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Optimization decision of supply chain data governance involving data governance service providers

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Building on the use of digital technology in supply chain management, this paper integrates data governance service providers into the supply chain. Given the distinct nature of data governance services, the paper illustrated the learning effect curve and simulated their output function. Building on this, four different supply chain data governance models were proposed, namely, manufacturer single governance model, retailer single governance model, manufacturer and retailer independent governance model, and manufacturer and retailer collaborative governance model. Constructed the profit model for the supply chain within the relevant framework. By vertically comparing the optimal decisions and system performance across various models, the study concluded that the collaborative governance model maximizes supply chain profit and is more responsive to factors that enhance overall profitability.

1. Introduction

As the internet evolves and cloud computing, along with other technologies, advances, global data volume is increasing rapidly, ushering humanity into the age of vast data. The rise of mobile payment and e-commerce platforms has gradually made consumer behavior digital and visual (Pantano & Dennis, 2019; Rita, & Ramos, 2022; Liu et al., 2023), and the resulting consumer purchase behavior data is also increasing. These data are of great value to supply chain enterprises. They can use these data to explore consumer demand preferences (Dekimpe & Geyskens, 2019; Gupta & Ramachandran, 2021; Nilashi et al., 2021), build consumer databases (Bradlow, Gangwar, Kopalle, & Voleti, 2017), and segment consumers to improve products and provide personalized services (Hossain, Akter, & Yanamandram, 2020; Huang & Rust, 2022). However, in reality, consumer data in the supply chain is scattered across different platforms and markets, which is disorganized and difficult to obtain. It needs to be governed urgently. Ordinary enterprises are limited by factors such as data collection technology, governance level, and funds. They are unable to obtain and mine the value of consumption data internally. Therefore, an external provider of data governance services (referred to as data governance service provider) has emerged. They use professional information technology to collect consumer data in the supply chain through tracking and survey. Then manage, analyze and summarize it, and sell the data analysis results to supply chain enterprises as information services (P. Liu & Yi, 2018). The introduction of data governance service providers complicates interactions within the supply chain, triggers structural changes, and influences governance decisions across supply chain participants. (Fosso Wamba, Gunasekaran, Dubey, & Ngai, 2018). Data governance service providers could extract knowledge from massive and complex consumer data to improve enterprise product R&D or sales services (Mikalef, Boura, Lekakos, & Krogstie, 2019). And manufacturers or retailers could gain competitive advantages from the knowledge. Specifically, manufacturers or retailers could obtain consumers' demand preference data through data governance services. Manufacturers will generate products that better align with consumer preferences and offer additional services, including product development and technical assistance (Dan, Zhang, & Zhou, 2018; Taleizadeh & Sadeghi, 2019). Retailers will offer personalized services to consumers, including retail showrooms, appealing shelf displays, product explanations in-store, and trial samples. (Pi, Fang, & Zhang, 2019; Zhou, Guo, & Zhou, 2018).

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From the perspective of enterprise practice, data governance helps enterprises achieve sustainable competitive advantage (Wamba et al., 2017). Manufacturers or retailers will choose data governance to improve product quality and further strengthen market competitiveness. But in reality, the situation of single data governance for manufacturers or retailers is common. And given the degree of cooperation between the two parties, there will be an independent governance model and collaborative governance model. Notably, the output of data governance services exhibits a learning effect when the data governance service provider first joins the supply chain. In each production cycle, the data governance service provider will summarize and learn and predict the laws of the collected data. The operation of data cleaning, governance and analysis will also become more and more proficient. Therefore, the output of data governance services will increase in each production cycle. In view of this, this paper introduces a data governance service provider into the supply chain. Considering the learning effect of the service provider, the output function of data governance is simulated. Based on this, four supply chain data governance models are proposed: manufacturer single governance model, retailer single governance model, manufacturer and retailer independent governance model, and manufacturer and retailer collaborative governance model. By constructing the supply chain profit model within the relevant framework, the optimal decisions and system performance across various models are compared. Explore the applicable scenarios and influencing factors of different data governance models. Some management insights are derived.

The remainder of the paper's structured as follows: Section 2 provides a review of the relevant literature. Section 3 outlines the problem, assumptions, and notations. In Section 4, profit models are developed for the four frameworks. Section 5 compares the equilibrium solutions and optimal profits across the different models. Section 6, the hypothesis of the model is verified by numerical simulation, and the degree of influence of various factors on the equilibrium solution and profit is analyzed. In Section 7, the paper summarizes our main conclusions.

2. Literature review

This paper mainly involves two research streams—supply chain data services and learning effects of outputs. Next, a review of the literature is presented from two perspectives, highlighting how this paper differs from existing research. The first stream is about the supply chain data services. As a key big data analysis technology, data governance is widely recognized for its ability to analyze large datasets using various methods, enabling more targeted business decisions and improving operational efficiency (Piccarozzi & Aquilani, 2022). According to (Pan Liu, 2019) big data technology helps enterprises better track consumer preferences and analyze data to offer more tailored products or services. (Louhghalam, Akbarian, & Ulm, 2017) highlighted that big data technology is effective in managing low-carbon data and optimizing structure layouts. Additionally, some scholars, such as (Belhadi et al., 2021), argue that data governance can help enterprises identify risks within the supply chain. Data analysis capabilities can help SMEs improve their supply chain systems under adverse circumstances (Chatterjee, Chaudhuri, Shah, & Maheshwari, 2022). For related quantitative studies. Chu et al. (2017) discussed incentives for data information sharing so that manufacturers can simultaneously make decisions about capacity and wholesale price. Chen et al. (2016) studied the contract mechanism for retailers to simultaneously coordinate information investment and sales efforts considering the costs of acquiring convex information. Liu and Yi (2018) analyzed the profitability of supply chain enterprises investing in big data services from both centralized and decentralized decision-making perspectives, concluding that such investments can lower operating costs.

