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Knowledge Composition and Its Influence on New Product Development Performance in the Big Data Environment

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Abstract: Product innovation is regarded as a primary means for enterprises to maintain their competitive advantage. Knowledge transfer is a major way that enterprises access knowledge from the external environment for new product innovation. Knowledge transfer may face the risk of infringement of the intellectual property rights of other enterprises and the termination of licensing agreements by the knowledge source. Enterprises must develop independent innovation knowledge at the same time they profit from knowledge transfers. Therefore, new product development by an enterprise usually consists of three types of new knowledge: big data knowledge transferred from big data knowledge providers, private knowledge transferred from other enterprises, and new knowledge developed independently by an enterprise in the big data environment. To find what the influences of different types of knowledge are on new product development (NPD) performance, a model is presented that maximizes the expected NPD performance. The results show that the greater the weight of independent innovation knowledge, the greater the performance of NPD. Enterprises tend to transfer knowledge from the external environment when the research and development (R&D) investment is much higher, and enterprises will speed up independent innovation when independent innovation knowledge is expected to bring a larger market share. The model can help enterprises to determine knowledge composition, the scale of R&D investment and predict the performance of NPD.

Keywords: Big data, knowledge transfer, independent innovation, new product development, R&D investment.

1 Introduction

Product innovation has been recognized as a primary means of organization renewal [Dougherty (1992)] and as an 'engine of renewal' Bowen et al. [Bowen, Clark and Holloway (1994)]. As Schumpeter [Schumpeter (1942)] describes, much of the microeconomic dynamics within markets is generated by temporary competitive advantages created by the introduction of new products or the adoption of new production processes. Enterprises need to continuously renew their products to survive and prosper in dynamic environments. Innovation derived only from the enterprises' internal technical breakthroughs is difficult to

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sustain in changing times [Li and Chen (2017); Hu (2018)]. Knowledge transfer is one major way that enterprises get knowledge from the external environment for new product innovation. The process of enterprises absorbing, applying and innovating knowledge through various channels is called knowledge transfer [Szulanski (2000)].

Fast changes in customer preference, information technologies, and competition strategies in the big data environment bring new challenges for product innovation. Users experience from big data is becoming increasingly important with the advent of the big data era. The big data era is the user experience driven or consumer driven era [Li and Chen (2017)]. Big data knowledge has become one important type of knowledge that enterprises need for new product innovation [Manyika, Chui, Brown et al. (2011); McGuire, Manyika and Chui (2012)]. Only by absorbing more external knowledge and integrating it with internal knowledge can enterprises give users a better experience. Enterprises usually transfer big data knowledge from big data knowledge providers by “service outsourcing” [Houacine, Bouzefrane and Adjaz (2016); Liu, Peng and Wang (2018)].

Private knowledge is another important type of knowledge that enterprises need for new product innovation [Wu, Chen and Li (2016); Wu (2017)]. Patent information gleaned from big data for new product innovation has a risk of infringement of the intellectual property rights of other enterprises [Wu, Zhu, Wu et al. (2014)]. The purchase of patents and components are the primary ways that enterprises transfer private knowledge to promote new product innovation [Parra (2014); Levitt (1996)]. This type of knowledge transfer may face the risk of the termination of licensing agreements by the knowledge source [Ding (2008); Ashish (2011)]. From the perspective of imitative innovation, enterprise transfer knowledge serves mainly to achieve imitative innovation. Imitative innovation is not to completely copy but to develop new products on the basis of the predecessors’ technology combined with an enterprise’s own actual situation and needs [Posen, Lee and Yi (2013)]. For example, Tencent’s first product, OICQ, was an imitation of the United States launched ICQ. However, Tencent’s product was not just a copy it got rid of the stale features and brought forth fresh innovation, forming its own characteristics [Hu (2018)]. Enterprises must develop independent innovation knowledge while utilizing knowledge transfer. Therefore, new product innovation from an enterprise usually consists of three types of new knowledge: big data knowledge transferred from big data knowledge providers, private knowledge transferred from other enterprises, and new knowledge developed independently by the enterprise.

