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Risk Control for Knowledge Transfer in the Big Data Environment

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ABSTRACT Firms need to continuously carry out product innovation to survive in dynamic market. In the big data environment, most firms, especially internet firms, realize new product innovation by taking imitation innovation as a stepping stone leading to independent innovation. Knowledge transfer, one of the main methods that firms acquire knowledge from external environment for imitation innovation, is a complex process of multiple knowledge transfer among different organizations and subject to various risks. Thus, it is necessary to understand knowledge transfer risks in the big data environment and help firms to carry out effective knowledge transfer in the process of new product innovation. Based on the influence factors of knowledge transfer risks and development process of innovation, a theoretical framework for risk control of knowledge transfer in the big data environment is proposed and a risk control model of knowledge transfer is presented. The model can be used to determine the maximum profit of a new product, the optimal time of knowledge transfer, and the update time of independent innovation knowledge in the big data environment. The results of simulation experiments are in line with the actual economic situation, and the model is valid.

INDEX TERMS Big data, knowledge transfer, risk control, independent innovation, imitation innovation

I. INTRODUCTION

A. BACKGROUND

TODAY'S business environment is characterized by a large amount of data whose size is growing with an exponential speed. In such a big data environment, firms need to continuously carry out product innovation to survive [1]. According to the source of innovation knowledge, there are two types of product innovation: independent innovation and imitation innovation [2]. Independent innovation is to complete the whole process of innovation with the knowledge deriving from the firms' internal independent research and development (R&D) activities, emphasize on its own technical breakthrough [2]. Imitation innovation refers to the innovation developed by introducing external predecessors' core knowledge or technical secret and combining with its own actual situation and needs [2]-[3]. Among all the different ways of knowledge acquisition in imitation innovation, knowledge transfer is the main method firms adopt to acquire knowledge from external environment [4]-[5].

Independent innovation can help firms get incremental profit from product market and grasp the initiative and ownership of new knowledge [2], but it also faces the risks of excessive investment and long development cycle in R&D and uncertainty of success. In the big data environment, the product life cycle becomes shorter and the pace of product renewal accelerates. Most firms, especially internet firms, realize product innovation via imitation innovation [6]. Imitative innovation can help firms generate profit in the short term by getting new knowledge for product innovation quickly, saving R&D investment in the early stage, summarizing and absorbing the experience and lessons of the first innovators, and avoiding the huge amount of uncertainty risks of new products in the market [2],[7]-[8]. However, knowledge transfer in imitation innovation will make the R&D department of a firm rely too much on external knowledge providers [9]-[10]. If the external knowledge providers terminate the intellectual property license of a new product, the economic loss of the recipient firm could be enormous [11]. Thus,

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how to control such kind of knowledge transfer risk becomes one of the main tasks of product innovation in the big data environment.

B. MOTIVATION

Knowledge transfer in the big data environment is different from conventional knowledge transfer. In the big data environment, the new knowledge that firms need to transfer from the external environment for product innovation mainly includes the big data knowledge and the private knowledge [12]. Big data knowledge, such as customers' demand and the users' preferences, is formed of different types of knowledge from various subjects, while private knowledge is usually the patent knowledge from other firms [13]. The transfer process of big data knowledge is also different from that of private knowledge in that big data knowledge transfer is the process that knowledge received from many subjects transfer to various subjects, while private knowledge transfer is the process that knowledge transfers from one subject to another. Thus, the big data knowledge and the private knowledge should be seen as two different types of knowledge when firms transfer knowledge for product innovation. The change of knowledge type brings about the change in knowledge structure and subjects of knowledge transfer. Knowledge transfer in the big data environment is a complex process of multiple knowledge transfer among different organizations [14]. This process involves numerous factors and subject to various risks. In this research, we define knowledge transfer risk as the likelihood of loss and serious consequences resulting from the activity of knowledge transfer [15]-[16].

Extensive research on risks of conventional knowledge transfer has been undertaken [17]-[21]. While some scholars have noticed the new characteristic of knowledge transfer in the big data environment [12],[14],[22], few of them have studied the problem of knowledge transfer risks in such environment. As a matter of fact, there are many problems need to be addressed in the big data environment. What kinds of risks will knowledge transfer bring? How do these risks affect product innovation? What measures should be taken to avoid the risks of knowledge transfer? These are all important questions that firms must consider when transferring knowledge. Therefore, it is necessary to understand knowledge transfer risks in the big data environment and help firms to carry out effective knowledge transfer. This paper will discuss the risk control method for knowledge transfer in the big data environment from the perspective of knowledge recipients.

C. CONTRIBUTION OF THE STUDY

In this study, we aim to identify the influential factors of knowledge transfer risks in the big data environment and find methods to control the knowledge transfer risks and to enhance the performance of new product innovation. The main contributions of this study are listed as follows.

First, we proposed a theoretical framework for risk control of knowledge transfer in the big data environment. We divide knowledge transfer risks in the big data environment into the big data knowledge transfer risk and the private knowledge transfer risk. To cope with the big data knowledge transfer risk, we suggest that firms should transfer big data knowledge from a big data knowledge provider to avoid infringement of privacy and intellectual property rights. As for the private knowledge transfer risk, we suggest that firms should take independent innovation while transferring knowledge within a certain period to avoid the risk of the termination of licensing agreement and the decrease of independent innovation ability.

Second, from the perspective of product innovation, we present a risk control model of knowledge transfer that can be used to determine the maximum profit of a new product, the optimal time of knowledge transfer, and the update time of independent innovation knowledge in the big data environment. This model has not only considered the new risks brought by the changes in the knowledge types, knowledge structure, and subjects of knowledge transfer in the big data environment, but also considered the process from imitative innovation to independent innovation.

Third, we conduct some simulation experiments in line with the real economic situation to simulate and validate the effectiveness of the risk control model. Some conclusions with practical application value are drawn, which can help firms to control knowledge transfer risks in the big data environment and enhance the innovation performance after knowledge transfer.

The rest of the paper proceeds as follows. In the second section, we review related studies. In the third section, theoretical framework and conceptual model for risk control of knowledge transfer in the big data environment are introduced, and some model hypotheses are given. In the fourth section, a risk control model of knowledge transfer is presented. The simulation experiments and the results of analysis of the model are described in section five. Conclusions are drawn in section six.

II. RELATED WORK

Knowledge transfer was first proposed by Teece [23]. Literature on inter-organizations knowledge transfer risk mainly focus on the following two aspects: influential factors of knowledge transfer risk and the approaches of risk control.

A. INFLUENTIAL FACTORS OF KNOWLEDGE TRANSFER RISKS

Many researchers have carried out studies on the influential factors of knowledge transfer risk across organizational boundaries. The results have revealed that the knowledge itself, subjects of knowledge transfer, and the context of knowledge transfer are the main factors causing knowledge transfer risk [20].

Knowledge itself could affect knowledge transfer because of its tacitness, ambiguity, uncertainty of intellectual input and output, the imperfection of knowledge contract, and the potential value of knowledge [17],[24]. Extensive research on risks of tacit knowledge transfer has been undertaken in the literature on private knowledge transfer [25]-[28]. In the big data environment, big data knowledge, which is characterized by open source, variety, dynamic, volume, and multi-source heterogeneity, is quite different from the private knowledge [22]. Thus, the selections of knowledge types and knowledge structure have become the important influential factors of knowledge transfer risks in the big data environment [12].

The disseminative ability and willingness and excessive or weak awareness of knowledge protection of knowledge source [29]-[30], absorptive ability and knowledge base of the recipient [31]-[34], incredibility between organizations, opportunism, weak environmental awareness are all the influential factors of knowledge transfer subjects [20]. In the big data environment, the big data knowledge providers, such as cloud computing companies, consulting companies or consultants, have become new knowledge transfer subjects [12]. The variety and multi-source heterogeneity of the big data knowledge make knowledge transfer subject in the big data environment show the intersection and complexity. The diversification of knowledge transfer subjects and the complexity of knowledge transfer process bring more knowledge transfer risks.