The second stream relates to the learning effects of outputs. Data governance service providers are similar to traditional manufacturing enterprises, and their service output process also has a learning effect. The learning curve theory of production operations management was first proposed by Wright (1936). In modern research, Tarakci (2016) quantified the impact of manufacturer learning effect on failure and believes that learning from failure is more important for suppliers. Research on learning effects has mainly focused on production operations and logistics operations activities (Giri & Glock, 2017). Jaber and El Saadany (2011) examine how learning during production and remanufacturing phases can enhance inventory management and improve the coordination between production and logistics operations. Giri and Masanta (2020) show that production learning plays a central role in optimal decision making in CLSC.

Formerly, most of the studies on the learning effect focused on the traditional manufacturing industry, and explored the trend of the unit product manufacturing time with the output. There are relatively few studies on the learning effects of knowledge service products, but they are particularly important. Furthermore, research should consider the differences between data governance services and manufacturing products. Firstly, compared with the mass repetitive production mode of manufacturing entities, data governance services are used to extract and generate consumer data. Therefore, data governance services are non-entity knowledge products, which can be sold many times after production is completed, and only bear the production cost once. Secondly, the manufacturing industry is to accumulate experience in repeated work to improve production efficiency, while data governance services are a summary of consumer data laws. Thirdly, the market environment of the supply chain is dynamic and disordered, consumer preference behavior is also advancing with the times, and relevant data information is changing rapidly, so the data governance service knowledge hysteresis is strong, which cannot be ignored in this study.

From the above research, it can be found from the above literature that current studies mostly start from incentive sharing of supply chain data governance. There are only centralized and decentralized decision-making models for supply chain member cooperation models, and rarely consider a member's single decision-making model. In addition, the learning effect and knowledge hysteresis of data governance providers play a crucial role in the research, and there are few studies that combine supply chain data governance and learning effects. In general, this paper has the following three contributions:

(1) Introduce data governance service providers into the supply chain, and propose manufacturer single governance model, retailer single governance model, manufacturer and retailer independent governance model, and manufacturer and retailer collaborative governance model based on different levels of cooperation.
(2) Consider the particularity of data governance service providers, the learning effect curve and output function of these services are analyzed and simulated.
(3) Consider the hysteresis of data information and learning ability as important factors, quantify them in the model, and draw relevant conclusions.

3. Problem definition

3.1 Problem definition and assumptions

This paper studies a secondary supply chain, consisting of upstream manufacturers M and downstream retailers R, in which the manufacturer dominates. This supply chain manufactures and sells certain products with a fixed production cycle. Consider a data governance service provider starting to join the supply chain. It follows the production cycle of this supply chain to provide data governance services for manufacturers and retailers. The operational model of the supply chain is illustrated in Fig.1. The dotted line represents the data governance service flow. The solid line represents the product flow.

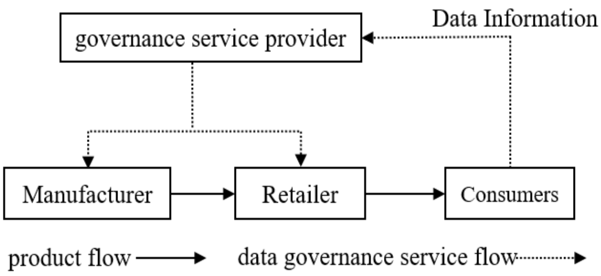

Fig. 1. A depiction of the supply chain network with data governance service providers

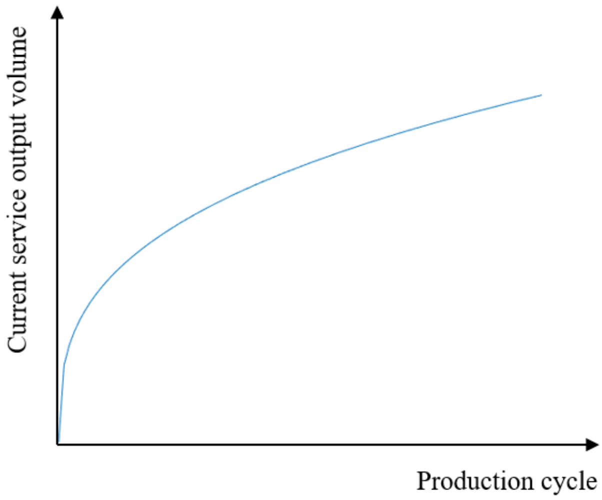

Fig. 2. Learning effect curve for data governance services

Data governance service providers provide data services to manufacturers and retailers. Manufacturers use these data to produce more competitive high-quality products. Retailers use this data to provide more comprehensive sales services to increase overall profits. The process of data governance service output has a learning effect, and the learning effect curve is shown in Fig. 2. Given the distinction between data governance services and manufacturing products, the output function of services at cycle "t" can be expressed as:

$$n_t = n_1 t^{\theta} \tag{1}$$

where, n_1 stand for the output of services in the first production cycle, and its value will refer to research in related fields and considering the general productivity setting of the actual data governance service provider, θ represents the learning ability of the service provider. $\frac{\partial n_t}{\partial t} => 0$, $\frac{\sigma^2_{n_t}}{\partial t^2} =< 0$, it indicate that the data governance service output is an increasing function of the production cycle, and the growth rate of service output is getting smaller. The image is an upward convex increasing curve as shown in Fig. 2. In practice, due to the learning effect of the enterprise, the service output of each cycle increases rapidly when the data governance service provider joins the supply chain. However, the data governance service provider's ability to collect and process data is limited, so the service output growth rate of the quantity is getting smaller, and the curve is in line with reality. Due to the complexity of the supply chain and the dynamic nature of consumer preferences, previous data governance services will not be suitable for the current supply chain environment and will gradually become obsolete. Therefore, data governance services, as knowledge products, have a certain degree of hysteresis. After the hysteresis effect, the cumulative available data governance service at cycle "t" can be written as follows:

$$N_t = (1-\gamma)N_{t-1} + n_t = \sum_{i=1}^{t}(1-\gamma)^{t-i}n_i \tag{2}$$

where, γ represents the knowledge hysteresis rate of data governance service. Referring to the literature (Xu, Dan, Zhang, & Liu, 2014), the demand function is $q = a - bp + \alpha v_M + \beta v_R$. a represents the base market demand of the products, b is the price elasticity of demand, p is the product price, α and β are the consumer sensitivity coefficients for product quality and sales service, respectively. In terms of basic quality and service, manufacturers bring additional value v_M to consumers by improving product quality, and retailers bring additional value v_R to consumers by optimizing sales services, thereby increasing market demand. Where $v_M = N_t^M \rho_M$, $v_R = N_t^R \rho_R$. ρ_M and ρ_R are the value conversion rate of the unit data governance service obtained by the manufacturer and the retailer to the consumer.

