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Analysis of Retailer-led Supply Chain Decision-making Models and Their Complex Systems in the Context of Artificial Intelligence

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Abstract

Against the backdrop of increasingly mature artificial intelligence (AI) technology, this paper explores the application of AI in retailer-led supply chain management, highlighting its potential to enhance efficiency and reduce costs. By constructing a model that incorporates service quality and cost, the study examines how online retailers can utilize generative language large models to optimize services and analyzes the impact of data integration capabilities and product timeliness on market demand. The article establishes static and dynamic models to analyze the optimal strategies under cost-sharing contracts and pricing strategies in long-term games. Numerical simulations show that appropriate cost-sharing and adjustment parameters are crucial for supply chain stability and profits. The research results indicate that AI technology can significantly improve supply chain efficiency, but it is necessary to handle data volume, cost-sharing, and dynamic adjustment strategies with caution.

Keywords

Artificial Intelligence; Supply Chain Management; Cost Sharing; Complex Dynamics; Generative Language Models; Dynamic Games.

1. Introduction

Artificial intelligence has become an important auxiliary tool in people's daily lives, and enterprises are gradually using it to serve themselves. According to the data from NMSC, the global market value of explainable artificial intelligence (XAI) was 4.4 billion US dollars in 2021. It is expected to reach 21 billion US dollars by 2030. It is predicted that from 2022 to 2025, the adoption rate of artificial intelligence in enterprises engaged in supply chain and manufacturing operations will increase. However, in the current market environment, artificial intelligence technology is often in the hands of large technology companies, which are also often retail giants. That is, downstream enterprises possess artificial intelligence technology and cooperate with upstream enterprises to conduct business activities. Although the rational application of artificial intelligence technology can bring huge profits to enterprises, artificial intelligence requires continuous data input and research and development by enterprises, and it grows continuously in this process. Therefore, in this process, retail enterprises need to face the high cost of developing artificial intelligence models and the uncertainty brought by using artificial intelligence for business activities. Consequently, retailers and manufacturers need to constantly adjust their decisions based on the improvement level and revenue effect of artificial intelligence, so as to bring more profits to themselves. Therefore, how to adjust the contract design according to the state of artificial intelligence is a key issue that enterprises in the upstream and downstream of the supply chain urgently need to solve.

The article "GPTs are GPTs" released by OpenAI in 2023 has drawn widespread attention from the entire society. The article predicts that artificial intelligence natural language processing modules will be almost applied to all industries, from supply chain management to product innovation. The introduction of artificial intelligence programs can greatly improve and enhance business operations. Such a huge market scale and industry influence are worth in-depth exploration. Regarding the research on artificial intelligence technology in the supply chain, a large number of scholars have begun to study the impact of artificial intelligence on various industries in recent years. Li et al. [1] found that generative artificial intelligence can effectively integrate supply chain management issues and fully coordinate supply chain performance issues. Li et al. [2] found from a practical perspective that artificial intelligence can effectively act on sustainable supply chain performance and provide a favorable guarantee for the effect of the circular economy. Weise et al. [3] found that the application of artificial intelligence is also deeply influenced by people's trust and proposed five levels to further explore the use and effects of artificial intelligence by managers based on different trust levels. Cadden et al. [4] designed a hypothesis based on the examination of the relationship between supply chain culture and artificial intelligence and confirmed that artificial intelligence has a transformative power for all industries. Modgil et al. [5] proved that in the event of extreme disasters, artificial intelligence can effectively handle a series of impacts caused by supply chain disruptions, thereby reducing the losses of enterprises. Han et al. [6] found that artificial intelligence can reduce the risk of supply chain centralization and thereby improve the performance of enterprises. Danach et al. [7] proposed a novel AI-driven strategy based on typical cases and verified its effectiveness for artificial intelligence supply chains. Sharma et al. [8] explained that in the current era, artificial intelligence has become the most important business science, and enterprises need to serve themselves based on artificial intelligence and thereby improve the process value of the supply chain. All the above scholars explored and explained the importance and value of artificial intelligence for supply chain activities from the perspectives of qualitative and quantitative analysis, but a small number of scholars further explained the disruptive impact of artificial intelligence technology on traditional supply chains from the perspective of mathematical model construction. Wang et al. [9] evaluated the impact of artificial intelligence technology on supply chain performance from the perspective of whether artificial intelligence is used in the front and back ends of the supply chain, and the experiment verified that the application of artificial intelligence will effectively affect the traditional supply chain. Zhang et al. [10] verified the effect of online retailers using artificial intelligence customer service, and the research showed that the operation of artificial intelligence customer service can effectively increase product sales and simultaneously increase the profits of online retailers. Arnab Adhikari et al. [11] verified the effect of using artificial intelligence in the medical supply chain during disasters, and the research proved that artificial intelligence technology can effectively handle the possible emergencies of traditional supply chains. Rajkishore et al. [12] verified that enterprise activities are deeply influenced by sustainable development, customer experience, and the implementation of artificial intelligence technology.