The context of knowledge transfer is another important factor that influence the activities of knowledge transfer [24]. Innovation network is the main context that inter-organizational knowledge transfer takes place [4]. Network structure, network position, and network characteristics have a significant effect on inter-organizational knowledge transfer [35]-[39]. In the big data environments, knowledge is linked by network, in which firms are embedded, and knowledge network has dual embeddedness [40]. In such a new context, the scale of innovation network becomes larger, the knowledge nodes are more complex, and innovation network shows the characteristics of complex dynamic knowledge network [12].

Although the existing research has revealed the factors of knowledge transfer risks, it has not examined the formation mechanism of the new risks brought by the changes of influential factors, nor put forward the corresponding risk control methods.

B. CONTROL METHODS OF KNOWLEDGE TRANSFER RISKS

According to the definition of knowledge transfer risk, risk control of inter-organizational knowledge transfer is to maximize the cooperative innovation performance based on the analysis of the influential factors of knowledge transfer risk [19]-[20],[41]. Decision tree is used to make risky decisions because risk control has been grounded in classical decision theory [42]. However, some researchers think that the approach of decision trees is ineffective due to environmental complexity and individuals' cognitive constraints [17]. Analytic hierarchy process (AHP) is usually applied to determine the weight of the risk indicators and the method of fussy comprehensive assessment is used to evaluate knowledge transfer risks [20],[18]. Risk matrix is established to define the influence level of knowledge transfer risks and occurrence probability [26]. Missing response-time constraint (i.e., real-time constraint, timing requirement, and deadline) is considered a typical systematic failure of risk control [43]-[44]. Szulanski et al. demonstrate that the choice of wise opportunity can reduce knowledge transfer risk by using empirical methods [45]. Wu et al. build a time optimization model of knowledge transfer to improve the innovation performance after knowledge transfer [14], [46]. In the big data environment, some scholars think that knowledge transfer in IT outsourcing is much important. For example, Lu et al. use the method of rough set (RS) to evaluate risk factors of IT outsourcing and support vector machines (SVM) in the decision-making data classification [47]. This method also presents the concept of finding out the influential factors of risk and improving the performance of IT outsourcing and knowledge transfer.

In summary, current research mainly focuses on the conventional knowledge transfer risks, lacking the comprehensive consideration of the risks of big data knowledge transfer and the risks of conventional private knowledge transfer. Meanwhile, the conventional risk control methods are not suitable for risk control of knowledge transfer in the big data environment. In addition, although the conventional risk control methods of knowledge transfer have considered the innovation performance after knowledge transfer, there is no relationship analysis between knowledge transfer and innovation mode of firms.

III. KNOWLEDGE TRANSFER RISKS AND CONTROL METHOD IN THE BIG DATA ENVIRONMENT

A. THEORETICAL FRAMEWORK FOR RISK CONTROL OF KNOWLEDGE TRANSFER IN THE BIG DATA ENVIRONMENT

In the big data environment, the new knowledge that firms need to transfer from the external environment for product innovation mainly includes big data knowledge and private knowledge. Thus, knowledge transfer risk in the big data environment can be divided into the big data knowledge transfer risk and the private knowledge transfer risk.

Big data knowledge contains a wide range of content, from individual privacy data to public data, from daily business activities data to government operational data [48]. Some of them are related to intellectual property rights, such as the documents submitted by firms to apply for new intellectual property rights, patents reported by the government, and so on [49]. Some of them are related to privacy right, such as customers' demand and the users' preferences. The risk of big data knowledge transfer is mainly caused by the infringement of privacy and intellectual property rights [50]-[51]. To cope with this type of risk, firms can transfer knowledge from big data knowledge providers via service outsourcing [52]-[53]. This method not only can help firm to avoid intellectual property disputes, but also can reduce the cost of big data knowledge.

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The risk of private knowledge transfer is related to measures impeding private knowledge transfer, such as the distortion and noise of knowledge and the disruption of intellectual property license by the knowledge source. Moreover, the innovation by transferring private knowledge from external environment is similar to imitation innovation. Therefore, the transfer of private knowledge will cause the risk of decrease in firms' independent innovation capabilities [9]-[10]. To reduce the risk of private knowledge transfer, firms can take imitation innovation first by private knowledge transfer within a certain period of time and develop independent innovation knowledge by digesting and absorbing the knowledge transferred [54]-[55]. The reason is that technological laggards must first catch up with the leading-edge technology before battling for technological leadership in the future [56]. For example, Tencent, the largest gaming and social media company in China as well as the world, developed its first messenger product OICQ by imitating the counterpart of ICQ developed by an Israeli company [2].

In addition, the purpose of risk control for knowledge transfer is to promote knowledge transfer and enhance the innovation performance [41]. Thus, to control the big data knowledge transfer risk and private knowledge transfer risk, firms must consider the product innovation performance of both imitation innovation and independent innovation. From the perspective of innovation development process, imitation innovation is taken as the start of independent innovation in the big data environment, and independent innovation, in turn, promotes a new round of imitation [57]. It is in a spiral development process of imitation innovation and independent innovation [6]. This paper only considers an evolutionary cycle from imitative innovation to independent innovation. Therefore, we proposed a risk control model for knowledge transfer in the big data environment based on the research idea of continuous knowledge transfer and diffusion of successive generations of new products in the market [58]-[60]. This model can help firms to achieve maximum total product innovation performance of imitation innovation and independent innovation by controlling the influential factors of knowledge transfer in the big data environment. The theoretical framework for risk control of knowledge transfer in the big data environment is shown in Fig.1.

B. MODEL HYPOTHESES

Table 1 lists notations and their definitions that are used in the study.

Hypothesis 1. V_i transfers one type of big data knowledge (the customer preference and user experience) from BD_k and one type of private knowledge (patents or components) from V_j at time period T_1. V_i also invests R at time period T_2 for independent R&D. After time period T_2 , V_i will update its product with independent innovation knowledge $(0 < T_1, T_2 < N)$.

Hypothesis 2. The weight of big data knowledge ω_1 and the weight of private knowledge ω_2 have the quantitative relationship of $\omega_1 + \omega_2 = 1$ $(0 \leq \omega_1, \omega_2 \leq 1)$.

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 only transfers the 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_2 periods immediately after V_i only transfers the private knowledge at the time period T_1 . $\rho_3(0 < \theta_1 < \rho_3 < 1)$ is the growth rate of the market share of V_i in the first L_3 periods immediately after independent knowledge update at time period T_2 .

Hypothesis 5. The total knowledge transfer cost $K_1(T)$ includes the fixed cost and variable cost. The fixed cost of $K_1(T)$ includes the fixed data processing fee of the big data knowledge k_1 and the fixed transfer cost of private knowledge k_2. The total independent innovation knowledge update cost $K_2(T_2)$ consists of the fixed R&D investment and variable learning cost. k_{Rf} is the fixed R&D investment of V_i at time period T_1. k_{lv} is the variable learning cost of independent innovation knowledge update at time period T_2. k_1, k_2 and k_{Rf} are constants.

Hypothesis 6. The life cycle of product N is renumbered after knowledge transfer or update.