Given the complexity of the issue addressed in this paper, we outline the following assumptions in accordance with economic principles.

Assumption 1. There is no loss in the product circulation process, and the production and demand of data governance services are equal.

Assumption 2. All supply chain members act rationally with the goal of maximizing their individual profits.

Assumption 3. Consumers are more sensitive to product quality preferences, and it is easier for data governance service providers to obtain relevant data information. Therefore, the additional demand for manufacturers to convert data governance services is greater than that of retailers, $N_t^M \alpha \rho_M > N_t^R \beta \rho_R$.

3.2 Variable parameter description

In the model, the subscript $i \in \{1,2,3,4\}$ represents the manufacturer single governance model, retailer single governance model, manufacturer and retailer independent governance model, and manufacturer and retailer collaborative governance model, respectively. Use the superscript $j \in \{M, R, D\}$ to denote the manufacturer, retailer, and data governance service provider respectively. The meanings of relevant parameters are shown in Table 1.

Table 1
Description of Relevant parameters

Parameter and variable	Meaning
a	The base market demand of the products
b	The price elasticity of demand
α	the consumer sensitivity coefficients for product quality
β	the consumer sensitivity coefficients for sales service
v_M	The additional value that manufacturers bring to consumers by improving product quality
v_R	The additional value that retailers bring to consumers by optimizing sales services
θ	Learning ability of the data governance service provider
t	Production cycle
n_t^j	Output volume of data governance services in cycle t
N_t^j	Cumulative volume of available data governance services in cycle t
γ	The knowledge stagnation rate of data governance service
c_M	Unit cost of product development and production for manufacturers
c_R	Retailer's cost per unit of product sold.
c_D	Cost per unit of service output for data governance service providers
k	Fixed costs for data governance service providers
w_i	Wholesale prices of products in different models
p_i	Retail price of products in different modes
q_i	Product demand in different modes
π_i^j	Profits of different supply chain members under different governance models
ρ_M	The value conversion rate of data governance services from the manufacturer to the consumer
ρ_R	The value conversion rate of data governance services from the retailer to the consumer
m	Pricing of data governance services by service providers

4. Model development

According to the degree of cooperation and sharing of supply chain members, this section develops the profit models for supply chain members across the four governance modes, retailer single governance model, manufacturer and retailer independent governance model, and manufacturer and retailer collaborative governance model.

4.1 Manufacturer single governance

When a manufacturer considers its own data quality and data security in order to produce higher-quality products, he will choose data governance to improve product quality and further strengthen market competitiveness. In this case, $q_1 = a - bp_1 + N_t^M \rho_M \alpha$, then at the production cycle "t", the profit function of each member of the supply chain is listed below:

$$\pi_1^M = (w_1 - c_M)q_1 - mn_t^M \tag{3}$$
$$\pi_1^R = (p_1 - w_1 - c_R)q_1 \tag{4}$$
$$\pi_1^D = (m - c_B)n_t^M - k \tag{5}$$

Using backward induction, we can determine the optimal decision:

$$w_1^* = \frac{a + [\sum_{i=1}^t (1-\gamma)^{t-i} n_i^M]\rho_M \alpha + b(c_M - c_R)}{2b} \tag{6}$$
$$p_1^* = \frac{3a + 3[\sum_{i=1}^t (1-\gamma)^{t-i} n_i^M]\rho_M \alpha + b(c_M + c_R)}{4b} \tag{7}$$
$$q_1^* = \frac{a + [\sum_{i=1}^t (1-\gamma)^{t-i} n_i^M]\rho_M \alpha - b(c_M + c_R)}{4} \tag{8}$$

The optimal profit of supply chain members can be calculated as:

$$\pi_1^{M*} = \frac{\{a + [\sum_{i=1}^t (1-\gamma)^{t-i} n_i^M]\rho_M \alpha - b(c_M + c_R)\}^2}{8b} - mn_t^M \tag{9}$$
$$\pi_1^{R*} = \frac{\{a + [\sum_{i=1}^t (1-\gamma)^{t-i} n_i^M]\rho_M \alpha - b(c_M + c_R)\}^2}{16b} \tag{10}$$

It should be noted that the prerequisite for the stable operation of the supply chain at this time is: $q_1^* > 0$

$$\frac{a + [\sum_{i=1}^t (1-\gamma)^{t-i} n_i^M]\rho_M \alpha}{b} > c_M + c_R \tag{11}$$

4.2 Retailer single governance

When a retailer considers its own data quality and data security in order to provide better sales services, he will choose data governance to improve service levels and further strengthen market competitiveness. In this case, $q_2 = a - bp_2 + N_t^R \rho_R \beta$, then at the production cycle "t", the profit function of each member of the supply chain is listed below:

$$\pi_2^M = (w_2 - c_M)q_2 \tag{12}$$
$$\pi_2^R = (p_2 - w_2 - c_R)q_2 - mn_t^R \tag{13}$$
$$\pi_2^D = (m - c_B)n_t^R - k \tag{14}$$