Many scholars have researched the significance of product innovation to business survival [Dougherty (1992); Bowen, Clark and Holloway (1994); Knudsen and Mette Præst (2010); Leonard-Barton (2010); Carlile (2002); Cooper and Kleinschmidt (2010); Davila (2016)]. Scholars also have researched the problems of knowledge transfer in the big data environment [McGuire, Manyika and Chui (2012); Houacine, Bouzefrane and Adjaz (2016); Sukumar and Ferrell (2013); Suchanek and Weikum (2013); Horst and Duboff (2015); Jun, Park and Jang (2015); Manyika, Chui, Brown et al. (2011); Koman and Kundrikova (2016); Wu, Zapevalova, Chen et al. (2018)]. However, few researchers have considered the influence of independent innovation knowledge on NPD performance in the big data environment. This paper categorizes the knowledge composition of new product innovation in the big data environment. A model of new product innovation is established by maximizing the present value of the total expected profit of the new product. The model can help enterprises to determine the weight of different types of knowledge and the scale of R&D investment when developing new products. After introducing knowledge composition and the necessity of independent innovation in the big data environment in Section 1, an optimization of knowledge update of new product is presented in Section 2. Parameters setting, simulation experiments and experimental results are described in Section 3. Conclusions are drawn in Section 4.

2 Optimization model of new product knowledge update

2.1 Model hypotheses

V_i is an enterprise in an innovation network $G=(V,E,BD)$ that will update a new product, producing just the one product. The total market volume of the new product is Q, the price of the product is p, and the marginal cost in the starting period is MC. The knowledge absorption capacity is $\alpha(0<\alpha<1)$. The market share of V_i in the starting period is ϕ. 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 the other periods. The discount rate is r, the life cycle of the product is N ,and N is renumbered after each knowledge transfer. For the details on assumptions, see Wu et al. [Wu, Zapevalova, Chen et al. (2018)]. In addition, six new hypotheses are proposed.

Hypothesis 1. V_i is an enterprise in $G=(V,E,BD)$. V_i needs to transfer one type of private knowledge from other enterprises, and V_i also needs to transfer one type of big data knowledge from the big data knowledge providers. The third type of knowledge is independent R&D knowledge. The three types of knowledge will be used for new product innovation simultaneously at time period T ($0<T<N$).

Hypothesis 2. ω_1, ω_2 and ω_3 are the weights of private knowledge, big data knowledge and the independent R&D knowledge $(0\le\omega_1,\omega_2,\omega_3\le 1;\quad \omega_1+\omega_2+\omega_3=1)$.

Hypothesis 3. The update rate of private knowledge from another enterprise is β_1, the update rate of big data knowledge is β_2, and the update rate of independent R&D knowledge is β_3. The update rate of total new knowledge at time period $n=0$ is β $(0<\beta<1)$.

Hypothesis 4. The fixed transfer cost of private knowledge transferred is k_1, the fixed transfer cost of big data knowledge is k_2, and the fixed R&D investment of independent R&D knowledge in the starting period is k_R. All the fixed costs are constants.

Hypothesis 5. $\rho\left(0<\theta_1<\rho<1\right)$ is the total growth rate of market share of V_i in the first L_2 periods immediately after V_i updates its new product knowledge at time period T. ρ_1 is the growth rate of the market share of V_i in the first L_2 periods immediately after V_i only transfers the private knowledge at time period T. ρ_2 is the growth rate of the market share of V_i in the first L_2 periods immediately after V_i only transfers the big data knowledge at time period T. ρ_3 is the growth rate of the market share of V_i in the first L_2 periods immediately after V_i only updates its new product by using independent R&D knowledge in the starting period. $(0<\theta_1<\rho_1,\rho_2,\rho_3<1)$.

Hypothesis 6. $\zeta(T)$ is the DEP of V_i before new product innovation, $\xi(T)$ is the DEP of V_i received after new product innovation at time point T, and $K(T)$ is the knowledge renewal cost. The total DEP of V_i is denoted as $\Psi(T)$ and $\Psi(T)=\zeta(T)+\xi(T)-K(T)$.

