfer private knowledge from other organizations and to transfer big-data knowledge[27]. Private knowledge and big-data knowledge are the dominant types of knowledge that enterprises need for innovation in big-data environments. However, because big-data knowledge is characterized as open-source, dynamic and massive and because it has multisource heterogeneity[28], the process of big-data knowledge transfer is different from that of private knowledge transfer.

The most common type of private knowledge is core patent knowledge and the most common type of big-data knowledge is non-core patent knowledge. These two types of knowledge are usually not independent. If the relationship between private knowledge and big-data knowledge is competitive, an enterprise will usually choose to transfer the big-data knowledge because it is cheaper and easier to acquire. Only when big-data knowledge cannot be obtained or involves violations of intellectual property rights will an enterprise transfer private knowledge from another organization[29]. Therefore, when the two types of knowledge are complementary, the enterprise will transfer the private knowledge and the big-data knowledge at the same time in a big-data environment. It is necessary to consider the mutual influence of these two types of complementary knowledge on the efficiency of knowledge transfer. However, at the moment, there are few studies on complementary knowledge transfer in big-data environments.

This study tries to identify the influence of these two types of complementary knowledge on knowledge-transfer efficiency.

MATERIALS AND METHODS

When an enterprise only needs to transfer two types of knowledge in a big-data environment and one type of knowledge is private knowledge from another enterprise while the other type is big-data knowledge from a big-data knowledge provider, the relationship between the two types of knowledge is complementary.

Model hypotheses: The model used in the present study is compared with models developed in previous study. Assumptions and variables remain unchanged. The expression of the dynamic knowledge network is G = (V, E, BD), V_i and V_j represent the two enterprises in G = (V, E, BD). The V_i produces only one product and transfers one type of private knowledge from V_j and one type of big-data knowledge from BD; ω_1, ω_2 ($0<\omega_1, \omega_2<1, \omega_1+\omega_2 = 1$) is the weight of private knowledge and big-data knowledge. The update rate of private knowledge is β_1, the update rate of the big-data knowledge is β_2 and the total update rate of external knowledge is β. The total market volume of the product is Q, the price of the product is p, the discount rate is r and the marginal cost in the starting period is MC. The absorption capacity is $\alpha(0<\alpha<1)$ and the market share of each enterprise in the starting period is N. 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. The growth rate of the market share of V_i is $\rho_1(0<\theta_1<\rho_1<1)$ in the first L periods when V_i only transfers private knowledge. The $\rho_2(0<\theta_1<\rho_2<1)$ is the growth rate of the market share of V_i in the first L periods when V_i only transfers big-data knowledge. The $\rho(0<\theta_1<\rho<1)$ is the growth rate of the market share of V_i in the first L_1 periods immediately after knowledge transfer. The lifecycle of the product is N; the detailed assumptions refer to Wu *et al.*[27] and Wu and Zeng[30]. Additionally, two new hypotheses are proposed:

- **Hypothesis 1:** The V_i will transfer private knowledge and big-data knowledge at the same time in time period T and private knowledge and big-data knowledge are complementary

- **Hypothesis 2:** The influence coefficient of two types of knowledge is $\sigma(\sigma>0)$

Quantitative expression of mutual influence between dualistic complementary types of knowledge: Following the previous hypotheses, when an enterprise produces a product using prior knowledge, its marginal cost in the starting period will be 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 time period n 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 $MC\beta^T$. Then, as the enterprise continues to accumulate production experience based on this marginal cost, the marginal cost in period n will reduce to $MC\beta^T\alpha^n$ $(n\geq T)$.

If two types of knowledge are independent, there is no need to consider the mutual influence of these two types of knowledge accumulating with time. According to the contribution of these two types of knowledge for the enterprise's innovation, the total update rate of the external knowledge can be determined[27] as $\beta = \omega_1\beta_1+\omega_2\beta_2$. Then, the enterprise will continue to accumulate production experience based on this efficiency. When the enterprise adopts new knowledge in time period T, the marginal cost will change from $MC\alpha^T$ to $MC(\omega_1\beta_1+\omega_2\beta_2)^T$ and the marginal cost in time period n will reduce to $MC(\omega_1\beta_1+\omega_2\beta_2)^T\alpha^n$ $(n\geq T)$.