Using backward induction, we can determine the optimal decision:

$$w_2^* = \frac{a + [\sum_{i=1}^t (1-\gamma)^{t-i} n_i^R]\rho_R \beta + b(c_M - c_R)}{2b} \tag{15}$$
$$p_2^* = \frac{3a + 3[\sum_{i=1}^t (1-\gamma)^{t-i} n_i^R]\rho_R \beta + b(c_M + c_R)}{4b} \tag{16}$$
$$q_2^* = \frac{a + [\sum_{i=1}^t (1-\gamma)^{t-i} n_i^R]\rho_R \beta - b(c_M + c_R)}{4} \tag{17}$$

The optimal profit of supply chain members can be calculated as:

$$\pi_2^{M*} = \frac{\{a + [\sum_{i=1}^t (1-\gamma)^{t-i} n_i^R]\rho_R \beta - b(c_M + c_R)\}^2}{8b} \tag{18}$$
$$\pi_2^{R*} = \frac{\{a + [\sum_{i=1}^t (1-\gamma)^{t-i} n_i^R]\rho_R \beta - b(c_M + c_R)\}^2}{16b} - mn_t^R \tag{19}$$

It should be noted that the prerequisite for the stable operation of the supply chain at this time is: $q_2^* > 0$

$$\frac{a+[\sum_{i=1}^{t}(1-\gamma)^{t-i}n_i^R]\rho_R\beta}{b}>c_M+c_R \tag{20}$$

4.3 Manufacturer and retailer independent governance

When both manufacturers and retailers want to optimize product quality and sale services through data governance, but the trust level between them is too low to enable them to share data, they will adopt independent data governance. In this case, the manufacturer and retailer obtain their respective data governance services. However, while gathering and analyzing consumer data, only a small portion of the services effectively capture consumer preferences for both product quality and sales services. So, there is an intersection of the services they get. The data governance service is a non-entity knowledge product, and data governance services sold multiple times will only bear production costs once. Therefore, The total services received by the manufacturer and retailer surpass the output of the data governance provider. n_t^D is the service output of the data governance service provider in the cycle t, as in Fig.3, then $n_t^M+n_t^R>n_t^D>n_t^M,n_t^R$.

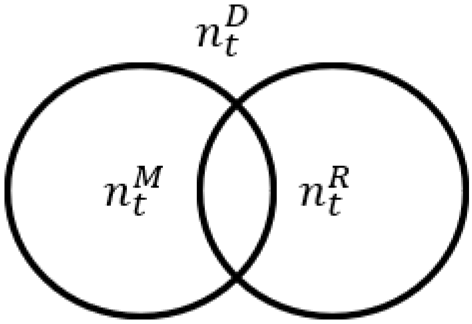

Fig.3. Demand for data governance services from manufacturers and retailers

In this case, $q_3=a-bp_3+N_t^M\rho_M\alpha+N_t^R\rho_R\beta$, then at the production cycle "t", The profit functions of supply chain members can be expressed as follows:

$$\pi_3^M=(w_3-c_M)q_3-mn_t^M \tag{21}$$
$$\pi_3^R=(p_3-w_3-c_R)q_3-mn_t^R \tag{22}$$
$$\pi_3^B=m(n_t^M+n_t^R)-n_t^Dc_B-k \tag{23}$$

Using backward induction, we can determine the optimal decision:

$$w_3^*=\frac{a+[\sum_{i=1}^{t}(1-\gamma)^{t-i}n_i^M]\rho_M\alpha+[\sum_{i=1}^{t}(1-\gamma)^{t-i}n_i^R]\rho_R\beta+b(c_M-c_R)}{2b} \tag{24}$$
$$p_3^*=\frac{3a+3[\sum_{i=1}^{t}(1-\gamma)^{t-i}n_i^M]\rho_M\alpha+3[\sum_{i=1}^{t}(1-\gamma)^{t-i}n_i^R]\rho_R\beta+b(c_M+c_R)}{4b} \tag{25}$$
$$q_3^*=\frac{a+[\sum_{i=1}^{t}(1-\gamma)^{t-i}n_i^M]\rho_M\alpha+[\sum_{i=1}^{t}(1-\gamma)^{t-i}n_i^R]\rho_R\beta-b(c_M+c_R)}{4} \tag{26}$$

The optimal profit of the supply chain is:

$$\pi_3^{M*}=\frac{\{a+[\sum_{i=1}^{t}(1-\gamma)^{t-i}n_i^M]\rho_M\alpha+[\sum_{i=1}^{t}(1-\gamma)^{t-i}n_i^R]\rho_R\beta-b(c_M+c_R)\}^2}{8b}-mn_t^M \tag{27}$$
$$\pi_3^{R*}=\frac{\{a+[\sum_{i=1}^{t}(1-\gamma)^{t-i}n_i^M]\rho_M\alpha+[\sum_{i=1}^{t}(1-\gamma)^{t-i}n_i^R]\rho_R\beta-b(c_M+c_R)\}^2}{16b}-mn_t^R \tag{28}$$

It should be noted that the prerequisite for the stable operation of the supply chain at this time is: $q_3^*>0$

$$\frac{a+[\sum_{i=1}^{t}(1-\gamma)^{t-i}n_i^M]\rho_M\alpha+[\sum_{i=1}^{t}(1-\gamma)^{t-i}n_i^R]\rho_R\beta}{b}>c_M+c_R \tag{29}$$

4.4 Manufacturer and retailer collaborative governance

Considering that when they adopt collaborative data governance, the manufacturer and retailer are fully cooperative with each other and share information to make decisions with the goal of maximizing common benefits. Therefore, the manufacturer and retailer can be combined into a supply chain member alliance. At this time, the amount of data governance services obtained by the supply chain member alliance is n_t^D. The manufacturer and retailer obtain n_t^M and n_t^R data governance services respectively. The supply chain member alliance's profit is π^U, in this case, $q_4=a-bp_4+N_t^M\rho_M\alpha+N_t^R\rho_R\beta$, then at the production cycle "t", the profit function of each member of the supply chain is listed below:

$$\pi^U = (p_4 - c_M - c_R)q_4 - mn_t^D \tag{31}$$
$$\pi_4^B = (m - c_B)n_t^D - k \tag{32}$$