2.2 DEP before new product innovation

Because there is no new knowledge at this stage, V_i produces product using prior knowledge. The DEP before an update in new product knowledge is shown in Eq. (1).

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

2.3 Knowledge renewal cost

The knowledge renewal cost K is formed by the fixed cost k_{fix} and the variable cost k_{var}. The fixed transfer cost k_{fix} can be calculated by the weight and the fixed transfer cost of each type of knowledge. From hypotheses 2 and 4, the fixed cost of new product can be calculated by Eq. (2).

$$k_{fix}=\omega_1 k_1+\omega_2 k_2 \ \ (0\le\omega_1,\omega_2,\omega_3\le 1;\ \omega_1+\omega_2+\omega_3=1) \tag{2}$$

The variable cost k_{var} is related to the knowledge-level gap between V_i and the updated rate of external new knowledge. From the modeling method, the weights of private knowledge and big data knowledge are calculated by the profit contribution rate of each type of knowledge. Thus, $\omega_1,\omega_2,\omega_3$ can also be seen as the weight of the update rate of each type of knowledge. The update rate of all external new knowledge β can be obtained by Eq. (3).

$$\beta = \omega_1\beta_1 + \omega_2\beta_2 + \omega_3\beta_3 \ \ (0 \le \omega_1, \omega_2, \omega_3 \le 1;\ \omega_1 + \omega_2 + \omega_3 = 1) \tag{3}$$

From hypotheses 2, 3 and 4, the variable cost can be computed by Eq. (4), where F is the coefficient of variable cost and a constant.

$$k_{\text{var}} = F[\alpha^T - (\omega_1\beta_1 + \omega_2\beta_2 + \omega_3\beta_3)^T] \quad (0 \le \omega_1, \omega_2, \omega_3 \le 1;\ \omega_1 + \omega_2 + \omega_3 = 1) \tag{4}$$

After discounting the transfer costs to the starting point, the total transfer cost of various types of knowledge can be expressed as Eq. (5).

$$K(T) = [\,\omega_1 k_1 + \omega_2 k_2 + F[\alpha^T - (\omega_1\beta_1 + \omega_2\beta_2 + \omega_3\beta_3)^T]]r^T \tag{5}$$

2.4 DEP after new product innovation

Suppose that $\omega_1, \omega_2, \omega_3$ are also the weights of the growth rates of the market shares of each type of knowledge. The total growth rate of market share ρ can be calculated by Eq. (6).

$$\rho = \omega_1\rho_1 + \omega_2\rho_2 + \omega_3\rho_3 \ \ (0 < \theta_1 < \rho_1, \rho_2, \rho_3 < 1) \tag{6}$$

If V_i transfers new knowledge at time period T, when $T \le L_1$, the market share of V_i in time period T is $\phi(1+\theta_1)^T$. When $T > L_1$, the market share of V_i is $\phi(1+\theta_1)^{L_1}(1-\theta)^{T-L_1}$. After the period of time T, new knowledge began to work on the market share of V_i. From previous hypotheses and hypothesis 5, the market share of V_i will increase at a rate of ρ in the L_2 periods immediately after time period T, and it will then decay at a rate of θ. Hence, the market share of V_i in period n can be denoted as Eq. (7).

$$\lambda(n,T) = \begin{cases} \phi(1+\theta_1)^T(1+\omega_1\rho_1+\omega_2\rho_2+\omega_3\rho_3)^n & n \le L_2,\ T \le L_1 \\ \phi(1+\theta_1)^{L_1}(1-\theta)^{T-L_1}(1+\omega_1\rho_1+\omega_2\rho_2+\omega_3\rho_3)^n & n \le L_2,\ T > L_1 \\ \phi(1+\theta_1)^T(1+\omega_1\rho_1+\omega_2\rho_2+\omega_3\rho_3)^n(1-\theta)^{n-L_2} & n > L_2,\ T \le L_1 \\ \phi(1+\theta_1)^{L_1}(1-\theta)^{T-L_1}(1+\omega_1\rho_1+\omega_2\rho_2+\omega_3\rho_3)^{L_2}(1-\theta)^{n-L_2} & n > L_2,\ T > L_1 \end{cases} \tag{7}$$