When two types of knowledge are complementary, the enterprise must consider the interaction between the two types of knowledge as it accumulates with time. Knowledge transfer is the process of transferring knowledge from an organization with high knowledge potential energy to an organization with low knowledge potential energy[31]. Then, mutual influence will relate to the knowledge distance between the two types of complementary knowledge.

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 the external big-data knowledge evolves to β_2^T in time period T. When the mutual influence of the two types of complementary knowledge is linear and within a certain potential threshold value, following hypothesis 2, the influence coefficient will be $\sigma(\sigma>0)$ and the mutual influence can be expressed as $\sigma|\beta_1^T-\beta_2^T|$. Because the influence of the complementary knowledge is positive, 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:

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

Optimization model: Following hypothesis 1, V_i will prefer transferring one type of private knowledge and one type of big-data knowledge at the same time in time period T. $\zeta(T)$ is the discount expectation of profits (DEP) of V_i before knowledge transfer, $\xi(T)$ is the DEP of V_i after knowledge transfer and K(T) is the knowledge-transfer cost. The total DEP of V_i can be denoted as $\psi(T)$, such that $\psi(T) = \zeta(T)+\xi(T)-K(T)$.

Expected profit before knowledge transfer: Because there is no new knowledge transfer during this period, the method of calculating the DEP before knowledge transfer is the same as given by Wu *et al.*[27], according to which the DEP before knowledge transfer is:

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

Transfer cost of dualistic complementary knowledge: Enterprises must pay a certain amount of knowledge-transfer cost when absorbing private knowledge. Similarly, in a big-data environment, enterprises must pay a knowledge-transfer cost when transferring big-data knowledge from big data knowledge providers. In a big-data environment, the knowledge-transfer cost K can be divided into the fixed cost and the variable cost. When an enterprise V_i transfers two types of complementary knowledge at the same time, the fixed transfer cost k should be composed of two parts: The fixed transfer cost of the private knowledge k_1 and the fixed transfer cost of the big-data knowledge k_2. The ω_1, ω_2 $(0<\omega_1,\ \omega_2<1;\ \omega_1+\omega_2 = 1)$ is the weight of the private knowledge and the big-data knowledge so $k = \omega_1k_1+\omega_2k_2$, where, k_1 and k_2 are constants.

Variable cost is related to the potential difference between external knowledge and internal knowledge. The potential energy of external knowledge is determined by the interaction of private knowledge and big-data knowledge. The update rate of external knowledge in time period T is shown in Eq. 1, such that 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 $F(\alpha^T - (\omega_1\beta_1^T + \omega_2\beta_2^T - \sigma|\beta_1^T - \beta_2^T|))$, where, F is a constant. By discounting the transfer cost to the beginning after adding the fixed and variable costs, the present value of the knowledge-transfer cost in a big-data environment can be expressed as Eq. 4:

$$K(T) = \left[\omega_1 k_1 + \omega_2 k_2 + F(\alpha^T - (\omega_1\beta_1^T + \omega_2\beta_2^T - \sigma|\beta_1^T - \beta_2^T|))\right] r^T (0 < \omega_1,\ \omega_2 < 1;\ \omega_1 + \omega_2 = 1) \quad (4)$$

Expected profits after transferring dualistic complementary knowledge: When the growth rate of market share is not influenced, ω_1, ω_2 are also the weights of the dualistic complementary knowledge for the growth rate of market share; the growth rate of total market share ρ can be calculated by Eq. 5:

$$\rho = \omega_1\rho_1 + \omega_2\rho_2\ (0<\omega_1,\ \omega_2<1;\ \omega_1+\omega_2 = 1) \quad (5)$$