The application of complex dynamic theory in the supply chain is relatively novel. It plays a very important role in predicting the instability of the system and thereby avoiding system chaos [13]. In the current research on supply chain games, most scholars mainly focus on single-cycle applications. However, in the long-term games of economic systems, some scholars have already adopted a dynamic research perspective and obtained better deterministic strategies. Lin et al. [14] explained how the social preferences of retailers in the context of low carbon affect the complexity of the system and, in this context, how decision-makers should make decisions so that the game can develop in an optimal direction. Zhang et al. [15] found that from the perspective of long-term game theory, consumer preferences will have a certain impact on the stability of the system, and the decisions of supply chain members in complex systems have an uncertain impact on their own benefits. Hu et al. [16] confirmed that in the event of unexpected situations, the green logistics supply chain can effectively provide solutions by using complex dynamic models, thereby reducing losses for enterprises. Trienekens et al. [17] demonstrated that the complexity and dynamics of the food supply chain, as well as the significance of transparency within it, can be fully verified by leveraging complex dynamic modelability, thereby enhancing the efficiency of enterprises by adjusting transparency. Kalla et al. [18] demonstrated that modern enterprises cannot merely rely on static structures to design strategic plans for themselves. Instead, they should make dynamic adjustments in a timely manner and find that enterprises that design complex adaptive systems based on their own conditions will have better corporate returns. Therefore, in this study, we will focus on analyzing the complex dynamic issues in the context of a supply chain dominated by service providers.

AI models optimize themselves and improve service quality by constantly absorbing and learning data. This multi-stage complex process requires enterprises to constantly adjust and optimize during the service provision process to adapt to market changes and user demands, ensuring the efficient operation of the supply chain and the optimization of cost-effectiveness. Therefore, this article aims to study and answer the following questions.

1. Will the information richness of generative language large models bring more profits to online retailers? What kind of impact will it have on the entire supply chain?

2. What changes will occur in the cost-sharing contract in dynamic games, what is its impact on the supply chain, and what is the optimal value of the cost-sharing coefficient in dynamic games?

3. Conduct an evolutionary analysis of the long-term dynamic game behavior of information decision-making and pricing strategies in the supply chain, with the aim of identifying the deeper causes of the chaos in the artificial intelligence supply chain and providing a theoretical basis for the strategies made by decision-making subjects such as manufacturers and retailers when facing the chaos of the supply chain system.

2. Organization of the Text

This article considers a two-level supply chain composed of a single retailer and a single manufacturer. Large retailers act as pioneers to make the first decisions on the amount of data they need to use and the marginal profit they want to obtain (marginal profit m= retail price p-wholesale price w), while manufacturers, as followers, determine the wholesale price w of the products they manufacture. From the above text, it can be seen that when manufacturers are aware of the existence of AI technology in the market (that is, when retailers use AI technology to serve themselves, improve service quality, and increase market demand), the basic demands of both parties for the market will gradually converge. And for better cooperation, it is assumed that both parties implement cost-sharing contracts and then conduct more in-depth cooperation. Increase market demand and profits for both parties.

Assumption 1： The products sold by online retailers all bring a certain amount of data e to the large model. Large online retailers such as JD and Taobao create AI big data models based on their own capabilities and demands to serve themselves. According to the research of Zhang et al. [19], it is assumed that $S = xe$ represents the service quality function of AI technology, and x represents the data integration capability of large retailers. $x \in (0,1)$.

Hypothesis 2： According to the research of Liang et al. [20], any product has its timeliness, which will affect market demand. When AI technology is adopted, the time required for the entire supply chain to complete the sale of the product is T, while without technology, the time required is t, and T<t. And people's preference for time (sensitivity coefficient) is assumed to be β.

Hypothesis 3： According to the research of Lou et al. [21], it is assumed that there is a perfectly competitive market, and thus the product price p is an exogenous variable. For the convenience of calculation, in this paper, the marginal profit m is taken as the decision variable. Its meaning is that the marginal profit m is equal to the difference between the retail price p and the wholesale price w, p=m+w, m=p-w. Meanwhile, the market sales volume at this price is affected by the amount of product data. Furthermore, assume the product sales volume $q = a - bp - T\beta + (xe)d$ (1), where a represents the basic market demand. Since this product has a certain number of loyal customers in the market, it satisfies a > 0, and d represents the degree of consumers' preference for artificial intelligence. This means that as the volume of product data conversion increases, the market sales volume will increase.