C. CONCEPTUAL MODEL OF KNOWLEDGE TRANSFER RISKS CONTROL IN THE BIG DATA ENVIRONMENT

Based on Hypotheses 1 and Table 1, V_i tries to transfer one type of big data knowledge and one type of private knowledge at time period T_1, and update a product with independent innovation at time period T_2. $\zeta_1(T_1)$ is the discount expectation of profits (DEP) of V_i received before knowledge transfer,$\xi_1(T_1)$ is the DEP of V_i received after knowledge transfer, and $\xi_2(T_2)$ is the DEP of V_i received after independent innovation knowledge update. $K_1(T)$ is the knowledge transfer cost of the big data knowledge and private knowledge, and $K_2(T_2)$ is the R&D investment and learning cost of independent innovation knowledge. The total DEP of V_i can be denoted as $\Psi(T_1, T_2)$. Therefore, $\Psi(T_1, T_2)$=$\zeta_1(T_1)$+$\xi_1(T_1)$-$K_1(T_1)$+$\xi_2(T_2)$-$K_2(T_2)$. The conceptual model is shown in Figure 2.

IV. RISK CONTROL METHOD OF KNOWLEDGE TRANSFER

A. EXPECTED PROFIT BEFORE KNOWLEDGE TRANSFER AT T_1

Because there is no knowledge transfer and V_i has not updated its product with independent innovation knowledge during this period, the firm produces new products using prior knowledge. The DEP before two types of knowledge transfer is shown as (1). The detailed calculation is introduced in Ref.[5].

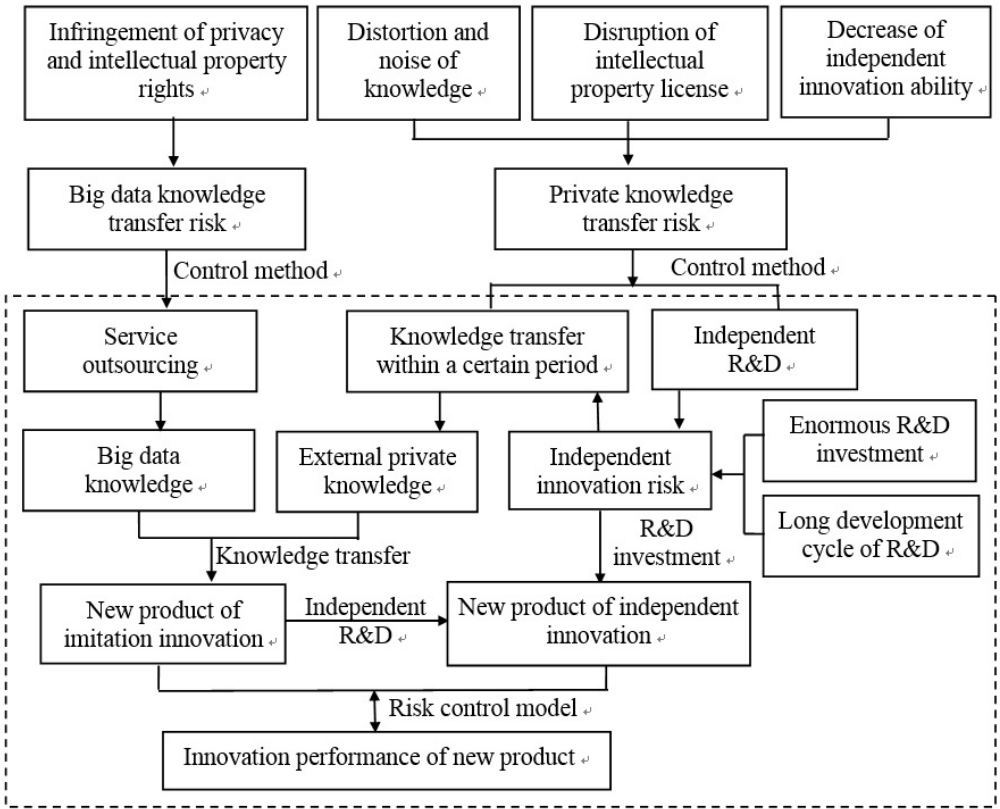

FIGURE 1. Theoretical framework of risk control for knowledge transfer in the big data environment.

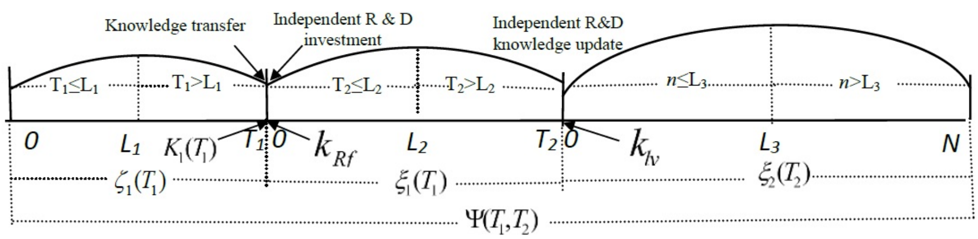

FIGURE 2. Conceptual Model for knowledge transfer risk control in the big data environment.

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

B. TRANSFER COST OF BIG DATA KNOWLEDGE AND PRIVATE KNOWLEDGE

According to Hypotheses 1, 2, 5 and Table 1, the knowledge transfer cost consists of the cost of big data knowledge and the cost of private knowledge, that include the fixed cost and variable cost respectively. ω_1 and ω_2 are the weights of big data knowledge and private knowledge respectively, so the fixed cost of big data knowledge and private knowledge can be computed by $\omega_1 k_1+\omega_2 k_2$. The variable cost is related to the potential difference between the update rate of knowledge transferred and the internal knowledge of V_i. Suppose F_1 is the variable cost coefficient, and F_1 is a constant. The variable costs of big data knowledge and private knowledge can be computed by $F_1(\alpha^{T_1}-(\omega_1{\beta_1}^{T_1}+\omega_2{\beta_2}^{T_1}))$. By discounting the total transfer cost to the starting point, the present value of the total transfer cost at time period T_1 can be expressed as (2).

TABLE 1. NOTATIONS IN THIS STUDY

Symbol	Definition
G	The expression of an innovation network in the big data environment
V_i	A firm in an innovation network G
V_j	A Private knowledge provider in innovation network G
BD_k	Big data knowledge provider in innovation network G
Q	Total market volume of a product
p	the price of the only one product of V_i
r	Discount rate
MC	Marginal cost in the starting period
α	Knowledge absorption capacity of V_i
ϕ	Market share of V_i in the starting period
N	the life cycle of the product of V_i
R	Independent R&D investment
ω_1	Weight of big data knowledge
ω_2	Weight of private knowledge
θ_1	Market growth rate in the first L_1 periods
θ	Market attenuation rate
ρ_1	Growth rate of the market share of V_i after V_i only transfers the big data knowledge
ρ_2	Growth rate of the market share of V_i after V_i only transfers the private knowledge
ρ_3	Growth rate of the market share of V_i after independent knowledge update
β_1	Update rate of big data knowledge in the starting period
β_2	Update rate of private knowledge in the starting period
β_3	Update rate of independent innovation knowledge in the starting period
k_1	Fixed cost of big data knowledge
k_2	Fixed transfer cost of private knowledge
k_{Rf}	Fixed R&D investment
k_{lv}	Learning cost of independent innovation knowledge update
$\zeta_1(T_1)$	Discount expectation of profits (DEP) of V_i received before knowledge transfer
$\xi_1(T_1)$	DEP of V_i received after knowledge transfer
$\xi_2(T_2)$	DEP of V_i received after independent innovation knowledge update
$K_1(T)$	Total Knowledge transfer cost of big data knowledge and private knowledge
$K_2(T_2)$	Total cost of independent innovation knowledge update
$\Psi(T_1, T_2)$	Total DEP of V_i

$$K_1(T_1) = \left[\omega_1 k_1 + \omega_2 k_2 + F_1(\alpha^{T_1} - (\omega_1 {\beta_1}^{T_1} + \omega_2 {\beta_2}^{T_1}))\right] r^{T_1} \quad (0 \le \omega_1, \omega_2 \le 1; \omega_1 + \omega_2 = 1) \tag{2}$$

C. EXPECTED PROFITS AFTER THE TRANSFER OF TWO TYPES OF KNOWLEDGE

From Hypotheses 4, 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 big data knowledge at time period T_1. 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 private knowledge at time period T_1. After the knowledge transfer, the market share of V_i decays at a rate of θ. Therefore, the market share of V_i in period n after the transfer of big data knowledge and private knowledge can be denoted as in (3).

