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Article

Pricing Method for Big Data Knowledge Based on a Two-Part Tariff Pricing Scheme

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Abstract: Nowadays big data knowledge is being bought and sold online for market research, new product development, or other business decisions, especially when customer demands and consumer preferences knowledge for new product development are needed. Previous studies have introduced two commonly used pricing schemes for big data knowledge transactions (e.g., cloud services): Subscription pricing and pay-per-use pricing from a big data knowledge provider's standpoint. However, few studies to date have investigated a two-part tariff pricing scheme for big data knowledge transactions, albeit this pricing scheme may increasingly attract the big data knowledge providers in this hyper-competitive market. Also, little research has been done from the perspective of the knowledge recipient firm which is an important and integral part of big data knowledge transactions. This study constructs a two-part tariff pricing decision model for big data knowledge transactions from the perspective of the knowledge recipient firms. The model is a more generalized pricing scheme decision model and can be used to compare the profitability of three pricing schemes: Subscription pricing, pay-per-use pricing, and two-part tariff pricing. It shows that the influence of free knowledge on new product development performance of knowledge recipient firms cannot be ignored, and the pay-per-use pricing scheme is the best solution for knowledge recipient firms.

Keywords: Big data knowledge; knowledge transaction; two-part tariff pricing; subscription pricing; pay-per-use pricing

1 Introduction

Nowadays, big data knowledge is being bought and sold online for market research, new product development, or other business decisions, especially when the needs for customer demands and consumer preferences knowledge in new product development are high [1–4]. For example, firms can get financial data from Xignite, social media data from Gnip, and various types of data from AggData. Similarly, some pharmaceutical companies can obtain anonymized, self-reported patient statistics for new drug development from big data knowledge providers (e.g., PatientsLikeMe) [4,5]. This need for large scale patient data also applies to the pressing vaccine development in our efforts to contain COVID-19.

Big data knowledge is generated from massive data sets, and it is compute-intensive, data-intensive, and knowledge-intensive [6]. The transaction of big data knowledge, which is a process of knowledge transfer, is different from that of ordinary commodities [7]. Given that big data processing requires unique services, and big data knowledge has the characteristics of open-source, dynamic, and multi-source heterogeneity, the transaction of big data knowledge is also different from that of private knowledge [1,8]. To illustrate, big data knowledge transactions are usually carried out in a two-sided market, and the providers are usually platforms [9]. Due to the limitations of free big data knowledge, some firms are paying for big data knowledge to sustain their business models and facilitate new product development. Therefore, similar to the private knowledge transaction (e.g., patent licensing), the pricing of big data knowledge is necessary [10–12]. Pricing of big data knowledge can regulate the supply and demand of big data knowledge, as well as the profits of big data knowledge providers and knowledge recipients [13–15].

Scholars have proposed many pricing methods for big data knowledge (e.g., cloud services) and argued that the most popular pricing methods for big data knowledge transaction are subscription pricing and pay-per-use pricing [16–19]. In a subscription pricing scheme, firms pay on a recurring basis to access big data knowledge for new product development [13]. However, subscription pricing can result in firms overpaying for big data knowledge. In a pay-per-use pricing scheme, firms only have to pay for the knowledge they need. There is no wasted knowledge. Sometimes big data knowledge providers provide some free knowledge when they take the pay-per-use pricing scheme. Although these big data providers offer a large number of free knowledge, as an exchange, they could get advertising revenues based on users' visits and collect users' personal information such as web surfing and purchasing behavior [20]. In addition, big data knowledge providers can unearth new knowledge of customer demands and user preferences from these data. However, most times big data knowledge providers charge a price for the data and knowledge they provide to the recipients. Prior research suggests that the pricing methods for big data knowledge transactions should include the two-part tariff pricing scheme, and claims that it is the most profitable pricing scheme for big data knowledge providers [20]. Nonetheless, prior work mainly analyzes or compares the profit, consumer surplus, and social welfare from a big data knowledge provider's perspective instead of the perspective of a recipient [21].