Assumption 4: There are two types of costs that technology service providers have to deal with: variable costs and fixed costs. Variable costs are represented by v, $v(e) = \frac{1}{2}ue^2$. u represents the sensitivity of service payment to service level, and u>0. F is the fixed investment made by the technology service provider in the early stage of researching large models, represented by F.

To achieve a win-win situation, retailers and manufacturers sign cost-sharing contracts. That is, manufacturers help online retailers bear part of the technology research and development costs. So we assume that w is the wholesale price, c is the production cost per unit of product, p is the retail price of the product, p=m+w, and 0 < c < w < p. The allocation coefficient of variable costs is 0< <1, and that of fixed costs is 0< <1. Therefore, the profit function has changed accordingly compared with the previous text. The changed profit function is as follows:

$$\pi_r = (p - w)q - (1 - \theta)v - (1 - \phi)F \tag{2}$$

$$\pi_m = (w - c)q - \theta v - \phi F \tag{3}$$

3. Static decision-making

In the expectation of static decision-making, only the optimal solution of the current decision is considered, and the optimal solution led by the retailer is solved first. Firstly, according to the manufacturer's profit formula in (3), it can be obtained $\frac{\partial^2 \pi_m}{\partial w^2} = -2b < 0$, that there is a maximum value of w in $\frac{\partial \pi_m}{\partial w} = 0$. Therefore, from this, we can obtain:

$$w^* = \frac{dex - T\beta + bc - bm + a}{2b} \tag{4}$$

After obtaining the response function of w with respect to π_r, substitute (4) back into (3) to obtain the updated function:

$$\pi_r^* = \phi F - F + \frac{1}{2}am - \frac{1}{2}bm^2 - \frac{1}{2}e^2u + \frac{1}{2}e^2\theta u - \frac{1}{2}T\beta m - \frac{1}{2}bcm + \frac{1}{2}demx \tag{5}$$

The joint concavity of the decision variables m and e in the updated Hesse matrix is as follows:

$$H = \begin{bmatrix} -b & \frac{dx}{2} \\ \frac{dx}{2} & \theta u - u \end{bmatrix}$$

According to the determination method of the Hesse matrix, it can be obtained $|H_1|$=-b<0，$|H_2| = bu - \frac{1}{4}d^2x^2 - b\theta u$.

So let $bu-\frac{1}{4}d^2x^2-b\theta u>0$, that is, $0<\theta<1-\frac{d^2x^2}{4bu}$ (limit the condition), at this time m and e are the joint concave functions of about π_r.

Based on the above conditions, take the first-order derivatives of m and e respectively with respect to π_r, and set them equal to zero for simultaneous solution.

$$\begin{cases}\frac{\partial}{\partial m}(\pi_r)=0\\ \frac{\partial}{\partial e}(\pi_r)=0\end{cases} \tag{6}$$

According to (6), the response functions of m and e with respect to π_r, that is, the equilibrium solutions of m and e, are as follows:

$$m^*=-\frac{2u(\theta-1)(T\beta+bc-a)}{d^2x^2+4b\theta u-4bu} \tag{7}$$

$$e^*=\frac{dx(T\beta+bc-a)}{d^2x^2+4b\theta u-4bu} \tag{8}$$

Substitute m^* and e^* back into w^* to obtain the equilibrium solution of w.

$$w^*=\frac{-(\theta-1)(T\beta-3bc-a)u+cd^2x^2}{4u(\theta-1)b+d^2x^2} \tag{9}$$

Substitute m^*, e^*, and w^* back into (2) and (3) to obtain the equilibrium solutions of π_r and π_m:

$$\pi_r^*=\frac{8\left(\frac{b^2c^2}{8}+\left(\frac{\beta Tc}{4}+(\phi-1)F-\frac{ac}{4}\right)b+\frac{(T\beta-a)^2}{8}\right)(\theta-1)u+2Fd^2x^2(\phi-1)}{8u(\theta-1)b+2d^2x^2} \tag{10}$$

$$\pi_m^*=\frac{bu^2(\theta-1)^2(T\beta+bc-a)^2}{16\left(u(\theta-1)b+\frac{d^2x^2}{4}\right)^2}-\phi F-\frac{d^2\theta ux^2(T\beta+bc-a)^2}{32\left(u(\theta-1)b+\frac{d^2x^2}{4}\right)^2} \tag{11}$$

From the above equilibrium solution, Corollary 1 can be obtained.