The two new types of knowledge adopted by V_i in time period T_1 has been updated by $(\omega_1\beta_1 + \omega_2\beta_2)^{T_1}$, which causes the marginal cost in time period T_1 to decrease to $MC(\omega_1\beta_1 + \omega_2\beta_2)^{T_1}$. According to Hypothesis 6, the periods n after knowledge transfer are renumbered from 1 to T_2, the marginal cost in period n becomes $MC(\omega_1\beta_1 + \omega_2\beta_2)^{T_1}\alpha^n$. Therefore, the total production cost in period n after knowledge transfer is $Q\lambda(n, T_1)MC(\omega_1\beta_1 + \omega_2\beta_2)^{T_1}\alpha^n$. By subtracting the total production cost from the sales revenue $pQ\lambda(n, T_1)$, the profit in period n after knowledge transfer is as in (4).

$$\Pi^* = pQ\lambda(n, T_1) - Q\lambda(n, T_1)MC(\omega_1\beta_1 + \omega_2\beta_2)^{T_1}\alpha^n \tag{4}$$

Discount the profits in period n to the starting point by multiplying (4) by $r^{T_1}r^n$ and sum up all the discount profits in period T_1, the DEP after the two types of knowledge transfer and before independent knowledge update is as in (5).

$$\xi_1(T_1) = r^n r^{T_1} \sum_{n=1}^{N} (pQ\lambda(n, T_1) - Q\lambda(n, T_1)MC(\omega_1\beta_1 + \omega_2\beta_2)^{T_1}\alpha^n) \tag{5}$$

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$$\lambda(n,T)=\begin{cases}\phi(1+\theta_1)^{T_1}(1+\omega_1\rho_1+\omega_2\rho_2)^n & n\le L_2, T\le L_1\\ \phi(1+\theta_1)^{L_1}(1-\theta)^{T_1-L_1}(1+\omega_1\rho_1+\omega_2\rho_2)^n & n\le L_2, T> L_1\\ \phi(1+\theta_1)^{T_1}(1+\omega_1\rho_1+\omega_2\rho_2)^{L_2}(1-\theta)^{n-L_2} & n> L_2, T\le L_1\\ \phi(1+\theta_1)^{L_1}(1-\theta)^{T_1-L_1}(1+\omega_1\rho_1+\omega_2\rho_2)^{L_2}(1-\theta)^{n-L_2} & n> L_2, T> L_1\end{cases} \quad (3)$$

Firms usually carry out R&D investment to achieve independent innovation while assimilating external knowledge. Assume that the independent innovation knowledge update occurs during the growth stage of the market share after knowledge transfer, that is $T_2 \le L_2$. Therefore, the efficiency of new knowledge transferred is up to T_2, not L_2. Based on (3) and (5), the expected profits after knowledge transfer and before independent knowledge update can be expressed as (6).

When $T_2 > L_2$, it means that the independent innovation knowledge update occurs in the decline stage of the market share after knowledge transfer. The market share will increase in time period L_2 and then decay in time period $(T_2 - L_2)$. Based on (3) and (5), the expected profits after knowledge transfer and before the independent innovation knowledge update can be expressed as (7).

D. TOTAL COST OF INDEPENDENT INNOVATION KNOWLEDGE UPDATE

While transferring knowledge from outside, V_i also carries out R&D investment. After knowledge transfer at time period T_1, V_i accumulates knowledge stock based on the efficiency of knowledge transferred. The knowledge absorption capacity is α, and the internal knowledge update rate after knowledge transfer in time period T_2 is $(\omega_1\beta_1+\omega_2\beta_2)^{T_1}\alpha^{T_2}$. The update rate of independent innovation knowledge in time period T_2 is ${\beta_3}^{(T_1+T_2)}$. Therefore, the knowledge potential difference can be expressed as $(\omega_1\beta_1+\omega_2\beta_2)^{T_1}\alpha^{T_2} - {\beta_3}^{(T_1+T_2)}$. Suppose F_2 is the coefficient of learning effect, and F_2 is a constant. The learning cost k_{lv} can be computed by $F_2[(\omega_1\beta_1+\omega_2\beta_2)^{T_1}\alpha^{T_2}-{\beta_3}^{(T_1+T_2)}]$. By discounting the learning cost and the R&D investment to the starting point, the present value of the total cost of independent innovation can be expressed as (8).

$$K_2(T_2) = k_{Rf}r^{T_1} + F_2[(\omega_1\beta_1+\omega_2\beta_2)^{T_1}\alpha^{T_2} - {\beta_3}^{(T_1+T_2)}]r^{(T_1+T_2)} \quad (0 < T_2 \le N) \quad (8)$$

E. EXPECTED PROFITS AFTER INDEPENDENT INNOVATION

From Hypotheses 4, the market share of V_i increases at the rate of ρ_3 in the first L_3 periods immediately after V_i updates the new product by using independent innovation knowledge at time period T_2. Then, it decays at a rate of θ. Therefore, the market share of V_i in period n after the transfer of private knowledge at the time period T_2 can be denoted as in (9).

New knowledge of R&D adopted by V_i at time period T_2 is ${\beta_3}^{(T_1+T_2)}$. The new knowledge can cause the marginal cost of the product in time period T_2 to decrease to $MC{\beta_3}^{(T_1+T_2)}$. From Hypotheses 6, the time periods n after independent innovation knowledge update should be renumbered from 1 to N, and the marginal cost in time period n becomes $MC{\beta_3}^{(T_1+T_2)}\alpha^n$. Therefore, the total production cost in period $n$after independent innovation knowledge update is $Q\lambda(n,T_2)MC{\beta_3}^{(T_1+T_2)}\alpha^n$. By subtracting the total production cost from the sales revenue $pQ\lambda(n,T_2)$, the profit in time period n after independent innovation knowledge update is as shown in (10).

$$\Pi^* = pQ\lambda(n,T_2) - Q\lambda(n,T_2)MC{\beta_3}^{(T_1+T_2)}\alpha^n \quad (10)$$

Discount the profits in time period n after independent innovation knowledge update to the starting point by multiplying with $r^{(T_1+T_2)}r^n$ and sum all the discount profits in the life cycle of product N. The DEP after independent innovation knowledge update is defined as (11).

$$\xi_2(T_2) = \sum_{n=1}^{N}[pQ\lambda(n,T_2) - Q\lambda(n,T_2)MC{\beta_3}^{(T_1+T_2)}\alpha^n]r^n r^{(T_1+T_2)} \quad (11)$$

When $T_2 \le L_2$, it means that the independent innovation knowledge update occurs during the growth stage of the market share after absorbing new knowledge of R&D. Based on (9) and (11), the expected profits after independent innovation knowledge update can be expressed as (12).

When $T_2 > L_2$, it means that independent innovation knowledge update occurs in the decline stage of the market share after absorbing new knowledge of R&D. Based on (9) and (11), the expected profits after independent innovation knowledge update can be expressed as (13).