This study differentiates itself from previous ones in several aspects. First, we analyzed pricing methods and the profitability from a knowledge recipient firm's standpoint, including the influence of free knowledge on its new product development performance. Second, we clarified the previous pricing method of a two-part tariff and extended it to a more generalized pricing scheme selection model for knowledge recipient firms that include the two pricing schemes of subscription and pay-per-use pricing. Third, we compared the results of a two-part tariff pricing scheme from subscription, pay-per-use, and recent real-world economic situations. Our model can help knowledge recipients predict their profitability, choose the suitable pricing schemes, and seize the optimal timing of knowledge transaction in the two-part pricing scheme.

The rest of the paper proceeds as follows. Section 2 discusses the two-part tariff model and hypotheses for big data knowledge pricing methods from the perspective of knowledge recipient firms. Section 3 presents a generalized two-part tariff pricing model of big data knowledge. Section 4 describes simulation experiments and comparative analysis of subscription pricing, pay-per-use pricing, two-part tariff pricing, and recent real-world economic situations. Section 5 concludes and discusses the limitations and potential future research work.

2 Conceptual Model and Model Hypotheses

2.1 Conceptual Model for Pricing Strategies of Big Data Knowledge

The transaction of big data knowledge is usually carried out in a two-sided market, while big data knowledge providers are usually platforms [9]. In two-sided markets, a subscription (or fixed) fee is a one-time fee charged by the platform for the knowledge buyer's qualifications, and a per-transaction fee is a fee charged for each transaction performed by the buyer. If the platform charges buyers both a subscription fee and a transaction fee, then it is called two-part tariff pricing [22,23]. Two-part tariff pricing is a common pricing method for two-sided markets [9].

Suppose a firm needs to purchase a type of big data knowledge, and the big data knowledge provider charges the firm both the subscription fee and the per-transaction fee. As we know, knowledge transaction is a process of knowledge transfer [7]. Therefore, the decision model of knowledge transfer can be used for the price decision for big data knowledge.

Knowledge recipient firms can obtain common big data knowledge on the platform after paying a subscription fee to big data knowledge providers. Sometimes, big data knowledge providers will waive the subscription fee in order to attract big data knowledge demanders. Thus, the subscription fee could be either one-time fixed fee or totally free. Meanwhile, the knowledge recipient firms can also acquire big data knowledge by paying per-transaction fee. In each transaction of big data knowledge, the knowledge recipient firms need to compare the two pricing schemes of subscription pricing and pay-per-use pricing and select a suitable one. In light of this rationale, in the two-part tariff pricing scheme, big data knowledge acquired by knowledge recipient firms includes two parts. One part comes from the paid subscription fee, and the other comes from the paid per-transaction fee. The effect of these two parts of knowledge on new product development performance of the knowledge recipient firm is determined by the proportion of the two parts of knowledge, and the proportion of knowledge can be calculated by the weight of knowledge contribution [24]. Therefore, a pricing decision model of the two-part tariff can be established based on the maximization of the discounted expected profit (DEP) of a knowledge recipient firm, that buys big data knowledge from a big data knowledge provider for new product development. In addition, the optimal timing of big data knowledge transaction based on a two-part tariff pricing scheme can be calculated by the total DEP of the knowledge recipient firm. The total DEP includes the DEP before knowledge transfer, the DEP after knowledge transfer, and the transfer cost. The pricing method of two-part tariff is shown in Fig. 1.

2.2 Model Hypotheses

We consider there is common big data knowledge of platform transferring with the payment of a subscription fee, and we call this part of big data knowledge subscription knowledge. At the same time, there is also knowledge transferring with each transaction, and we call this part of big data knowledge per-transaction knowledge. For simplicity, we assume that firms only take a one time big data knowledge transaction, and that the two parts of knowledge are transferred simultaneously. To make the pricing-decision model of a two-part tariff more practical and simple, we formulate the following hypotheses:

Hypothesis 1. V_i is a firm that needs to buy big data knowledge for new product development, BD_k is a big data knowledge provider and it will charge V_i as both a registration fee and a transaction fee in the big data knowledge transaction. V_i produces only one product.

Hypothesis 2. k_1 is the subscript fee, and k_2 is the price cap of transaction knowledge [25], k_1, k_2 are constants. When $k_1 = 0$, it means that it is free for subscription knowledge.

Hypothesis 3. $q\,(0 \leq q \leq 1)$ represents the usage ratio of transaction knowledge.