From hypothesis 3, the update rate of all external new knowledge at time period $n = 0$ is β. Considering the time cumulative effect, the external new knowledge at time period T has been updated by β^T, which can make the marginal cost of V_i at time period T reduce to $MC\beta^T$. The knowledge absorption capacity of V_i is α. Then, the marginal cost of V_i at time period T will become $MC\beta^T\alpha^n$. By replacing β^T with Eq. (3), the marginal cost at time period T of V_i can be calculated by Eq. (8).

$$MC\beta^T\alpha^n = MC(\omega_1\beta_1+\omega_2\beta_2+\omega_3\beta_3)^T\alpha^n \tag{8}$$

The total production cost in time period n after knowledge transfer is $Q\lambda(n,T)MC(\omega_1\beta_1+\omega_2\beta_2+\omega_3\beta_3)^T\alpha^n$. By subtracting the total production cost from the sales revenue $pQ\lambda(n,T)$, the profit at time period n after knowledge transfer can be obtained by Eq. (9).

$$\Pi^* = pQ\lambda(n,T) - Q\lambda(n,T)MC(\omega_1\beta_1+\omega_2\beta_2+\omega_3\beta_3)^T\alpha^n \tag{9}$$

Through discounting the profits in period n to the starting point by multiplying Eq. (9) with $r^T r^n$ and summing up all the discounted profits in the life cycle N, the DEP after knowledge transfer is as shown in Eq. (10).

$$\xi(T) = r^T\sum_{n=1}^{N}(pQ\lambda(n,T) - Q\lambda(n,T)MC(\omega_1\beta_1+\omega_2\beta_2+\omega_3\beta_3)^T\alpha^n)r^n \tag{10}$$

By using Eqs. (7) and (10), the expected profits after knowledge transfer can be expressed as Eq. (11).

$$\xi(T)=\begin{cases}
pQ\phi(1+\theta_1)^T r^T\sum_{n=1}^{L_2}(1+\omega_1\rho_1+\omega_2\rho_2+\omega_3\rho_3)^n r^n \\
-MCQ\phi(1+\theta_1)^T r^T(\omega_1\beta_1+\omega_2\beta_2+\omega_3\beta_3)^T\sum_{n=1}^{L_2}(1+\omega_1\rho_1+\omega_2\rho_2+\omega_3\rho_3)^n\alpha^n r^n \\
+pQ\phi(1+\theta_1)^T(1+\omega_1\rho_1+\omega_2\rho_2+\omega_3\rho_3)^{L_2} r^T\sum_{n=L+1}^{N}(1-\theta)^{n-L_2}r^n \\
-MCQ\phi(1+\theta_1)^T r^T(\omega_1\beta_1+\omega_2\beta_2+\omega_3\beta_3)^T(1+\omega_1\rho_1+\omega_2\rho_2+\omega_3\rho_3)^{L_2}\sum_{n=L+1}^{N}(1-\theta)^{n-L_2}\alpha^n r^n & T\le L_1 \\
pQ\phi(1+\theta_1)^{L_1}(1-\theta)^{T-L_1}r^T\sum_{n=1}^{L_2}(1+\omega_1\rho_1+\omega_2\rho_2+\omega_3\rho_3)^n r^n \\
-MCQ\phi(1+\theta_1)^{L_1}(1-\theta)^{T-L_1}\beta^T r^T\sum_{n=1}^{L_2}(1+\omega_1\rho_1+\omega_2\rho_2+\omega_3\rho_3)^n\alpha^n r^n \\
+pQ\phi(1+\theta_1)^{L_1}(1-\theta)^{T-L_1}(1+\omega_1\rho_1+\omega_2\rho_2+\omega_3\rho_3)^{L_2} r^T\sum_{n=L+1}^{N}(1-\theta)^{n-L_2}r^n \\
-MCQ\phi(1+\theta_1)^{L_1}(1-\theta)^{T-L_1}r^T(\omega_1\beta_1+\omega_2\beta_2+\omega_3\beta_3)^T(1+\omega_1\rho_1+\omega_2\rho_2+\omega_3\rho_3)^{L_2}\sum_{n=L+1}^{N}(1-\theta)^{n-L_2}\alpha^n r^n & T>L_1
\end{cases} \tag{11}$$