F. TOTAL DEP MODEL OF KNOWLEDGE TRANSFER RISKS CONTROL

The optimization problem of knowledge transfer risks control is to find the maximum of $\Psi(T_1, T_2)$ for the given parameters. Therefore, the optimization model of knowledge transfer risks control can be expressed as (14). Equation (14) is a piecewise continuous differential function . The maximum profit of the new product can be found. The optimal time of a firm adopting its own intellectual property rights after knowledge transfer can be calculated.

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

V. SIMULATION AND RESULTS

A. PARAMETER SETTING AND SIMULATION RESULTS WHEN $\omega_1 = 1, \omega_2 = 0$

When $\omega_1 = 1, \omega_2 = 0$, it means that firm V_i only transfer big data knowledge at the first stage, the independent innovation

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$$\xi_1(T_1)=\begin{cases} pQ\phi(1+\theta_1)^{T_1}r^{T_1}\sum\limits_{n=1}^{T_2}(1+\omega_1\rho_1+\omega_2\rho_2)^n r^n & \\ -MCQ\phi(1+\theta_1)^{T_1}r^{T_1}(\omega_1\beta_1+\omega_2\beta_2)^{T_1}\sum\limits_{n=1}^{T_2}(1+\omega_1\rho_1+\omega_2\rho_2)^n\alpha^n r^n & T_1\le L_1, T_2\le L_2 \\ pQ\phi(1+\theta_1)^{L_1}(1-\theta)^{T_1-L_1}r^{T_1}\sum\limits_{n=1}^{T_2}(1+\omega_1\rho_1+\omega_2\rho_2)^n r^n & \\ -MCQ\phi(1+\theta_1)^{L_1}(1-\theta)^{T_1-L_1}(\omega_1\beta_1+\omega_2\beta_2)^{T_1}r^{T_1}\sum\limits_{n=1}^{T_2}(1+\omega_1\rho_1+\omega_2\rho_2)^n\alpha^n r^n & L_1<T_1, T_2\le L_2 \end{cases} \tag{6}$$

$$\xi_1(T_1)=\begin{cases} pQ\phi(1+\theta_1)^{T_1}r^{T_1}\sum\limits_{n=1}^{L_2}(1+\rho_1)^n r^n & \\ -MCQ\phi(1+\theta_1)^{T_1}r^{T_1}(\omega_1\beta_1+\omega_2\beta_2)^{T_1}\sum\limits_{n=1}^{L_2}(1+\omega_1\rho_1+\omega_2\rho_2)^n\alpha^n r^n & \\ +pQ\phi(1+\theta_1)^{T_1}(1+\omega_1\rho_1+\omega_2\rho_2)^{L_2}r^{T_1}\sum\limits_{n=L_2+1}^{T_2}(1-\theta)^{n-L_2}r^n & \\ -MCQ\phi(1+\theta_1)^{T_1}r^{T_1}(\omega_1\beta_1+\omega_2\beta_2)^{T_1}(1+\omega_1\rho_1+\omega_2\rho_2)^{L_2}\sum\limits_{n=L_2+1}^{T_2}(1-\theta)^{n-L_2}\alpha^n r^n & T_1\le L_1, T_2>L_2 \\ pQ\phi(1+\theta_1)^{L_1}(1-\theta)^{T_1-L_1}r^{T_1}\sum\limits_{n=1}^{L_2}(1+\omega_1\rho_1+\omega_2\rho_2)^n r^n & \\ -MCQ\phi(1+\theta_1)^{L_1}(1-\theta)^{T_1-L_1}(\omega_1\beta_1+\omega_2\beta_2)^{T_1}r^{T_1}\sum\limits_{n=1}^{L_2}(1+\omega_1\rho_1+\omega_2\rho_2)^n\alpha^n r^n & \\ +pQ\phi(1+\theta_1)^{L_1}(1-\theta)^{T_1-L_1}(1+\omega_1\rho_1+\omega_2\rho_2)^{L_2}r^{T_1}\sum\limits_{n=L_2+1}^{T_2}(1-\theta)^{n-L_2}r^n & \\ -MCQ\phi(1+\theta_1)^{L_1}(1-\theta)^{T_1-L_1}r^{T_1}(\omega_1\beta_1+\omega_2\beta_2)^{T_1}(1+\omega_1\rho_1+\omega_2\rho_2)^{L_2}\sum\limits_{n=L_2+1}^{T_2}(1-\theta)^{n-L_2}\alpha^n r^n & L_1<T_1, T_2>L_2 \end{cases} \tag{7}$$

$$\lambda(n,T_2)=\begin{cases} \phi(1+\theta_1)^{T_1}(1+\omega_1\rho_1+\omega_2\rho_2)^{T_2}(1+\rho_3)^n & n\le L_3,\ T_2\le L_2,\ T_1\le L_1 \\ \phi(1+\theta_1)^{L_1}(1-\theta)^{T_1-L_1}(1+\omega_1\rho_1+\omega_2\rho_2)^{T_2}(1+\rho_3)^n & n\le L_3,\ T_2\le L_2,\ T_1>L_1 \\ \phi(1+\theta_1)^{T_1}(1+\omega_1\rho_1+\omega_2\rho_2)^{L_2}(1-\theta)^{T_2-L_2}(1+\rho_3)^n & n\le L_3,\ T_2>L_2,\ T_1\le L_1 \\ \phi(1+\theta_1)^{L_1}(1-\theta)^{T_1+T_2-L_1-L_2}(1+\omega_1\rho_1+\omega_2\rho_2)^{L_2}(1+\rho_3)^n & n\le L_3,\ T_2>L_2,\ T_1>L_1 \\ \phi(1+\theta_1)^{T_1}(1+\omega_1\rho_1+\omega_2\rho_2)^{T_2}\ (1+\rho_3)^{L_3}(1-\theta)^{n-L_3} & n>L_3,\ T_2\le L_2,\ T_1\le L_1 \\ \phi(1+\theta_1)^{L_1}(1-\theta)^{T_1-L_1}(1+\omega_1\rho_1+\omega_2\rho_2)^{T_2}(1+\rho_3)^{L_3}(1-\theta)^{n-L_3} & n>L_3,\ T_2\le L_2,\ T_1>L_1 \\ \phi(1+\theta_1)^{T_1}(1+\omega_1\rho_1+\omega_2\rho_2)^{L_2}(1-\theta)^{T_2-L_2}(1+\rho_3)^{L_3}(1-\theta)^{n-L_3} & n>L_3,\ T_2>L_2,\ T_1\le L_1 \\ \phi(1+\theta_1)^{L_1}(1-\theta)^{T_1+T_2-L_1-L_2}(1+\omega_1\rho_1+\omega_2\rho_2)^{L_2}(1+\rho_3)^{L_3}(1-\theta)^{n-L_3} & n>L_3,\ T_2>L_2,\ T_1>L_1 \end{cases} \tag{9}$$