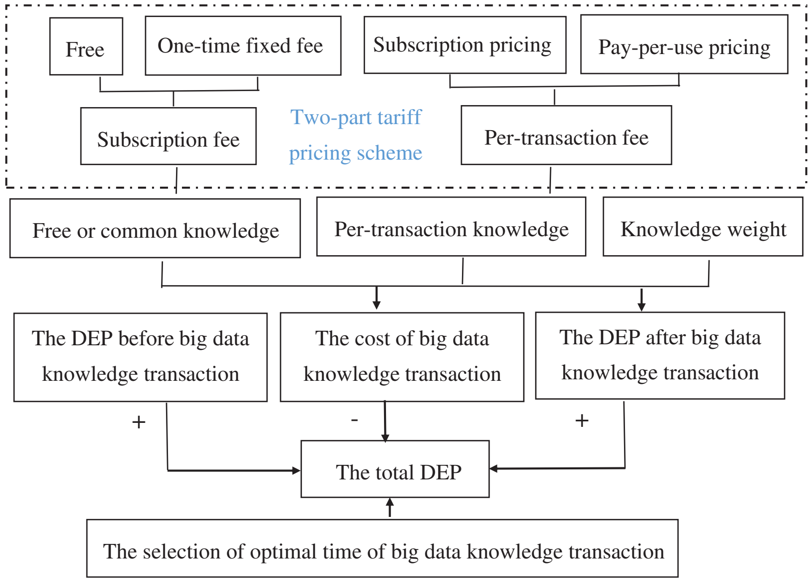

Figure 1: Conceptual model of two-part tariff pricing scheme of big data knowledge

Hypothesis 4. The cost of big data knowledge transaction K is formed by the fixed cost k_{fix} and the variable cost k_{var}. The fixed cost k_{fix} is related to the subscription fee and per-transcription fee, and the variable cost k_{var} is determined by the knowledge distance gap between the inside and outside knowledge level [26].

Hypothesis 5. ω_1, ω_2 is the weight of the two parts of big data knowledge to the total update rate of outside knowledge that V_i purchases from BD_k for new product development $(0 \leq \omega_1, \omega_2 \leq 1$, $\omega_1 + \omega_2 = 1)$.

Hypothesis 6. The update rate of subscription knowledge in the starting point is $\beta_1(0 < \beta_1 < 1)$, the update rate of per-transaction knowledge in the starting point is $\beta_2(0 < \beta_2 < 1)$, and the total update rate of outside knowledge after V_i adopting the two-part tariff knowledge transaction in the starting point is $\beta\,(0 < \beta < 1)$.

Hypothesis 7. The total market volume 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. $\rho_1(0 < \theta_1 < \rho_1 < 1)$ is the growth rate of the market share of V_i in the first L_2 periods when V_i only purchases a part of the subscription knowledge; $\rho_2(0 < \theta_1 < \rho_2 < 1)$ is the growth rate of the market share of V_i in the first L_2 periods when V_i only purchases a part of per-transaction knowledge; $\rho\,(0 < \theta_1 < \rho < 1)$ is the total growth rate of the market share of V_i in the first L_2 periods when V_i adopts a two-part tariff pricing scheme in the big data knowledge transaction.

Hypothesis 8. $\zeta(T)$ is the discount expected profits (DEP) of V_i before the knowledge transaction, $\xi(T)$ is the DEP of V_i after the big data knowledge transaction by adopting a two-part tariff pricing scheme at time period T, and $K(T)$ is the cost of the knowledge transaction, that is the cost of the big data knowledge transaction. The total DEP of V_i is denoted as $\psi(T)$ and we will have $\psi(T) = \zeta(T) + \xi(T) - K(T)$.

We take some other assumptions and variables as follows: The price of the new product is p; the total market volume of the new product is Q; the marginal cost of the new product in the starting period is MC; the market share of V_i in the starting period is ϕ; the knowledge absorption capacity of V_i is $\alpha(0 < \alpha < 1)$; the discount rate is r; the life cycle of the new product is N, and N is renumbered after the big data knowledge transaction and new product development. The detailed assumptions can be referred to in Wu et al. [26].