Following previous hypotheses, the market share of V_i will increase at a rate of ρ in the first L periods immediately after the time period T and then it will decay at a rate of θ. Hence, the market share of V_i in period n is denoted in Eq. 6:

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

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

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

Discounting the profits in time period n to the starting point by multiplying Eq. 7 by r^T r^n and including all the discount profits in period N, the DEP after knowledge transfer is:

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

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

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

Total DEP model: The optimization problem of dualistic complementary knowledge transfer is to find the maximum of $\zeta(T)+\xi(T)-K(T)$ within the given parameters. Therefore, the optimization model of knowledge transfer can be expressed as Eq. 10:

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

RESULTS

Model solution: Equation 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 lifecycle of the product can be found. Considering the power of the numerical calculation and simulation functions, MATLAB should be used to compile a program. Numerous experiments could be conducted by adjusting the model's parameters.

Parameter-setting: To simulate an actual situation of knowledge transfer in a big-data environment, certain parameters were chosen for testing. To compare with Wu *et al.*[27] the values of the same parameters are the same as in Wu *et al.*[27] and the new parameters set the new values. These parameters are set as follows: The total product sales is $Q = 1000$; the relative value of price per unit product is $p = 60$; the market share of V_i in the starting period is $\phi = 8\%$; the growth rate of total market volume in the first $L_1 (L_1 = 3)$ periods is $\theta_1 = 3\%$; the natural attenuation rate of market volume in the other periods is $\theta = 3\%$; the growth rate of the two types of knowledge on market share in the first L = 5 periods immediately after knowledge transfer is $\rho_1 = 6\%$, $\rho_2 = 8\%$; the marginal cost in the starting period is MC = 40; the fixed transfer cost is $k_1 = 300$; the fixed transfer cost is $k_2 = 80$; the coefficient of the variable cost is F = 1000; knowledge absorption capacity is $\alpha = 95\%$; the update rate of private knowledge is $\beta_1 = 88\%$; the update rate of big-data knowledge is $\beta_2 = 84\%$; the influence coefficient of dualistic complementary knowledge is $\sigma = 0.5$ and the lifecycle of the product is N = 10. Assuming the market risk is neutral, the discount rate is 10% and $r = 1/(1+10\%) \approx 0.9$.

Validation of the model:

- When $\sigma = 0$, the influence coefficient between the two types of complementary knowledge is zero, which means that the two types of knowledge are independent. To compare with the previous study, ω_1, ω_2, β_1 and β_2 are set as $\omega_1 = 0.5$, $\omega_2 = 0.5$, $\beta_1 = \beta_2 = 88\%$, which implies that V_i transfers two types of independent knowledge and the weight of each type of knowledge is 50%

Figure 1 show the experimental results of the DEP before knowledge transfer (DEPb), DEP after knowledge transfer (DEPa), transfer cost and the total DEP. Because experimental results in Fig. 1 are the same as described by Wu *et al.*[27], the model is valid:

- Let $\omega_1 = 0.5$, $\omega_2 = 0.5$, $\beta_1 = 88\%$, $\beta_2 = 84\%$ and change the influence coefficient σ from $\sigma = 0$ to $\sigma = 0.5$, which indicates that the relationship between the two types of knowledge changes from independent to complementary. Figure 2 and 3 show the variation of the