$$\xi_2(T_2)=\begin{cases} pQ\phi(1+\theta_1)^{T_1}(1+\omega_1\rho_1+\omega_2\rho_2)^{T_2}r^{(T_1+T_2)}\sum\limits_{n=1}^{L_3}(1+\rho_3)^n r^n & \\ -QMC\phi(1+\theta_1)^{T_1}(1+\omega_1\rho_1+\omega_2\rho_2)^{T_2}r^{(T_1+T_2)}\beta_3{}^{(T_1+T_2)}\sum\limits_{n=1}^{L_3}(1+\rho_3)^n\alpha^n r^n & \\ +pQ\phi(1+\theta_1)^{T_1}(1+\omega_1\rho_1+\omega_2\rho_2)^{T_2}r^{(T_1+T_2)}(1+\rho_3)^{L_3}\sum\limits_{n=L_3+1}^{N}(1-\theta)^{n-L_3}r^n & \\ -QMC\phi(1+\theta_1)^{T_1}(1+\omega_1\rho_1+\omega_2\rho_2)^{T_2}r^{(T_1+T_2)}(1+\rho_3)^{L_3}\beta_3{}^{(T_1+T_2)}\sum\limits_{n=L_3+1}^{N}(1-\theta)^{n-L_3}\alpha^n r^n & T_2\le L_2, T_1\le L_1 \\ pQ\phi(1+\theta_1)^{L_1}(1-\theta)^{T_1-L_1}(1+\omega_1\rho_1+\omega_2\rho_2)^{T_2}r^{(T_1+T_2)}\sum\limits_{n=1}^{L_3}(1+\rho_3)^n r^n & \\ -QMC\phi(1+\theta_1)^{L_1}(1-\theta)^{T_1-L_1}(1+\omega_1\rho_1+\omega_2\rho_2)^{T_2}r^{(T_1+T_2)}\beta_3{}^{(T_1+T_2)}r^{(T_1+T_2)}\sum\limits_{n=1}^{L_3}(1+\rho_3)^n\alpha^n r^n & \\ +pQ\phi(1+\theta_1)^{L_1}(1-\theta)^{T_1-L_1}(1+\omega_1\rho_1+\omega_2\rho_2)^{T_2}r^{(T_1+T_2)}(1+\rho_3)^{L_3}\sum\limits_{n=L_3+1}^{N}(1-\theta)^{n-L_3}r^n & \\ -MCQ\phi(1+\theta_1)^{L_1}(1-\theta)^{T_1-L_1}(1+\omega_1\rho_1+\omega_2\rho_2)^{T_2}r^{(T_1+T_2)}(1+\rho_3)^{L_3}\beta_3{}^{(T_1+T_2)}\sum\limits_{n=L_3+1}^{N}(1-\theta)^{n-L_3}\alpha^n r^n & T_2\le L_2, T_1>L_1 \end{cases} \tag{12}$$

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$$\xi_2(T_2)=\begin{cases} pQ\phi(1+\theta_1)^{T_1}(1+\omega_1\rho_1+\omega_2\rho_2)^{L_2}(1-\theta)^{T_2-L_2}r^{(T_1+T_2)}\sum_{n=1}^{L_3}(1+\rho_3)^n r^n & \\ -QMC\phi(1+\theta_1)^{T_1}(1+\omega_1\rho_1+\omega_2\rho_2)^{L_2}(1-\theta)^{T_2-L_2}r^{(T_1+T_2)}\beta_3{}^{(T_1+T_2)}\sum_{n=1}^{L_3}(1+\rho_3)^n\alpha^n r^n & \\ +pQ\phi(1+\theta_1)^{T_1}(1+\omega_1\rho_1+\omega_2\rho_2)^{L_2}(1-\theta)^{T_2-L_2}r^{(T_1+T_2)}(1+\rho_3)^{L_3}\sum_{n=L_3+1}^{N}(1-\theta)^{n-L_3}r^n & \\ -QMC\phi(1+\theta_1)^{T_1}(1+\omega_1\rho_1+\omega_2\rho_2)^{L_2}(1-\theta)^{T_2-L_2}r^{(T_1+T_2)}(1+\rho_3)^{L_3}\beta_3{}^{(T_1+T_2)}\sum_{n=L_3+1}^{N}(1-\theta)^{n-L_3}\alpha^n r^n & T_2>L_2, T_1\le L_1 \\ pQ\phi(1+\theta_1)^{L_1}(1-\theta)^{T_1+T_2-L_1-L_2}(1+\omega_1\rho_1+\omega_2\rho_2)^{L_2}r^{(T_1+T_2)}\sum_{n=1}^{L_3}(1+\rho_3)^n r^n & \\ -QMC\phi(1+\theta_1)^{L_1}(1-\theta)^{T_1+T_2-L_1-L_2}(1+\omega_1\rho_1+\omega_2\rho_2)^{L_2}r^{(T_1+T_2)}\beta_3{}^{(T_1+T_2)}\sum_{n=1}^{L_3}(1+\rho_3)^n\alpha^n r^n & \\ +pQ\phi(1+\theta_1)^{L_1}(1-\theta)^{T_1+T_2-L_1-L_2}(1+\omega_1\rho_1+\omega_2\rho_2)^{L_2}r^{(T_1+T_2)}(1+\rho_3)^{L_3}\sum_{n=L_3+1}^{N}(1-\theta)^{n-L_3}r^n & \\ -MCQ\phi(1+\theta_1)^{L_1}(1-\theta)^{T_1+T_2-L_1-L_2}(1+\omega_1\rho_1+\omega_2\rho_2)^{L_2}r^{(T_1+T_2)}(1+\rho_3)^{L_3}\beta_3{}^{(T_1+T_2)}\sum_{n=L_3+1}^{N}(1-\theta)^{n-L_3}\alpha^n r^n & T_2>L_2, T_1>L_1 \end{cases} \tag{13}$$

knowledge can be seen as the private knowledge transferred from other firms. Then, the control model of knowledge transfer risks is similar to the model of continuous knowledge transfer [58]. Let the parameter values of knowledge transfer the same as those of the big date knowledge transfer, and the parameter values of independent innovation knowledge update the same as those of the private knowledge transfer. 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 ; the knowledge absorption capacity $alpha = 95\%$; the life cycle of the product $N = 10$; and the discount rate is 10%, then $r = 1/(1 + 10\%)$; the fixed transfer cost of big data knowledge $k_1 = 80$; the R&D investment of independent innovation knowledge $k_{Rf} = 300$; $L_1 = 4$; $L_2 = 2$ (L_2 is the period of total market volume increased after the big data knowledge transfer, the big data knowledge is updated quickly, and the cycle of knowledge efficiency is shorter, so the total market volume is assumed to increase in the first $L_2 = 2$ periods after big data knowledge transfer); $L_3 = 4$; the growth rate of market share in the first $L_2 = 2$ periods immediately after big data knowledge transfer $\rho_1 = 4\%$; the growth rate of market share in the first $L_3 = 4$ periods immediately after knowledge update $\rho_3 = 8\%$; the update rate of big data knowledge $\beta_1 = 90\%$; the update rate of independent innovation knowledge $\beta_3 = 88\%$; the variable cost coefficient of big data knowledge $F_1 = 250$; the variable cost coefficient of independent innovation knowledge $F_2 = 250$. The values of the parameters are shown in Table 2.

From the experimental results in Table 3 and Fig. 3, the optimal time of T_1 is 5, and the optimal time of T_2 is 4. Compared with continuous knowledge transfer, the optimal time of T_1 and T_2 is the same, but the total DEP is different. The reason is that k_{Rf} is the R&D investment at time period T_1, not the fixed transfer cost of private knowledge at time period T_2. The R&D investment of a firm usually takes a

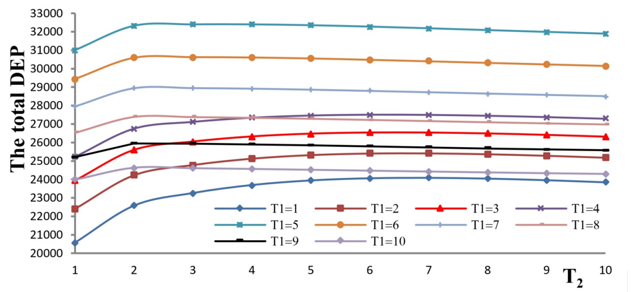

FIGURE 3. Changes in total DEP with T_1 and T_2 when $\omega_1 = 1, \omega_2 = 0$.

period of time to be transformed into a new product. The model is valid. It can provide more effective decisions for firms that must carry out independent R&D while knowledge transfer in the big data environment.