Using backward induction, we can determine the optimal decision:

$$p_4^* = \frac{a + [\sum_{i=1}^{t}(1-\gamma)^{t-i}n_i^M]\rho_M\alpha + [\sum_{i=1}^{t}(1-\gamma)^{t-i}n_i^R]\rho_R\beta + b(c_M - c_R)}{2b} \tag{33}$$
$$q_4^* = \frac{a + [\sum_{i=1}^{t}(1-\gamma)^{t-i}n_i^M]\rho_M\alpha + [\sum_{i=1}^{t}(1-\gamma)^{t-i}n_i^R]\rho_R\beta - b(c_M - c_R)}{2} \tag{34}$$

The optimal profit of each member of the supply chain is:

$$\pi^{U*} = \frac{\{a + [\sum_{i=1}^{t}(1-\gamma)^{t-i}n_i^M]\rho_M\alpha + [\sum_{i=1}^{t}(1-\gamma)^{t-i}n_i^R]\rho_R\beta - b(c_M + c_R)\}^2}{4b} - mn_t^D \tag{35}$$

It should be noted that the prerequisite for the stable operation of the supply chain at this time is: $q_4^* > 0$

$$\frac{a + [\sum_{i=1}^{t}(1-\gamma)^{t-i}n_i^M]\rho_M\alpha + [\sum_{i=1}^{t}(1-\gamma)^{t-i}n_i^R]\rho_R\beta}{b} > c_M + c_R \tag{36}$$

5. Comparative analysis

From the equilibrium solutions and optimal profits of the four governance models, the following conclusions can be drawn.

Proposition 1: In terms of the wholesale price of products, the wholesale price of the single data governance model is the highest, and the wholesale price of the retailer's single data governance is the lowest, $w_3 > w_1 > w_2$.

The wholesale price of a product is influenced by its quality. Therefore, manufacturer data governance improves product quality, which in turn raises the wholesale price. When manufacturer and retailer adopt independent data governance, the data governance services obtained by the retailer give the manufacturer a free-rider effect, increasing the overall demand in the market and the wholesale price of the product, thus $w_3 > w_1 > w_2$. Based on functions (6)(15)(24), the proof is as follows:

$$w_1 - w_2 = \frac{a + [\sum_{i=1}^{t}(1-\gamma)^{t-i}n_i^M]\rho_M\alpha + b(c_M - c_R)}{2b} - \frac{a + [\sum_{i=1}^{t}(1-\gamma)^{t-i}n_i^R]\rho_R\beta + b(c_M - c_R)}{2b}$$
$$= \frac{[\sum_{i=1}^{t}(1-\gamma)^{t-i}n_i^M]\rho_M\alpha - [\sum_{i=1}^{t}(1-\gamma)^{t-i}n_i^R]\rho_R\beta}{2b}$$

Due to $N_t^M\alpha\rho_M > N_t^R\beta\rho_R$, so $w_1 - w_2 > 0$, e. t. $w_1 > w_2$.

$$w_3 - w_2 = \frac{a + [\sum_{i=1}^{t}(1-\gamma)^{t-i}n_i^M]\rho_M\alpha + [\sum_{i=1}^{t}(1-\gamma)^{t-i}n_i^R]\rho_R\beta + b(c_M - c_R)}{2b}$$
$$- \frac{a + [\sum_{i=1}^{t}(1-\gamma)^{t-i}n_i^R]\rho_R\beta + b(c_M - c_R)}{2b} = \frac{[\sum_{i=1}^{t}(1-\gamma)^{t-i}n_i^M]\rho_M\alpha}{2b} > 0$$

e. t. $w_3 > w_2$.
In summary: $w_3 > w_1 > w_2$.

Proposition 2: For market demand, the demand is greatest for the collaborative governance model and least for the retailer single governance model. The demand of independent governance model is greater than manufacturer single governance model, $q_4 > q_3 > q_1 > q_2$.

The additional value provided to consumers in the independent and collaborative governance model are greater than the single governance models, and the demand is positively correlated with the additional value. Correspondingly, the demand is greater. In this case, the independent governance model provides the same additional value to consumers as the collaborative governance model, but the additional costs borne by the independent governance model increase its price. Consequently, the demand decreases, $q_4 > q_3$. Similarly, the additional value provided to consumers by the manufacturer's single governance model is greater than that provided by the retailer's single governance model, so $q_1 > q_2$. Based on functions (8)(17)(26)(34), the proof is as follows:

$$q_1 - q_2 = \frac{a + [\sum_{i=1}^{t}(1-\gamma)^{t-i}n_i^M]\rho_M\alpha - b(c_M + c_R)}{4} - \frac{a + [\sum_{i=1}^{t}(1-\gamma)^{t-i}n_i^R]\rho_R\beta - b(c_M + c_R)}{4}$$
$$= \frac{[\sum_{i=1}^{t}(1-\gamma)^{t-i}n_i^M]\rho_M\alpha - [\sum_{i=1}^{t}(1-\gamma)^{t-i}n_i^R]\rho_R\beta}{4} > 0$$

$$q_3 - q_1 = \frac{a + [\sum_{i=1}^{t}(1-\gamma)^{t-i} n_i^M]\rho_M \alpha + [\sum_{i=1}^{t}(1-\gamma)^{t-i} n_i^R]\rho_R \beta - b(c_M + c_R)}{4} - \frac{a + [\sum_{i=1}^{t}(1-\gamma)^{t-i} n_i^M]\rho_M \alpha - b(c_M + c_R)}{4} = \frac{[\sum_{i=1}^{t}(1-\gamma)^{t-i} n_i^R]\rho_R \beta}{4} > 0$$

$$q_4 - q_3 = \frac{a + [\sum_{i=1}^{t}(1-\gamma)^{t-i} n_i^M]\rho_M \alpha + [\sum_{i=1}^{t}(1-\gamma)^{t-i} n_i^R]\rho_R \beta - b(c_M - c_R)}{2} - \frac{a + [\sum_{i=1}^{t}(1-\gamma)^{t-i} n_i^M]\rho_M \alpha + [\sum_{i=1}^{t}(1-\gamma)^{t-i} n_i^R]\rho_R \beta - b(c_M + c_R)}{4} = \frac{a + [\sum_{i=1}^{t}(1-\gamma)^{t-i} n_i^M]\rho_M \alpha + [\sum_{i=1}^{t}(1-\gamma)^{t-i} n_i^R]\rho_R \beta - b(c_M + c_R)}{4} > 0$$

In summary： $q_4 > q_3 > q_1 > q_2$

Proposition 3: Supply chain members in the independent governance model earn higher profits compared to those in the single governance model, $\pi_3^M > \pi_1^M$, $\pi_3^R > \pi_2^R$.