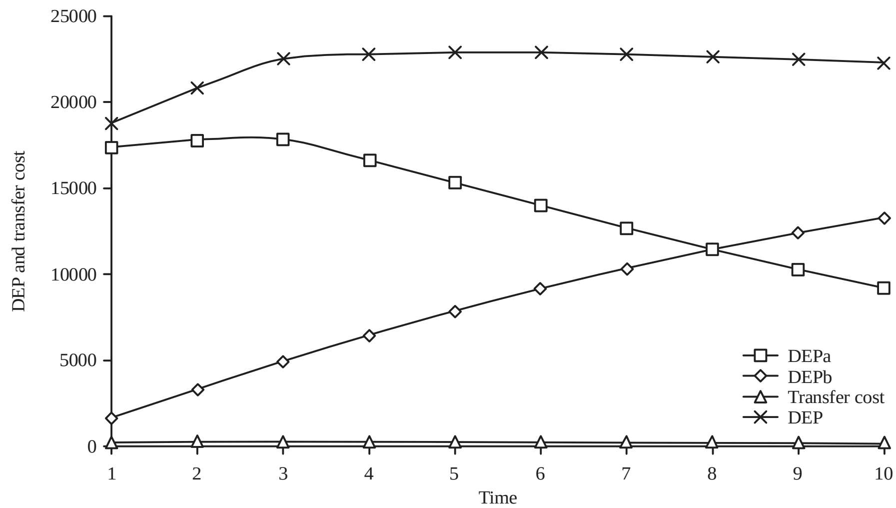

Fig. 1: Changes in DEP and transfer cost with $\sigma = 0$, $\beta_1 = \beta_2 = 88\%$

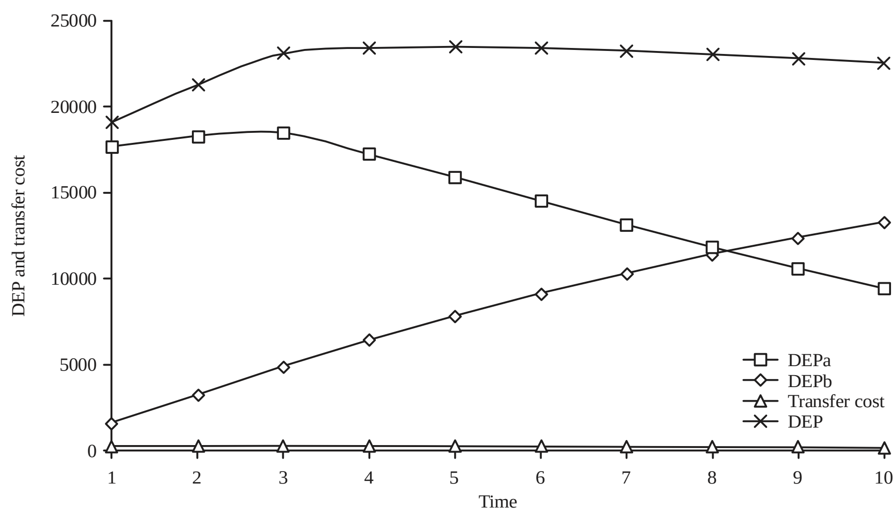

Fig. 2: Changes in DEP and transfer cost with $\sigma = 0$, $\beta_2 = 84\%$

experimental results of the variables from 1-10. From the experimental results in Fig. 2 and 3, the DEP before knowledge transfer (DEPb) in Fig. 2 are the same as in Fig. 3; the DEP after knowledge transfer (DEPa), transfer cost and the total DEP in Fig. 3 are much greater than the values of the variables in Fig. 2. As the complementary types of knowledge are conducive to mutual efficiency, the profits increase proves the validity of the model

Simulation with influence coefficient as a variable: To determine the degree of the coefficient's influence on the DEP and transfer cost, the weights of the two types of complementary knowledge ω_1, ω_2 are set as $\omega_1 = 0.5$, $\omega_2 = 0.5$, weighting private knowledge and big-data knowledge equally and each type of knowledge accounts for 50% of the total. All parameters except σ have the same values and the influence coefficient σ changes from $\sigma = 0.1$ to $\sigma = 10$.

Figure 4 and 5 show the total DEP and the transfer cost varying with σ from 0.1-10. The total DEP and the transfer cost will increase when the influence coefficient σ is enhanced. Thus, when the influence coefficient of dualistic complementary knowledge is enhanced, profits and transfer costs increase because the greater the mutual influence between the types of complementary knowledge is the more knowledge is transferred and transfer costs increase with profits.