B. PARAMETER SETTING AND SIMULATION RESULTS WHEN $\omega_1 = 0, \omega_2 = 1$

When $\omega_1 = 1, \omega_2 = 0$, it means that firm V_i only transfers one type of private knowledge at time period T_1 first, then takes independent innovation. Let the variable cost coefficient of private knowledge be $F = 1000$ and the learning cost of independent innovation knowledge be $F_2 = 280$. The reason is that independent innovation knowledge is developed in V_i, and the learning cost of independent innovation knowledge is much lower than that of private knowledge from other firms. At the same time, the independent innovation knowledge is one type of private knowledge, and it is a little more complex than big data knowledge. As a result, the learning cost of independent innovation knowledge F_2 is set a bit higher than that of the big data knowledge. To compare the experimental results when $\omega_1 = 1, \omega_2 = 0$, the market share and the update rate of independent innovation knowledge are set the same as that of the private knowledge transferred from other firms. The adjusted values of parameters are shown in Table 4.

From the experimental results in Table 5 and Fig. 4, the optimal knowledge transfer time of private knowledge T_1

TABLE 2. PARAMETER VALUES WHEN $\omega_1 = 1, \omega_2 = 0$

Parameter	Q	p	MC	θ_1	θ	ϕ	α	N	r	k_1	L_1	L_2	L_3	ρ_1	ρ_3	β_1	β_3	F_1	F_2	k_{Rf}
Value	1000	60	40	3%	3%	8%	95%	10	0.9	80	4	2	4	4%	8%	90%	88%	250	1000	300

TABLE 3. TOTAL DEP WITH T_1 AND T_2 WHEN $\omega_1 = 1, \omega_2 = 0$

T_2	1	2	3	4	5	6	7	8	9	10	
DEP	20571	22575	23260	23692	23942	24058	24081	24039	23953	23838	$T_1 = 1$
DEP	22406	24226	24779	25124	25318	25403	25411	25364	25282	25176	$T_1 = 2$
DEP	23939	25598	26047	26324	26476	26537	26534	26486	26409	26311	$T_1 = 3$
DEP	25230	26748	27114	27338	27457	27501	27491	27444	27371	27283	$T_1 = 4$
DEP	31009	32321	32395	**32396**	32350	32275	32184	32087	31990	31896	$T_1 = 5$
DEP	29451	30588	30622	30603	30551	30479	30398	30313	30230	30150	$T_1 = 6$
DEP	27949	28936	28944	28913	28859	28792	28720	28647	28576	28508	$T_1 = 7$
DEP	26529	27388	27378	27341	27288	27227	27164	27100	27040	26983	$T_1 = 8$
DEP	25204	25953	25932	25893	25843	25789	25733	25679	25627	25580	$T_1 = 9$
DEP	23983	24637	24610	24571	24525	24476	24428	24381	24338	24298	$T_1 = 10$

TABLE 4. PARAMETER VALUES WHEN $\omega_1 = 0, \omega_2 = 1$

Parameter	Q	p	MC	θ_1	θ	ϕ	α	N	r	k_2	L_1	L_2	L_3	ρ_1	ρ_3	β_1	β_3	F_1	F_2	k_{Rf}
Value	1000	60	40	3%	3%	8%	95%	10	0.9	300	4	2	4	8%	8%	88%	88%	1000	280	300

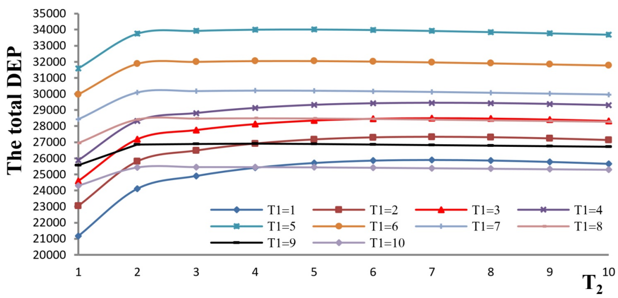

FIGURE 4. Changes in total DEP with T_1 and T_2 when $\omega_1 = 0, \omega_2 = 1$.

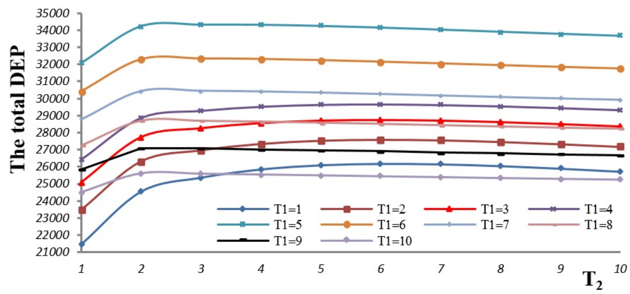

FIGURE 5. Changes in total DEP with β_3.

remains 5. However, the independent innovation time T_2 changes from 4 to 5. The reason is that although the learning cost of independent innovation knowledge is reduced, the private knowledge from other firm is more efficient and cheaper than the independent innovation knowledge in a short term. It shows that knowledge transfer will hinder the independent innovation of firms. As a result, firms will lack vitality and long-term core competitiveness. The simulation experimental results are in line with the actual economic situation. The model is valid, and it can provide decision support for firms to cope with knowledge transfer risks in the big data environment.

C. SIMULATION RESULTS WITH β_3 AS A VARIABLE

Because the independent R&D investment is usually higher than the fixed transfer cost of private knowledge, k_{Rf} is assumed to be 600. To determine the influence of the update rate of independent innovation knowledge β_3 on the DEP and the optimal time of independent innovation knowledge update in the big data environment, all the parameter except β_3 and k_{Rf} are set with the same values as in section (2). The change of β_3's value from 88% to 86% means that the update rate of the independent innovation knowledge increases. Table 6 and Fig. 5 show that the DEP varies with β_3.

From the experimental results in Table 6 and Fig. 5, the optimal time of independent innovation knowledge update T_2 changes from 4 to 3. It can be concluded that when the update rate of the independent innovation knowledge increases, the optimal time of independent innovation knowledge update T_2 becomes earlier. The reason is that the more efficient the independent innovation knowledge, the sooner firm V_i will update its own knowledge. Comparing the experimental results with that in section (2), it can be seen that despite the increase in R&D investment, firms will continue to update their independent innovation knowledge as soon as possible.

D. SIMULATION WITH ρ_3 AS A VARIABLE

Let $k_{Rf} = 600$. To determine the influence of the growth rate of market share of the independent innovation knowledge β_3 on the DEP and the optimal time of independent innovation knowledge update in the big data environment, all the pa-

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TABLE 5. TOTAL DEP WITH T_1 AND T_2 WHEN $\omega_1 = 1, \omega_2 = 0$

T_2	1	2	3	4	5	6	7	8	9	10	
DEP	21172	24108	24902	25410	25709	25857	25897	25862	25776	25657	$T_1 = 1$
DEP	23037	25804	26479	26912	27169	27297	27334	27305	27233	27131	$T_1 = 1$
DEP	24584	27185	27761	28132	28353	28465	28498	28476	28414	28327	$T_1 = 1$
DEP	25875	28316	28809	29129	29320	29418	29448	29430	29378	29303	$T_1 = 1$
DEP	31596	33750	33924	34001	**34011**	33980	33922	33849	33770	33689	$T_1 = 1$
DEP	29980	31877	32000	32050	32050	32019	31968	31907	31841	31775	$T_1 = 1$
DEP	28420	30091	30176	30206	30199	30169	30124	30073	30018	29964	$T_1 = 1$
DEP	26946	28414	28472	28488	28476	28447	28409	28365	28320	28275	$T_1 = 1$
DEP	25572	26862	26899	26905	26890	26864	26830	26793	26755	26717	$T_1 = 1$
DEP	24305	25438	25460	25459	25443	25419	25389	25357	25325	25295	$T_1 = 1$