3 Two-Part Tariff Pricing Model of a Big Data Knowledge Transaction

3.1 DEP Before a Big Data Knowledge Transaction in a Two-Part Tariff Pricing Scheme

Because V_i has not purchased new big data knowledge from big data knowledge providers at this stage, it produces a product using its prior knowledge. The DEP before a big data knowledge transaction in a two-part tariff pricing scheme can be calculated by sales revenue minus production costs, that is shown in Eq. (1). The detailed calculation method of the DEP can be referred to the research of Wu et al. [26].

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

3.2 Cost of a Big Data Knowledge Transaction in a Two-Part Tariff Pricing Scheme

According to hypotheses 2, 3, and 4, the cost of big data knowledge transaction K is formed by the fixed cost k_{fix} and the variable cost k_{var}. The fixed cost k_{fix} is related to the subscription fee and per-transaction fee. The subscript fee of common knowledge is k_1, the price cap of per-transaction knowledge is k_2, and the usage ratio of per-transaction knowledge is q. Then, the fixed cost k_{fix} can be calculated by Eq. (2).

$$k_{fix} = k_1 + qk_2 (0 \le q \le 1) \tag{2}$$

In Eq. (2), the pricing scheme can represent subscription pricing when $q = 0$ and $k_1 > 0$, pay-per-use pricing when $k_1 = 0$, $k_2 > 0$ and $0 < q < 1$, and two-part tariff pricing when $k_1 > 0$, $k_2 > 0$ and $0 < q < 1$. In Eq. (2), when $k_2 > 0$ and $q = 1$, it means the firm has purchased all the license rights of the per-transaction knowledge in the pay-per-use pricing scheme, and the pricing scheme of the per-transaction can be considered the subscription pricing. Therefore, the pricing scheme is subscription pricing when $q = 0$ and $k_1 > 0$, pay-per-use pricing when $k_1 = 0$, $k_2 > 0$, and $0 < q < 1$, or $k_2 > 0$ and $q = 1$.

According to hypotheses 3, 5, and 6, q represents the usage ratio of per-transaction knowledge, β_1 is the update rate of subscription knowledge at the starting point, β_2 is the update rate of per-transaction knowledge at the starting point, and ω_1, ω_2 are the weights of two parts of knowledge to the update rate of knowledge that V_i purchases from BD_k for new product development. Then, the total update rate of outside knowledge β can be calculated by Eq. (3).

$$\beta = \omega_1\beta_1 + \omega_2 q\beta_2 \tag{3}$$

The variable cost k_{var} is determined by knowledge distance between the original inside knowledge and outside new knowledge. Suppose F is the coefficient of variable cost, and it is a constant. Then, the variable cost of two-part big data knowledge transaction can be computed by Eq. (4).

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

After discounting the fixed cost and the variable cost to the starting point, the total knowledge transaction cost can be expressed as Eq. (5) when V_i adopts two-part tariff pricing scheme.

$$K(T) = [k_1 + qk_2 + F[\alpha^T - (\omega_1\beta_1 + \omega_2 q\beta)^T]]r^T \tag{5}$$

3.3 DEP after Big Data Knowledge Transaction in Two-Part Tariff Pricing Scheme

From Hypothesis 5, ω_1, ω_2 are the weights of two parts of big data knowledge to the total update rate of outside knowledge. Then, ω_1, ω_2 can also be seen as the weights of the growth rates of the market shares of each part of knowledge, and the total growth rate of market share ρ can be calculated by Eq. (6).

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

If V_i takes two-part tariff big data knowledge transaction 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, the subscription knowledge and the per-transaction knowledge begin to work on the market share of V_i. From Hypothesis 7, 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) after it takes two-part big data knowledge transaction.

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

From Hypothesis 6, the total update rate of outside knowledge after V_i adopting two-part tariff knowledge transaction at the starting point is $\beta\,(0 < \beta < 1)$. Considering the time cumulative effect, the total new big data 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 $MC\beta^T\alpha^n$.

The total production cost in time period n after the two-part big data knowledge transaction is $Q\lambda(n,T)MC\beta^T\alpha^n$. By subtracting the total production cost from the sales revenue $pQ\lambda(n,T)$ and discounting the profits in time period n to the starting point by multiplying r^Tr^n, and replacing β^T with Eq. (3), the DEP after the two-part big data knowledge transaction is shown in Eq. (8).