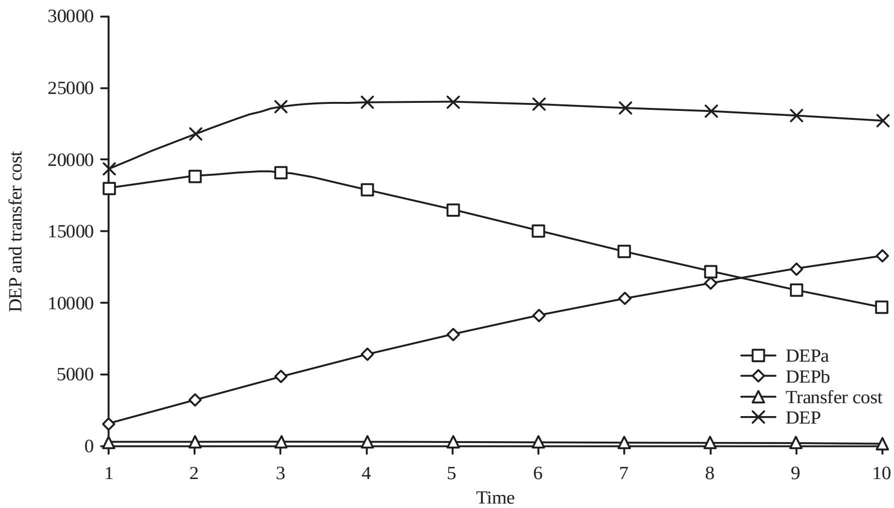

Fig. 3: Changes in DEP and transfer cost with $\sigma = 0.5$, $\beta_2 = 84\%$

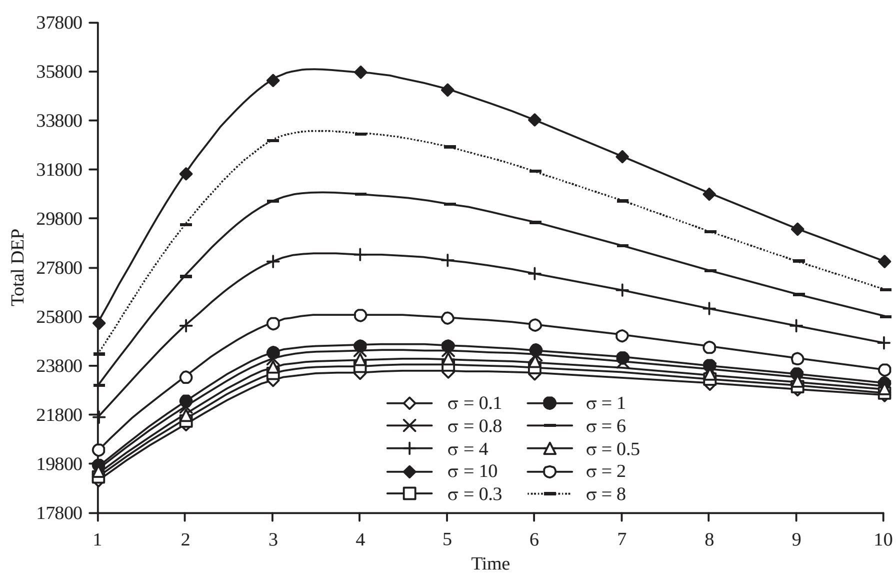

Fig. 4: Changes in total DEP with σ

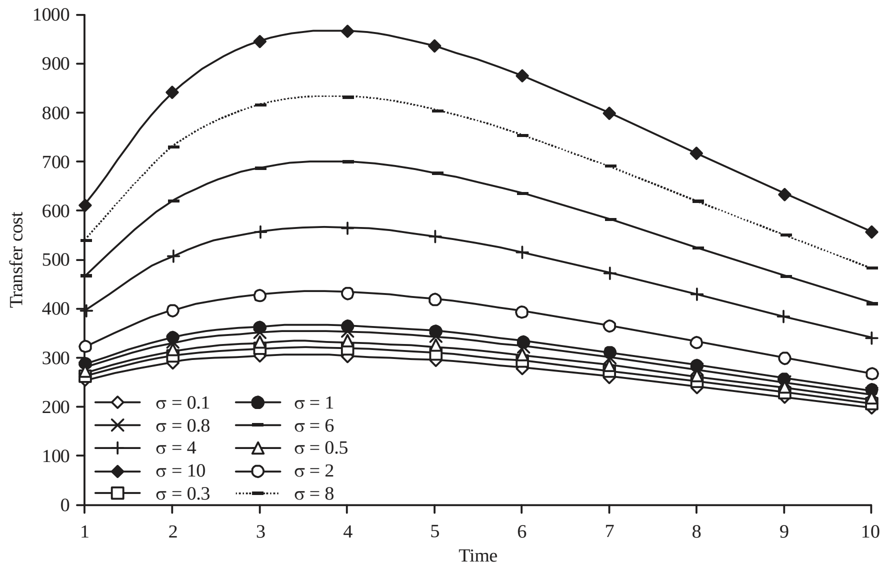

Fig. 5: Changes in transfer cost with σ

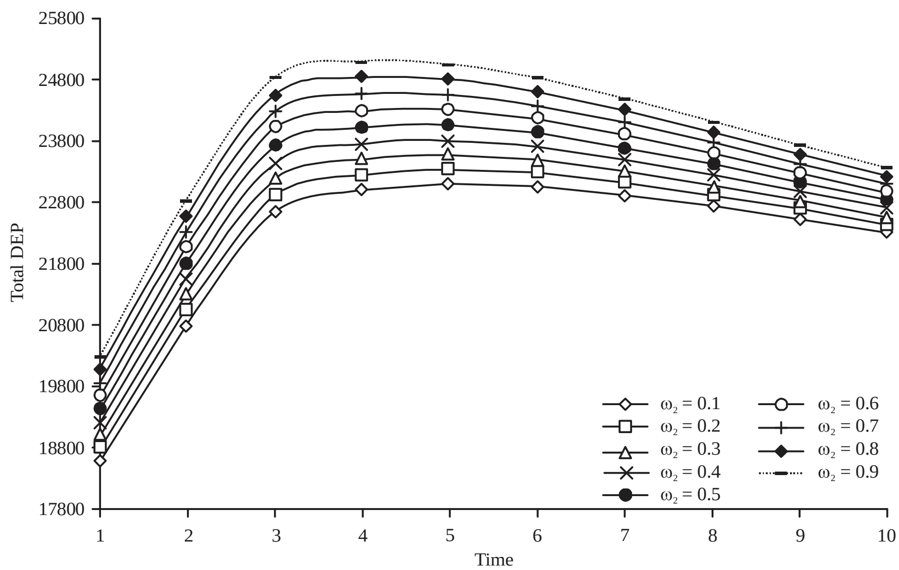

Fig. 6: Changes in total DEP with ω_1, ω_2

The influence coefficient can be greater than 1. If the influence coefficient of the dualistic complementary knowledge is greater than 1, the degree of influence of the two types of knowledge is above the average influence level.

Simulation with the weights of two types of knowledge: To determine how much influence the weights of the two types of complementary knowledge have on the DEP and transfer cost, the influence coefficient is set as $\sigma = 0.5$. This value indicates that there is mutual influence between the two types of complementary knowledge. All parameters except ω_1, ω_2 are set with the same values. Figure 6 show that the total DEP varies with the weights of the two types of complementary knowledge. Figure 7 show that the transfer costs vary with the weights of the two types of complementary knowledge, $\omega_2 = 0.1$ is used to express $\omega_1 = 0.9$, $\omega_2 = 0.1$, etc. By enhancing the weight of big-data knowledge, the total DEP in Fig. 6 increases but the transfer costs in Fig. 7 decline. Big-data knowledge can help enterprises in decision-making, trimming costs and lifting sales[21]. The simulation's experimental results are also in accordance with the actual economic situation. The models