TABLE 6. TOTAL DEP WITH β_3

T_2	1	2	3	4	5	6	7	8	9	10	
DEP	21464	24551	25364	25844	26088	26170	26140	26037	25887	25710	$T_1 = 1$
DEP	23474	26328	26974	27351	27538	27592	27557	27462	27328	27173	$T_1 = 2$
DEP	25096	27740	28256	28555	28699	28735	28698	28611	28494	28358	$T_1 = 2$
DEP	26415	28869	29285	29523	29636	29659	29622	29545	29442	29323	$T_1 = 4$
DEP	32091	34237	**34323**	34316	34250	34150	34032	33909	33786	33670	$T_1 = 5$
DEP	30415	32294	32333	32306	32238	32147	32045	31941	31839	31743	$T_1 = 6$
DEP	28794	30439	30448	30409	30343	30262	30174	30087	30002	29923	$T_1 = 7$
DEP	27258	28701	28690	28646	28584	28512	28437	28363	28293	28228	$T_1 = 8$
DEP	25828	27092	27070	27025	26968	26905	26841	26779	26721	26668	$T_1 = 9$
DEP	24512	25620	25592	25548	25496	25442	25387	25336	25287	25243	$T_1 = 10$

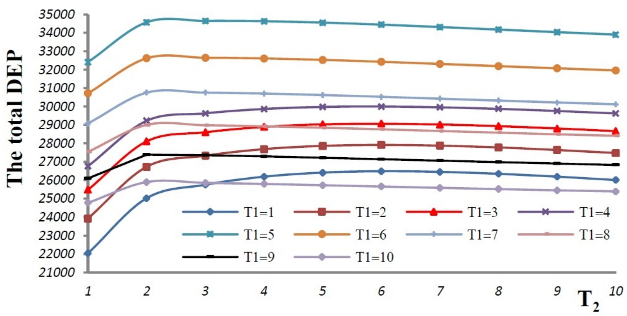

FIGURE 6. Changes in total DEP with ρ_3.

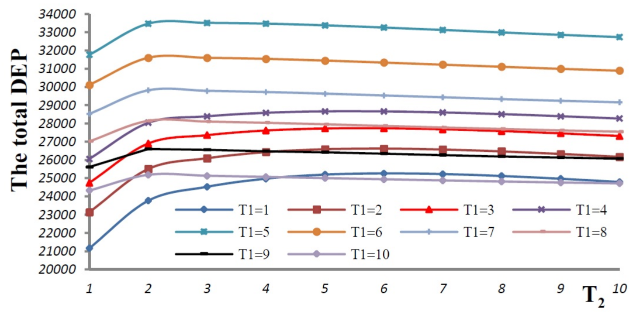

FIGURE 7. Changes in total DEP when $\omega_1 = 0.5, \omega_2 = 0.5$.

rameters except ρ_3 and k_{Rf} are set with the same values as in section (2). Changing ρ_3 from 8% to 10% means that the growth rate of market share of the independent innovation knowledge increases. It can be seen from the experimental results in Table 7 and Fig. 6, the optimal time of independent innovation knowledge update T_2 changes from 4 to 3. It can be seen that despite the increase in R&D investment, the optimal time of independent innovation knowledge update is earlier. The reason is that the higher the efficiency of the independent innovation knowledge, the earlier the firm V_i will update its own knowledge.

E. SIMULATION RESULTS WHEN $\omega_1 = 0.5, \omega_2 = 0.5$

To determine the influence of the weights of two types of knowledge transferred on the total DEP and the optimal time of independent innovation knowledge update, let $\omega_1 = 0.5, \omega_2 = 0.5$ and $\beta_3 = 86\%$. The experimental results in Table 8 and Fig. 7 show that the optimal time of independent innovation knowledge update T_2 is the same as that in section (3), but all the total DEPs are much smaller. The outcome means that when the weight of big data knowledge increases, the total profit of knowledge transfer decreases, but the optimal time of independent innovation knowledge update remains unchanged. The reason is that big data knowledge has little effect on the optimal time of independent innovation knowledge update.

VI. CONCLUSION

This paper analyzes the characteristics of new product innovation of firms in the big data environment, and considers that imitation innovation may serve as a stepping stone leading to independent innovation. Knowledge transfer, one of the main methods that firms used to acquire knowledge from external environment for imitation innovation, is a complex process of multiple knowledge transfer among different organizations and subject to various risks. Based on the influence factors of knowledge transfer risks and development process of inno-

TABLE 7. TOTAL DEP WITH ρ_3

T_2	1	2	3	4	5	6	7	8	9	10	
DEP	22040	25030	25761	26197	26420	26492	26458	26352	26198	26015	$T_1 = 1$
DEP	23931	26736	27337	27692	27869	27920	27882	27783	27644	27481	$T_1 = 2$
DEP	25486	28113	28607	28896	29037	29071	29030	28938	28813	28666	$T_1 = 3$
DEP	26772	29229	29636	29871	29982	30003	29960	29875	29761	29630	$T_1 = 4$
DEP	32416	34578	34652	34634	**34559**	34447	34317	34179	34041	33908	$T_1 = 5$
DEP	30722	32623	32652	32615	32535	32432	32316	32196	32078	31965	$T_1 = 6$
DEP	29089	30758	30757	30707	30628	30532	30429	30325	30224	30127	$T_1 = 7$
DEP	27545	29010	28987	28931	28854	28767	28675	28585	28498	28416	$T_1 = 8$
DEP	26106	27390	27355	27296	27223	27143	27063	26984	26908	26839	$T_1 = 9$
DEP	24780	25906	25862	25803	25735	25663	25592	25523	25458	25398	$T_1 = 10$

TABLE 8. TOTAL DEP WITH ρ_3

T_2	1	2	3	4	5	6	7	8	9	10	
DEP	21159	23767	24529	24975	25197	25264	25226	25119	24968	24792	$T_1 = 1$
DEP	23140	25504	26093	26429	26587	26621	26571	26467	26328	26169	$T_1 = 2$
DEP	24747	26902	27359	27613	27724	27736	27681	27582	27455	27314	$T_1 = 3$
DEP	26060	28034	28391	28584	28662	28660	28603	28511	28398	28271	$T_1 = 4$
DEP	31763	33471	**33512**	33469	33377	33256	33123	32987	32856	32732	$T_1 = 5$
DEP	30116	31600	31598	31539	31447	31337	31220	31104	30994	30891	$T_1 = 6$
DEP	28524	29816	29788	29722	29634	29535	29434	29336	29243	29158	$T_1 = 7$
DEP	27018	28145	28103	28034	27953	27866	27779	27696	27618	27547	$T_1 = 8$
DEP	25614	26599	26550	26484	26410	26334	26260	26190	26125	26066	$T_1 = 9$
DEP	24323	25185	25134	25072	25006	24940	24877	24818	24764	24715	$T_1 = 10$

vation, we proposed a theoretical framework for risk control of knowledge transfer in the big data environment. We also built a risk control model of knowledge transfer that can be used to determine the maximum profit of a new product, the optimal time of knowledge transfer, and the update time of independent innovation knowledge. Simulation experiments were carried out to verify the validity of the model. The experimental results show that knowledge transfer will increase profit and improve the innovation performance in the short term, but it will hinder the independent innovation of firms. Consequently, firms will lack vitality and long-term core competitiveness. Our results suggest that firms should take on independent innovation when knowledge transfer is implemented. Otherwise, the firms could face the risks of infringement of intellectual property rights or enormous economic losses caused by the termination of intellectual property licensing agreements.

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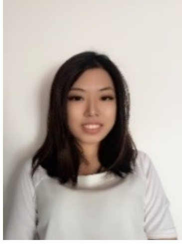

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