Corollary 1. Because a is much larger than the other parameters, so $\frac{\partial m}{\partial\theta}=\frac{u(a-T\beta-bc)d^2x^2}{8\left(u(\theta-1)b+\frac{d^2x^2}{4}\right)^2}>0$, $\frac{\partial e}{\partial\theta}>0$, $\frac{\partial w}{\partial\theta}>0$, $\frac{\partial\pi_r}{\partial\theta}>0$, $\frac{\partial\pi_r}{\partial\phi}>0$, $\frac{\partial\pi_m}{\partial\phi}<0$, $\frac{\partial\pi_m}{\partial\theta}=\frac{u\left(-\frac{d^2x^2}{8}+b\theta u\right)(T\beta+bc-a)^2x^2d^2}{16\left(u(\theta-1)b+\frac{d^2x^2}{4}\right)^3}$. At this point, a case-by-case discussion is needed, when $0<\theta<\frac{d^2x^2}{8bu}$, $\frac{\partial\pi_m}{\partial\theta}<0$, when $\frac{d^2x^2}{8bu}<\theta<1-\frac{d^2x^2}{4bu}$, $\frac{\partial\pi_m}{\partial\theta}>0$.

Corollary 1 explains the impact of the allocation coefficients of fixed and variable costs on decision variables and profits. As the variable cost-sharing coefficient increases, m^*, e^*, w^* and π_r^* increase accordingly, while z first decreases and then increases. It can also be seen that the fixed cost allocation coefficient is independent of m^*, e^* and w^*, but is related to π_r^* and π_m^*. π_r^* increases as it increases, and π_m^* decreases as it decreases. From this, it can be seen that for retailers, the larger the cost-sharing coefficient, the higher the profit. However, for manufacturing, only when the variable cost-sharing coefficient is within a certain range, such as $0<\theta<\frac{d^2x^2}{8bu}$, can a higher profit be achieved. Therefore, in order to achieve a win-win cooperation effect, only by controlling the variable cost allocation coefficient within the range of $0<\theta<\frac{d^2x^2}{8bu}$ can the overall profit effect of the supply chain be relatively optimal.

4. Static decision-making

After analyzing the single-cycle model, we will examine how the long-term game between pricing strategies and information injection strategies has evolved. The supply chain system is a dynamic and complex system with long-term changing characteristics. And this complex feature will intensify as the number of members and channels in the supply chain increases. In previous studies, scholars often only considered the situation of a single period, but were lacking in the research on the complex characteristics of multiple periods. This study assumes that the pricing strategy of service technology providers is set under bounded rationality conditions and the price is adjusted according to marginal profit.

$$\begin{cases} m(t+1)= m(t)+\alpha_1 m(t)\dfrac{\partial}{\partial m(t)}\left(\pi_r(m,e)\right) \\ e(t+1)= e(t)+\alpha_2 e(t)\dfrac{\partial}{\partial e(t)}\left(\pi_r(m,e)\right) \end{cases} \tag{12}$$

Among them, α_1 is the marginal profit adjustment parameter, α_2 is the data volume adjustment parameter, and α_1, α_2 > 0. Substituting equation (6) into equation (12), the discrete dynamical system of the game model can be obtained as:

$$\begin{cases} m(t+1)=m(t)+\alpha_1 m(t)\left(\dfrac{1}{2}a-bm-\dfrac{1}{2}T\beta-\dfrac{1}{2}bc+\dfrac{1}{2}dex\right) \\ e(t+1)=e(t)+\alpha_2 e(t)(-eu+e\theta u+\dfrac{1}{2}dmx) \end{cases} \tag{13}$$

Equation (13) represents the decision variables of online retailers. The marginal profit of the decision and the input of big data are related to the adjustment parameters, while the wholesale price of the manufacturer is related to the overall demand. According to Equation (4), it can be known that the dynamic wholesale price is:

$$w(t+1)=\frac{\alpha_1 m\left(c+2m\right)b^2+\left(\left(-2+\left(-dex+T\beta-a\right)\alpha_1\right)m+2c\right)b+d^2x^2\alpha 2em+2xe\left(1+\alpha 2u\left(\theta-1\right)e\right)d-2T\beta+2a}{4b} \tag{14}$$