The independent governance model, where both the manufacturer and retailer handle data governance, has a significantly stronger influence on consumer demand compared to the single governance model. Therefore, supply chain members in the independent governance model earn higher profits than those in the single governance model.. The single data governance model for manufacturers or retailers is common in reality. The asymmetry of data information leads some enterprises to interface with data governance service providers alone in order to achieve data control over consumer preferences. But this does not maximize profits, and performing data governance alone means incurring significant costs and providing a free-rider effect to other supply chain members. Besides, the inequality of data information will make the supply chain less stable and lead to a decrease in overall supply chain profits. Based on functions (9)(19)(27)(28), the proof is as follows:

$$\pi_3^M - \pi_1^M = \frac{\{a + [\sum_{i=1}^{t}(1-\gamma)^{t-i} n_i^M]\rho_M \alpha + [\sum_{i=1}^{t}(1-\gamma)^{t-i} n_i^R]\rho_R \beta - b(c_M + c_R)\}^2}{8b} - mn_t^M - \frac{\{a + [\sum_{i=1}^{t}(1-\gamma)^{t-i} n_i^M]\rho_M \alpha - b(c_M + c_R)\}^2}{8b} - mn_t^M = \frac{\{a + [\sum_{i=1}^{t}(1-\gamma)^{t-i} n_i^M]\rho_M \alpha + [\sum_{i=1}^{t}(1-\gamma)^{t-i} n_i^R]\rho_R \beta - b(c_M + c_R)\}^2}{8b} - \frac{\{a + [\sum_{i=1}^{t}(1-\gamma)^{t-i} n_i^M]\rho_M \alpha - b(c_M + c_R)\}^2}{8b} > 0$$

The same reason can be proved： $\pi_3^R - \pi_2^R > 0$

6. Numerical analysis

To verify the effectiveness of the designed models, we conduct tests. Similar to (P. Liu & Yi, 2018), the parameters are set as follows: $a = 30, b = 0.6, c_M = 4, c_R = 3, \rho_M\alpha = 0.6, \rho_R\beta = 0.7, n_1^M = 15, n_1^R = 10, n_1^B = 20, \theta = 0.3, \gamma = 0.3$.

The variation of total supply chain profit with production cycle under different models is shown in Fig.4.

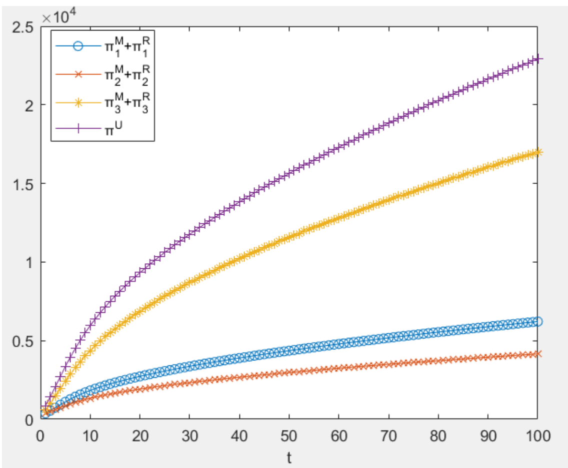

Fig.4. The total profit change chart of the four models

A comprehensive comparison reveals that, regardless of cycle length, the collaborative governance model consistently yields the highest total profit for supply chain participants. As the cycle continues, this profit advantage becomes more and more significant. Therefore, to maximize profits, supply chain members must enhance cooperation, share data, and adopt collaborative governance strategies. In the initial stage when data governance service providers join the supply chain operation, the overall profit of the supply chain increases rapidly. As the production cycle advances, the growth rate of the total system profit slows down. After about the 50th production cycle, the slope of the profit curve changes smaller, the supply chain starts to stabilize.

In actual production, the data governance decisions of supply chain members are often affected by various factors. To further analyze the fluctuation of data governance decisions, the paper selects the supply chain when t=50 taking the operation status of the chain as an example, we will further analyze various influencing factors.

6.1 Impact of price elasticity of demand

The supply chain produces various products, each with distinct price elasticities of demand. To examine how goods with different elasticities affect supply chain performance, while holding other parameters constant, a demand elasticity range of b (0, 5) is selected for most products. Fig. 5 illustrates how the supply chain's overall profit varies with changes in demand elasticity.