2.5 Total DEP of new product

From the modeling idea and methods, the time optimization problem of multiple simultaneous knowledge transfer of various types of knowledge must find the maximum of the total DEP $\Psi(T)$ of V_i for the given parameters. Therefore, the optimization model of multiple simultaneous knowledge transfer can be expressed as Eq. (12).

$$\max\Psi(T)=\max(\zeta(T)+\xi(T)-K(T)) \tag{12}$$

3 Simulation experiments

3.1 Model solution

It can be seen from Eq. (12) that $\Psi(T)$ is a piecewise continuous differential function of T. Therefore, $\Psi(T)$ can reach its maximum in a closed interval $0 \le T \le N$, and the maximum profits in the life cycle of the product can be found. Then, the optimal time of multiple knowledge transfers can be obtained.

MATLAB 7.0 has been used to compile a program that considers the power of the numerical calculation and simulation functions. Some simulation experiments of actual situations can be conducted by adjusting the model's parameters.

3.2 Simulation experiments

(1) Parameter setting and simulation with $\omega_1 = 0.5, \omega_2 = 0.5, \omega_3 = 0$

To compare knowledge transfer models in a big data environment, the same parameters are set at the same values. The R&D investment is usually higher than the fixed cost of private knowledge transfer, and independent innovation knowledge usually brings higher market share and a higher knowledge update rate. Therefore, the parameters are set as follows. The total product sales $Q = 1000$; the price per unit product $p = 60$; the marginal cost in the starting period $MC = 40$; the growth rates of total market volume in the first L_1 periods $\theta_1 = 3\%$; the natural attenuation rate of market volume in the other periods $\theta = 3\%$; the market share of V_i in the starting period $\phi = 8\%$; the period of total market volume increased before knowledge update of the new product $L_1 = 3$; the period of total market volume increased after knowledge update of the new product $L_2 = 5$; the knowledge absorption capacity $\alpha = 95\%$; the life cycle of the product $N = 10$; the variable cost coefficient $F = 1000$; the discount rate is 10%, then $r = 1/(1+10\%) \approx 0.9$; the fixed transfer cost of the private knowledge $k_1 = 300$; the fixed transfer cost of the big data knowledge $k_2 = 80$; the R&D investment of independent innovation knowledge in the starting period $k_{Rf} = 600$; the growth rate of the market share of V_i in the first $L_2 = 5$ periods immediately after V_i only transfers the private knowledge $\rho_1 = 6\%$. The growth rate of the market share of V_i in the first L_2 periods immediately after V_i only transfers the big data knowledge $\rho_2 = 8\%$. the growth rate of the market share of V_i in the first L_2 periods immediately after V_i only updates its new product by using independent R&D knowledge in the starting period $\rho_3 = 10\%$; the update rate of private knowledge $\beta_1 = 88\%$; the update rate of big data knowledge $\beta_2 = 88\%$; the update rate of independent innovation knowledge $\beta_3 = 84\%$. The values of these parameters are shown in Tab. 1.

Table 1: Parameter values

Parameter	Q	p	MC	θ_1	θ	ϕ	L_1	L_2	α	N	F	r
Value	1000	60	40	3%	3%	8%	3	5	95%	10	1000	0.9
Parameter	ω_1	ω_2	ω_3	k_1	k_2	k_3	ρ_1	ρ_2	ρ_3	β_1	β_2	β_3
Value	0.5	0.5	0	300	80	600	6%	8%	10%	88%	88%	84%

When $\omega_1 = 0.5, \omega_2 = 0.5$ and $\omega_3 = 0$, it means that V_i only transfers knowledge from the external environment to update new products, and the proportion of big data knowledge and private knowledge are all 50%. Tab. 2 shows the experimental results of the DEP before knowledge transfer (DEPb), the DEP after knowledge transfer (DEPa), the transfer costs, and the total DEP of the new product. The total DEPs are the same as the experimental results of Wu et al. [Wu, Chen and Li (2016)], and the model is valid.