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

Substitute $\lambda(n,T)$ in Eq. (8) by using Eq. (7); the DEP after the two-part big data knowledge transaction can be expressed as Eq. (9).

$$\xi(T)=\begin{cases} pQ\phi(1+\theta_1)^T r^T \sum_{n=1}^{L_2}(1+\omega_1\rho_1+\omega_2 q\rho_2)^n r^n \\ -MCQ\phi(1+\theta_1)^T r^T(\omega_1\beta_1+\omega_2 q\beta_2)^T \sum_{n=1}^{L_2}(1+\omega_1\rho_1+\omega_2 q\rho_2)^n \alpha^n r^n \\ +pQ\phi(1+\theta_1)^T(1+\omega_1\rho_1+\omega_2 q\rho_2)^{L_2} r^T \sum_{n=L_2+1}^{N}(1-\theta)^{n-L_2} r^n \\ -MCQ\phi(1+\theta_1)^T r^T(\omega_1\beta_1+\omega_2 q\beta_2)^T(1+\omega_1\rho_1+\omega_2 q\rho_2)^{L_2} \sum_{n=L_2+1}^{N}(1-\theta)^{n-L_2}\alpha^n r^n \qquad T\le L_1 \\ pQ\phi(1+\theta_1)^{L_1}(1-\theta)^{T-L_1} r^T \sum_{n=1}^{L_2}(1+\omega_1\rho_1+\omega_2 q\rho_2)^n r^n \\ -MCQ\phi(1+\theta_1)^{L_1}(1-\theta)^{T-L_1}\beta^T r^T \sum_{n=1}^{L_2}(1+\omega_1\rho_1+\omega_2 q\rho_2)^n \alpha^n r^n \\ +pQ\phi(1+\theta_1)^{L_1}(1-\theta)^{T-L_1}(1+\omega_1\rho_1+\omega_2 q\rho_2)^{L_2} r^T \sum_{n=L_2+1}^{N}(1-\theta)^{n-L_2} r^n \\ -MCQ\phi(1+\theta_1)^{L_1}(1-\theta)^{T-L_1} r^T(\omega_1\beta_1+\omega_2 q\beta_2)^T(1+\omega_1\rho_1+\omega_2 q\rho_2)^{L_2} \\ \quad \sum_{n=L_2+1}^{N}(1-\theta)^{n-L_2}\alpha^n r^n \qquad T>L_1 \end{cases} \tag{9}$$

3.4 Total DEP of a Big Data Knowledge Transaction in a Two-Part Tariff Pricing Scheme

In the big data environment, when a knowledge recipient firm purchases big data knowledge for new product development, its main purpose is to maximize the expected profitability of the new product. The optimal pricing scheme and transaction time of big data knowledge transactions are to find the maximum of the total DEP $\psi(T)$ of V_i for the given parameters. Therefore, the two-part tariff pricing decision model of V_i can be expressed as Eq. (10).

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

4 Simulation Experiments

4.1 Model Solution and Parameter Setting

The two-part tariff pricing model of knowledge recipient firms is a piecewise continuous differential function of knowledge transaction time. Therefore, we can find the maximum of $\psi(T)$ in a closed interval $0\le T\le N$, which is the maximum profits in the life cycle of the new product. Then, the optimal pricing schemes for the knowledge recipient firm can be investigated and the optimal time of the big data knowledge transaction can be obtained.

Because the two-part tariff pricing scheme of big data knowledge transfer is based on previous decision model of knowledge transfer, some similar parameters are set to the same values [27–30]. These parameters are as follows: The total product sales $Q=1000$; the price of per unit product $p=60$; the marginal cost at the starting point $MC=40$; the total market volume of V_i increases in the first $L_1=3$ period; the growth rate of market volume in the first $L_1=3$ period $\theta_1=3\%$; the natural attenuation rate of market volume $\theta=3\%$; the market share of V_i in the starting period $\phi=8\%$; the knowledge absorption capacity $\alpha=95\%$; the growth rate of the market share of V_i in the first $L_2=5$ periods when V_i only purchases the part of subscription knowledge $\rho_1=6\%$, the growth rate of the market share of V_i in the first $L_2=5$ periods when V_i only purchases the part of per-transaction knowledge $\rho_2=8\%$; the update rate of subscription knowledge in the starting point $\beta_1 = 88\%$; the update rate of per-transaction knowledge in the starting point $\beta_2 = 88\%$; the discount rate is 10% and $r = 1/(1 + 10\%) \approx 0.9$; the variable cost coefficient $F = 1000$.