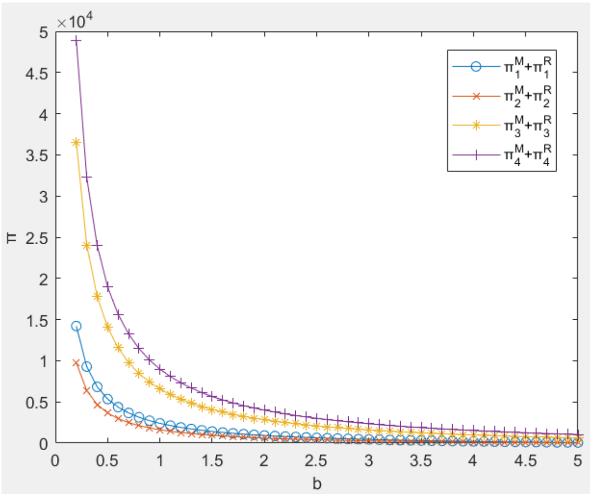

Fig. 5. Impact of price elasticity of demand on total supply chain profit

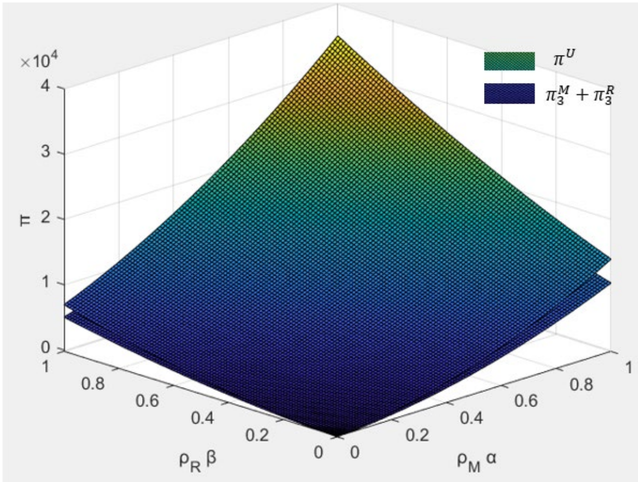

Fig. 6. Profit impact of demand conversion rate on independent and collaborative governance models

As shown in Fig. 5, the overall profit of the supply chain clearly decreases as the price elasticity of demand increases under different models, and it decreases rapidly when it is inelastic (b<1) and slowly when it is elastic (b>1). When demand elasticity is low, the total profit under the collaborative data governance model significantly exceeds that of the other models. The gap between the total supply chain profit of the four models becomes smaller and smaller as the price elasticity of demand increases. Data governance by supply chain members will provide additional value for consumers, resulting in higher prices. In this scenario, for products with lower price elasticity of demand, consumers will not significantly reduce their demand, and thus supply chain profits are better. A comprehensive comparison reveals that the collaborative data governance model yields the highest profit, with the gap between the four models narrowing as the price elasticity of demand increases. Indicate that for products lacking price elasticity of demand, the collaborative data governance model is more effective in enhancing the supply chain profit. Therefore, supply chain members should strengthen cooperation, realize information sharing, and implement data governance for products with low price elasticity of demand under the collaborative data governance model.

6.2 Impact of demand conversion rate on supply chain performance

The demand conversion rate directly affects the increased demand for the services obtained by manufacturers and retailers. To analyze how varying demand conversion rates affect total profit under the independent and collaborative governance models, while keeping other parameters constant, $\rho_M \alpha$、 $\rho_R \beta$ are taken as (0, 1). Fig. 6 illustrates how the total supply chain profit changes with the demand conversion rate of data governance products. Fig. 6 illustrates that the supply chain profit under the collaborative data governance model consistently exceeds that of the independent model. As the demand conversion rate rises, both total profit and the profit gap between the two models increase. The demand conversion rate directly affects the amount of demand converted by the acquired data governance services. The increment of demand increases with the rate of demand conversion and the total profit increases with it. In addition, the collaborative governance model is more sensitive to the increase in conversion rate. The increase in conversion rate brings more incremental profits to the collaborative governance model. Therefore, manufacturers and retailers should strengthen the analysis capability of data governance services to improve the demand conversion rate, and choose a collaborative governance model to maximize its utility.

6.3 Impact of learning capability of data governance service providers on supply chain decision-making and performance

The learning capability of the data governance service provider determines the incremental output of data governance services in each production cycle. To examine how learning capability affects decision-making and performance in the supply chain, keeping other parameters constant, and to obtain more effective conclusions and combine them with reality, θ is taken as (0, 0.5). The changes of product demand and system profit with the learning capability of the data governance service provider are shown in Fig.7 and Fig.8.