Table 2: DEPs and Transfer costs when $\omega_1 = 0.5, \omega_2 = 0.5, \omega_3 = 0$

Period	DEP before transfer	DEP after transfer	Transfer costs	Total DEP
1	1632	17370	234	18768
2	3275	17772	258	20789
3	4913	17837	267	22483
4	6438	16619	266	22791
5	7849	15312	257	**22904**
6	9146	13985	245	22887
7	10333	12684	229	22788
8	11415	11437	213	22639
9	12396	10265	195	22466
10	13284	9176	178	22283

(2) Simulation with ω_1, ω_2 and ω_3

When $\omega_1 = 0.4, \omega_2 = 0.4$ and $\omega_3 = 0.2$, it means that V_i updates its product by using three types of new knowledge. Among the three types of new knowledge, big data knowledge is 40%, private knowledge is 40%, and independent innovation knowledge of V_i is 20%. Tab. 3 shows the experimental results of the DEPb, the DEPa, the transfer costs, and the total DEP of a new product when $\omega_1 = 0.4, \omega_2 = 0.4$ and $\omega_3 = 0.2$.

When $\omega_1 = 0.2, \omega_2 = 0.2$ and $\omega_3 = 0.6$, it means that big data knowledge is 20%, private knowledge is 20%, and independent innovation knowledge of V_i is 60%. Tab. 4 shows the experimental results of the DEPb, the DEPa, the transfer costs, and the total DEP of the new product. From the experimental results in Tabs. 3, 4 and Fig. 1, the optimal knowledge update time of new product T change from 5 to 4, and the total DEPs increase. It can be concluded that the performance of NPD increases with the weight of independent innovation knowledge, and the enterprise will update its product with new knowledge as soon as possible. This model is in line with the actual economic situation, and the model is valid. This model can help enterprises to determine the weight of different types of knowledge and predict the performance of NPD.

Table 3: DEPs and Transfer costs when $\omega_1 = 0.4, \omega_2 = 0.4, \omega_3 = 0.2$

Period	DEP before transfer	DEP after transfer	Transfer costs	Total DEP
1	1032	17892	207	18716
2	2675	18386	238	20822
3	4313	18499	252	22560
4	5838	17258	255	22841
5	7249	15910	249	**22910**
6	8546	14531	238	22840
7	9733	13175	223	22685
8	10815	11874	207	22481
9	11796	10649	190	22255
10	12684	9512	173	22023

Table 4: DEPs and Transfer costs when $\omega_1 = 0.2, \omega_2 = 0.2, \omega_3 = 0.6$

Period	DEP before transfer	DEP after transfer	Transfer costs	Total DEP
1	1032	18973	153	19852
2	2675	19657	199	22132
3	4313	19864	223	23953
4	5838	18568	232	24174
5	7249	17126	230	24145
6	8546	15636	222	23961
7	9733	14162	209	23686
8	10815	12746	194	23367
9	11796	11413	178	23031
10	12684	10177	162	22700

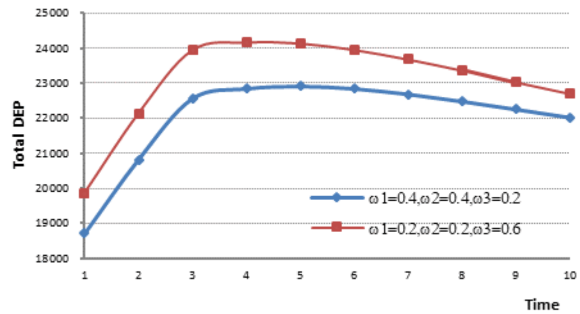

Figure 1: Changes of total DEP with ω_1, ω_2 and ω_3

(3) Simulation with k_R

k_R is the R&D investment in the starting period. Let k_R change from 600 to 1200, all the other parameters are set at the same values as that when $\omega_1 = 0.2, \omega_2 = 0.2$ and $\omega_3 = 0.6$. It means that new independent innovation knowledge needs more R&D investment. From the experimental results in Tabs. 4, 5 and Fig. 2, all total DEPs have become smaller, and the optimal time of knowledge update has no obvious changes. It means that increasing R&D investment will lead to a decline in NPD performance, but the growth of R&D investment to a certain extent does not affect the speed of new product updates. When the R&D investment is much higher, enterprises tend to increase the proportion of knowledge transferred from the external environment.