4.2 Simulation Experiment

4.2.1 Simulation and Model Verification

In Eqs. (2), (3), and (6), the pricing scheme represents subscription pricing when $q = 0$, $k_1 > 0$, and $\omega_1 = 1$, $\omega_2 = 0$. At the same time, when $k_2 > 0$, $q = 1$, and $\omega_1 = 0$, $\omega_2 = 1$, it means a firm has purchased all the license rights of the per-transaction knowledge in the pay-per-use pricing scheme, and the pricing scheme of the per-transaction can also be considered as the subscription pricing. In the decision model of knowledge transfer, the fixed cost is a constant, which can be regarded as a firm purchases a type of knowledge by adopting a subscription pricing scheme. Then, let $k_1 = 300$, $q = 0$ and $\omega_1 = 1$, $\omega_2 = 0$, which means that the firm V_i only purchases one type of big data knowledge from a big data knowledge provider with a subscript fee $k_1 = 300$. The experimental results in Fig. 2 are the same as those of the decision model of knowledge transfer in the research of Wu et al. [26] when the subscription fee is the same as the fixed cost of knowledge transfer [8].

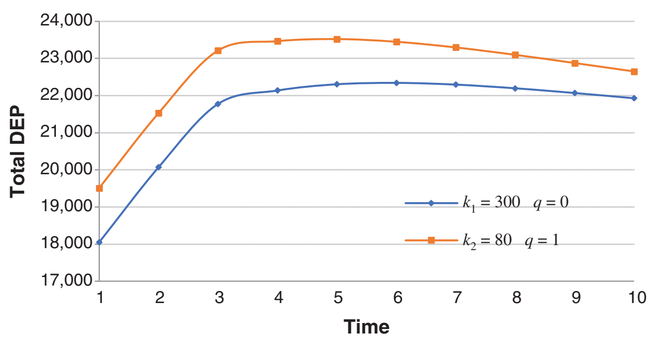

Figure 2: Changes of total DEP with subscription pricing scheme

Let $k_1 = 0$, $k_2 = 80$, $q = 1$, and $\omega_1 = 0$, $\omega_2 = 1$, which means that the firm V_i purchases all the license rights of the per-transaction knowledge. In this situation, there is no common knowledge of platform transferring and V_i doesn't need to pay the registration fee. The pricing scheme of the per-transaction knowledge can also be considered subscription pricing. Again, the experimental results in Fig. 2 are the same as those of the decision model of knowledge transfer in the research of Wu et al. [26] where the price cap of the per-transaction knowledge is the same as the fixed cost of knowledge transfer [8]. Thus, our model is valid.

4.2.2 Simulation Results of Two-Part Pricing Scheme with ω_1,ω_2

In this model, k_1 is the subscription fee, k_2 is the price cap of per-transaction knowledge, and sometimes the big data knowledge providers do not charge the subscription. We believe that the subscription fee is less than the price cap of per-transaction knowledge. Then, let $k_1 = 80$ and $k_2 = 300$. Suppose the usage ratio of per-transaction knowledge is $q = 0.6$, which means that V_i purchases 60% of the total per-transaction knowledge when it adopts the pay-per-use pricing scheme in per-transaction. If we change the weights of subscription knowledge and per-transaction knowledge to the total update rate of outside knowledge from $\omega_1 = 0.1$, $\omega_2 = 0.9$ to $\omega_1 = 0.9$, $\omega_2 = 0.1$, it can be seen from the simulation results in Fig. 3 that the total DEP decreases with the increase in the contribution of subscription knowledge weight.