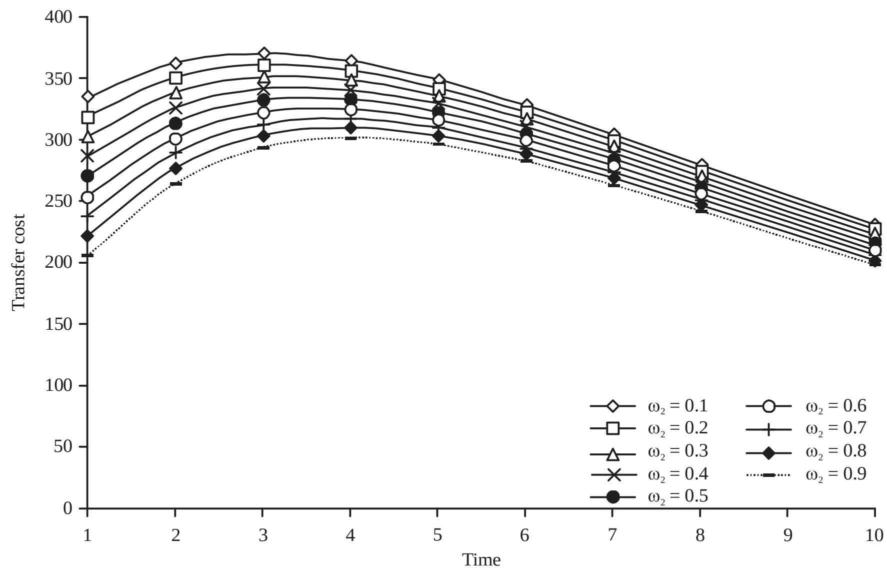

Fig. 7: Changes in transfer cost with ω_1, ω_2

can provide decision-making support for solving dualistic complementary knowledge transfer problems in a big-data environment.

DISCUSSION

Currently, no study exists on complementary knowledge transfer in big-data environments. The literature on decision-making problems related to knowledge transfer in big-data environments focus on two types of independent knowledge[27]. Many results from qualitative research provide proof of the importance of knowledge complementarity for the formation of cooperation[32-36]. Scholars have analyzed the technology knowledge diffusion of related technologies by using the Bass model or Lotka-Volterra model[37-40], which are primarily concerned with technical knowledge diffusion in the whole market and are rarely used to focus on changes to knowledge transfer efficiency for enterprises that have adopted new technical knowledge.

The experimental results of the simulation predicted the expected profits and transfer costs according to different influence coefficients and dualistic complementary knowledge weights. These predictions can be verified in actual economic situations.

CONCLUSION

In this study, the problem of complementary knowledge transfer in big-data environments is analyzed. Based on this analysis, models of dualistic complementary knowledge transfer are developed. Some parameters are given to verify the validity of the models. The calculation results are the same as those of previous studies, which do not consider the mutual influence of these two types of knowledge. Forecasts are developed for different influence coefficients and dualistic complementary knowledge weights. The experimental results of the simulation are consistent with an actual economic situation. The results of the present study can help enterprises understand the degree of mutual influence between the two types of complementary knowledge and determine the appropriate proportion of dualistic complementary knowledge when transferring knowledge in big-data environments.

Clearly, this study is focused on the linear relationship of the influence between the two types of dualistic complementary knowledge in a big-data environment. While, such a hypothesis could introduce calculative deviation, it is important to analyze the nonlinear relationship between private knowledge and big-data knowledge.

SIGNIFICANT STATEMENTS

- The need to analyze the mutual influence of two types of complementary knowledge is considered
- Models of dualistic complementary knowledge transfer are presented and the validity of the models is verified
- Forecasts are developed for different influence coefficients and dualistic complementary knowledge weights

- The results of this study can help enterprises understand the mutual influence of these two types of complementary knowledge and determine the proportion of dualistic complementary knowledge according to the degree of mutual influence and discounted profits when transferring knowledge in a big-data environment

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