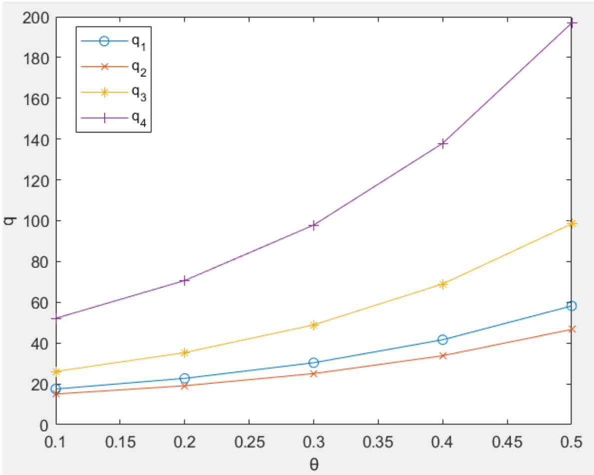

Fig.7. Effect of learning ability on demand

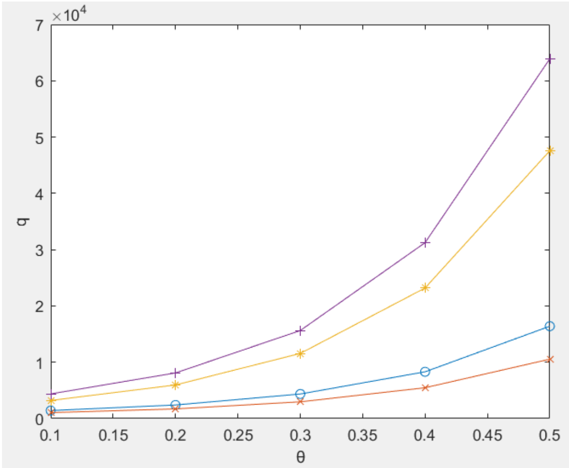

Fig. 8. Effect of learning ability on total profit

From Fig. 7 and Fig. 8, we observe that both the product demand and system profit in different governance models are on the rise with the improvement of the learning capability of data governance service providers. The demand and profit of independent governance model and collaborative governance model are significantly superior to the case of single data governance. Where, the demand and profit of collaborative data governance models are the highest. Data governance service provider learning capability directly affects the output of data governance services. The volume of service output from data governance service providers increases with the learning capability. Accordingly, the price consumers are willing to pay increases, and the supply chain can use this data information to expand market demand and thus increase profits. A comprehensive comparison reveals that the enhanced learning ability of data governance service providers makes the collaborative data governance model superior to other governance models. And its system profit tends to accelerate with the increase of θ, which to a certain extent also demonstrates the future development potential of the collaborative data governance model. Firstly, based on learning effect theory, the learning ability of data governance service providers improves with advancements in technology and the length of governance service. In this context, the selection of the data governance model plays a critical role in maintaining and enhancing the competitiveness of the supply chain and its member enterprises. Secondly, as the learning ability of data governance service providers increases, it will inevitably elevate the overall data governance level across the entire supply chain, thereby improving supply chain performance. And then, promote the improvement of the overall performance of the supply chain. Therefore, data governance service providers should enhance their data collection and processing capabilities and strengthen their learning ability to optimize the overall efficiency of the supply chain.

6.4 The impact of knowledge hysteresis rate of data governance services on supply chain decisions and performance

The knowledge hysteresis rate of data governance services reflects the time lag and effectiveness of the service, with its level impacting the cumulative services available to supply chain members. To analyze how varying lag rates affect supply chain decisions and performance, keeping other parameters constant, γ is taken as (0, 1). The changes of product demand and system profit with the knowledge hysteresis rate of data governance products are shown in Fig.9 and Fig.10. From Fig. 9 and Fig. 10, we observe that under different governance models, both product demand and system profit tend to decrease as the knowledge hysteresis rate increases. And the demand and profit of independent governance model and collaborative governance model are significantly superior to the case of single data governance. The knowledge hysteresis rate determines the present-day availability of governance services. The cumulative availability of data governance services increases as the knowledge lag rate decreases. The price and demand for the product also increases, thereby increasing total profit. As the hysteresis rate increases, the profit gap of each governance model becomes smaller. The profit of the collaborative governance model is much larger than the other models when the hysteresis rate is low, and the profit under each model is at a lower level when $\gamma > 0.6$. Therefore, on the one hand, for governance model selection, the collaborative data governance model can maximize overall supply chain profit when the knowledge lag rate is low. On the other hand, for data governance service providers, as the knowledge hysteresis rate decreases, supply chain profit increases. So, data governance service providers should focus on researching consumers' long-term demand preferences, providing data governance services with lower knowledge hysteresis rate, and appropriately reducing the output and input of services for short-term preferred products.

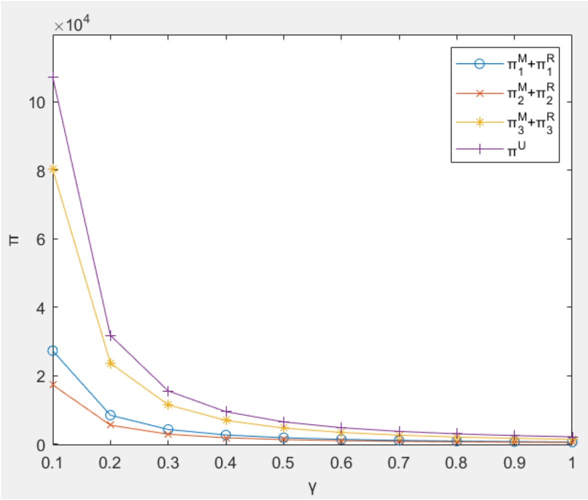

Fig. 9. Impact of knowledge hysteresis rate on demand

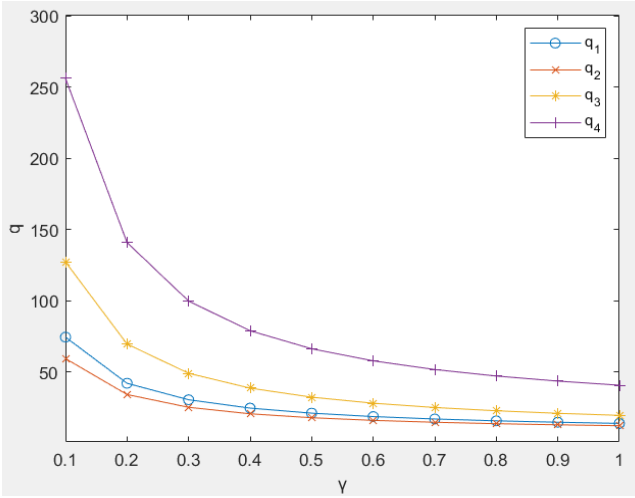

Fig. 10. Impact of knowledge hysteresis rate on d total profit

7. Conclusions

As the economy grows and living standards rise, consumer demand is becoming increasingly diverse. Supply chain members are in urgent need of consumer demand data in order to provide products and services that meet consumer preferences. In view of this, supply chains introduce data governance service providers to collect and process consumer demand preference data. Ultimately, data governance services are generated for supply chain members to boost enterprise and supply chain profits. This paper examines the supply chain with data governance service providers, develops models under four different frameworks, and presents the following conclusions.

(1) Data governance by supply chain members can increase their revenue, and as the production cycle advances, the collaborative governance model achieves the highest overall profit and demand.

(2) When supply chain members engage in data governance, selecting inelastic products, improving the demand conversion rate of manufacturers and retailers, improving the learning ability of data governance service providers, and reducing the knowledge lag rate can significantly boost supply chain profits. The sensitivity to these factors is highest, and the profit increase is greatest under the collaborative governance model.

(3) Many enterprises choose the single data governance to obtain data governance services exclusively in reality, but it is not the best choice for enterprises. Supply chain members should strengthen cooperation and information sharing, and manufacturers and retailers should adopt a collaborative governance model to maximize profits.

This study analyzes the profits of supply chain members across four different governance models involving data governance service providers. Draws a series of relevant conclusions through the comparison of all results and simulations, which provide references for real-life supply chain decisions and have important practical significance and theoretical basis.

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