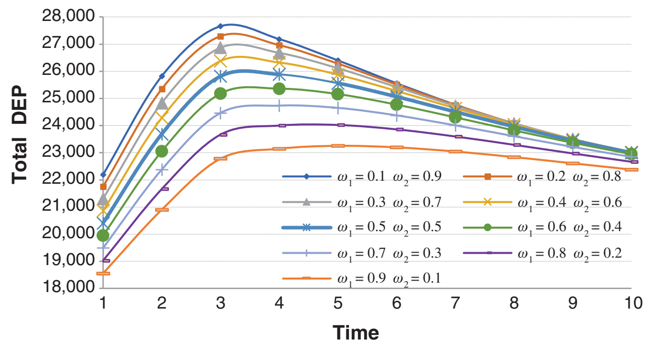

Figure 3: Changes of total DEP with weight of each part of knowledge

This result could be attributed to the composition of big data knowledge. Subscription knowledge is the common big data knowledge of platform transferring with the payment of a subscription fee, and per-transaction knowledge is the knowledge transferring with each transaction. Sometimes big data knowledge providers do not charge a subscription fee for the common knowledge on the platform. Therefore, the biggest difference of purchased knowledge between two firms comes from per-transaction knowledge. Thus, the greater the proportion of per-transaction knowledge in the new product, the higher the profitability.

In addition, it can be seen from the experimental results in Fig. 3 that the optimal time of big data knowledge transaction changes from $T = 3$ to $T = 5$. It reveals that as the proportion of per-transaction knowledge decreases, the optimal time of big data knowledge transaction is delayed. The reason is that the common knowledge on the platform is less attractive to a firm when it is developing new products.

4.2.3 Comparison of the Results between Two-Part Tariff Pricing and Subscription Pricing

We believe that the common big data knowledge acquired by paying a subscription fee has less contribution to the new product development, and the firm needs to purchase other big data knowledge separately in the two-part tariff pricing scheme. Then, let $\omega_1 = 0.2$ and $\omega_2 = 0.8$. In addition, according to Eq. (2), when $k_2 > 0$ and $q = 1$, the pricing scheme equals the subscription pricing. When $k_1 > 0$, $k_2 > 0$, and $0 < q < 1$, the pricing scheme is two-part tariff pricing. Let $k_1 = 80$ and $k_2 = 300$ as shown in Fig. 3, change the usage ratio of per-transaction knowledge q varies from 0.2 to 1. The results of q ranging from 0.2 to 0.8 in Fig. 4 are the total DEPs in the two-part tariff pricing scheme, and the results of $q = 1$ are the total DEPs in the subscription pricing scheme. As shown in Fig. 4, the total DEPs in a two-part tariff pricing scheme are much higher than those in a subscription pricing scheme.

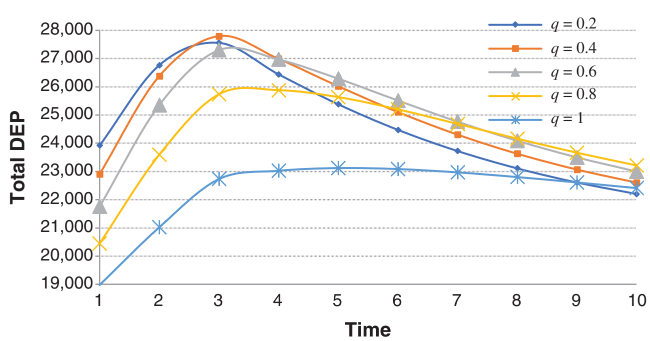

Figure 4: Comparison of two-part tariff pricing and subscription pricing

Meanwhile, the optimal time of big data knowledge transaction in a subscription pricing scheme is $T = 5$, and the optimal time of big data knowledge transaction in a two-part tariff pricing scheme changes between $T = 3$ and $T = 4$. It means that firms prefer taking big data transaction earlier in a two-part tariff pricing scheme than in the subscription pricing scheme. The subscription pricing fixes the cost of big data knowledge and the cost of knowledge is the price cap of knowledge regardless of the actual amount of knowledge consumption. However, those firms prefer a two-part tariff pricing scheme, and their knowledge consumption is intermediate. In this case, the cost of knowledge is relatively high, and firms need to make decisions of knowledge transaction carefully.