Table 5: DEPs and Transfer costs with k_R

Period	DEP before transfer	DEP after transfer	Transfer costs	Total DEP
1	432	18973	153	19252
2	2075	19657	199	21532
3	3713	19864	223	23353
4	5238	18568	232	**23574**
5	6649	17126	230	23545
6	7946	15636	222	23361
7	9133	14162	209	23086
8	10215	12746	194	22767
9	11196	11413	178	22431
10	12084	10177	162	22100

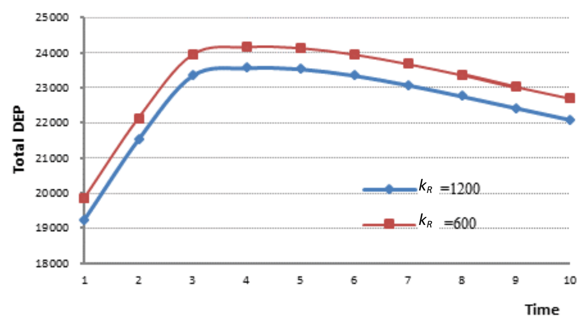

Figure 2: Changes of total DEP with k_R

(4) Simulation of ρ_3

Let the growth rate of the market share of independent innovation knowledge ρ_3 change from 10% to 18%, all the other parameters are set at the same values as that when $\omega_1 = 0.2, \omega_2 = 0.2$ and $\omega_3 = 0.6$. The meaning is that new independent innovation knowledge will bring a significant increase in market share. From the experimental results in Tab. 4, 6 and Fig. 3, the total DEPs have become larger. It means that the performance of NPD increases. The optimal time for a knowledge update of a new product changes from $T = 4$ to $T = 3$. The reason is that if the independent innovation knowledge can bring a larger market share in the future, enterprise will speed up NPD.

Table 6: DEPs and Transfer costs with ρ_3

Period	DEP before transfer	DEP after transfer	Transfer costs	Total DEP
1	1032	22506	153	23385
2	2675	23283	199	25758
3	4313	23503	223	27593
4	5838	21953	232	27559
5	7249	20237	230	27256
6	8546	18468	222	26792
7	9733	16721	209	26245
8	10815	15045	194	25666
9	11796	13469	178	25087
10	12684	12008	162	24530

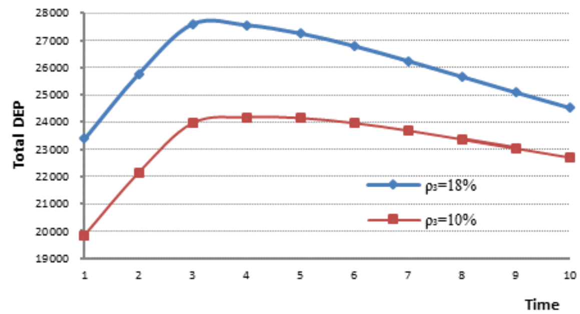

Figure 3: Changes of total DEP with ρ_3

4 Conclusion

This paper categorizes the knowledge composition of new product innovation in the big data environment. A model of new product innovation is established by maximizing the present value of the total expected profit of the new product. The model can help enterprises to determine the weight of different types of knowledge and the scale of R&D investment, and it predicts performance of NPD when developing new products. The results show that the greater the weight of independent innovation knowledge, the greater the performance of NPD. Enterprises tend to transfer knowledge from the external environment when R&D investment is much higher, and enterprises will speed up independent innovation when independent innovation knowledge is expected to bring larger market share.

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