4.2.4 Comparison of Results between Two-Part Tariff Pricing and Pay-Per-Use Pricing

From Eq. (2), the pricing scheme is pay-per-use pricing when $k_1 = 0$, $k_2 > 0$, and $0 < q < 1$, and two-part tariff pricing when $k_1 > 0$, $k_2 > 0$ and $0 < q < 1$. When $k_1 = 0$, it means that the big data knowledge providers waive the subscription fee in our two-part tariff pricing model, but there is free common knowledge on platform transferring with the knowledge transaction. Let $\omega_1 = 0.2$ and $\omega_2 = 0.8$, which means the contribution of free knowledge or subscription knowledge to new product development of V_i is 20%. If we change the subscription fee k_1 from 0 to 80, the results when $k_1 = 0$ in Fig. 4 are the total DEPs in the pay-per-use pricing scheme, and the experimental results when $k_1 = 80$ are the total DEPs in the two-part tariff pricing scheme. As shown in Fig. 5, the total DEPs in a pay-per-use pricing scheme are higher than those in the two-part tariff pricing scheme. Meanwhile, the optimal time of big data knowledge transaction remains unchanged in different pricing schemes. It shows that the free knowledge affects the new product development performance of knowledge recipient firms, and the pay-per-use pricing scheme is more profitable for knowledge recipient firms than a two-part tariff pricing scheme. That is why many big data knowledge providers usually waive the subscription fee when they take the two-part tariff pricing scheme, or provide some free knowledge when they take the pay-per-use pricing scheme by relying on advertising revenues [20].

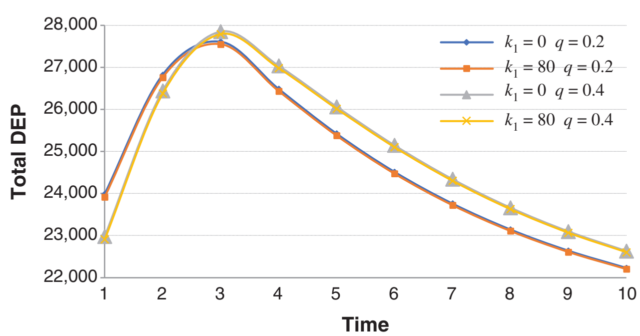

Figure 5: Comparison of two-part tariff pricing and pay-per-use pricing

At the same time, the results in Fig. 5 show that the optimal time of big data knowledge transactions changes with the usage ratio of the big data knowledge in the pay-per-use pricing scheme. The optimal time of big data knowledge transaction will be earlier when the big data knowledge usage ratio is low. In a pay-per-use pricing scheme, knowledge recipient firms only have to pay for the amount of knowledge they need. When the usage ratio of big data knowledge is low, the cost that a firm spends on purchasing big data knowledge is also low. In a pay-per-use pricing scheme, firms can acquire new knowledge for new product development at a lower cost when the usage ratio is low. Hence firms will conduct knowledge transactions and new product development earlier.

5 Conclusions

This paper constructs a two-part tariff pricing decision model for big data knowledge transactions from the perspective of knowledge recipient firms. The model is a more generalized pricing scheme decision model and can be used to compare the profitability of three pricing schemes, i.e., subscription pricing, pay-per-use pricing, and two-part tariff pricing. It shows that the influence of the free knowledge or subscription knowledge on new product development performance of knowledge recipient firms should not be ignored, and the pay-per-use pricing scheme is the best solution for knowledge recipient firms. This model can help knowledge recipients predict their profitability, choose the suitable pricing schemes, and seize the optimal timing of knowledge transaction in the two-part pricing scheme.

However, this paper has several limitations. First, we assume that the subscription knowledge and the per-transaction knowledge are transferred simultaneously, and we did not consider the time difference between them. In reality, big data knowledge providers usually provide some free knowledge or common knowledge on their platforms first, and then knowledge recipient firms decide to conduct other knowledge transactions. Future research should consider big data knowledge transactions at different time points. Second, new product development usually requires not only big data knowledge, but also private knowledge in the big data environment. In future work, the pricing schemes of multiple knowledge transactions need to be analyzed. In addition, since different knowledge providers may choose different pricing schemes, the choice of knowledge transaction contract by knowledge providers and differences among the pricing schemes should be considered in future work.

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