First, based on the definition of fixed points, the three equilibrium points of Equation (10) are obtained as E_1=(0,0) , E_2=($-\frac{T\beta+bc-a}{2b}$,0) and E_3=(m^*, e^*) respectively, among which E_1 and E_2 are boundary equilibrium points, and E_3 is the Stackelberg equilibrium point. To analyze the stability of the system equilibrium point, the Jacobian matrix of Equation (18) is first calculated:

$$\begin{cases} f_1 = m + \alpha_1 m\left(\frac{1}{2}a - bm - \frac{1}{2}T\beta - \frac{1}{2}bc + \frac{1}{2}dex\right) \\ f_2 = e + \alpha_2 e(-eu + e\theta u + \frac{1}{2}dmx) \end{cases} \tag{15}$$

$$J(E) = \begin{pmatrix} \frac{\partial}{\partial m}(f_1) & \frac{\partial}{\partial e}(f_1) \\ \frac{\partial}{\partial m}(f_2) & \frac{\partial}{\partial e}(f_2) \end{pmatrix} \quad J(E) = \begin{pmatrix} 1+\alpha_1\rho_1 & \frac{\alpha_1 dmx}{2} \\ \frac{\alpha 2dex}{2} & 1+\alpha_2\rho_2 \end{pmatrix} \tag{16}$$

Among them, $\rho_1 = \frac{(-c-4m)b}{2} + \frac{dex}{2} - \frac{T\beta}{2} + \frac{a}{2}$, $\rho_2 = \frac{(4u(\theta-1)e + dmx)}{2}$.

The characteristic equation of $J(E)$ is $\lambda^2 - Tr(J(E))\lambda + Det(J(E)) = 0$, and according to Jury's criterion, the necessary and sufficient condition for the local stability of the Jacobian matrix is:

$$\begin{cases} 1 + Tr(J) + Det(J) > 0 \\ 1 + Tr(J) - Det(J) > 0 \\ 1 - Det(J) > 0 \end{cases} \tag{17}$$

$$Tr(J(E)) = \frac{\left(xe_2(h+1)d - bc - 4bw + a\right)\alpha}{2} + 2 + \frac{\left(wx(h+1)d - 4\varpi mh^2 e_2 - 2v_0 u + 2zk\right)\beta}{2}$$

$$Det(J(E)) = \frac{\left(\left(4dux(\theta-1)e^2 - 4\left((c+4m)b + T\beta - a\right)(\theta-1)ue - dm\left((c+4m)b + T\beta - a\right)x\right)\alpha 2 + 2dex + (-2c-8m)b - 2T\beta + 2a\right)\alpha_1}{4} + 1 + \frac{\left(8u(\theta-1)e + 2dmx\right)\alpha_2}{4}$$

From the above characteristic equation, Corollary 2 and Corollary 3 can be obtained.

Corollary 2. When $E_1(0,0)$ is substituted in, $\lambda_1 = -\frac{\sqrt{(T\beta+bc-a)^2\alpha_1^2}}{4} + \frac{(-T\beta-bc+a)\alpha_1}{4} + 1$ and $\lambda_2 = \frac{\sqrt{(T\beta+bc-a)^2\alpha_1^2}}{4} + 1 + \frac{(-T\beta-bc+a)\alpha_1}{4}$. Since a is much greater than the other parameters, it is easy to prove that $|\lambda_i| > 1$. Therefore, E_1 is unstable.

When $E_2(\frac{a-T\beta-bc}{2b}, 0)$ is substituted in, $\lambda_1 = \frac{2\alpha_1 b^2 c + \left((2T\beta-2a)\alpha_1 - dx\alpha_2 c - 2\frac{(a-T\beta-bc)\left(\frac{\alpha_2 dx}{2} + \alpha_1 b\right)}{b} + 8\right)b - dx\alpha_2(T\beta - a)}{8b}$ and

$$\lambda_2 = \frac{2\alpha_1 b^2 c + \left((2T\beta-2a)\alpha_1 - dx\alpha_2 c + 2\frac{(a-T\beta-bc)\left(\frac{\alpha_2 dx}{2} + \alpha_1 b\right)}{b} + 8\right)b - dx\alpha_2(T\beta - a)}{8b}$$

, that is, $\lambda_1 = \frac{-dx(a-T\beta-bc)\alpha_2 + 4b}{4b}$ and $\lambda_2 = 1 + \frac{\alpha_1(a-T\beta-bc)}{2}$. It is easy to prove that $|\lambda_1| < 1$ and $|\lambda_2| > 1$. Therefore, E_2 is unstable and a saddle point.

Corollary 3. $E_3(m^*, e^*)$ is the Stackelberg equilibrium point. At this time, the necessary and sufficient condition for it to be a stable point is as follow:

$$\begin{cases} 1+Tr(J(E_3))+Det(J(E_3))>0 \\ 1+Tr(J(E_3))-Det(J(E_3))>0 \\ 1-Det(J(E_3))>0 \end{cases} \tag{18}$$

$$Tr(J(E_3))=\frac{2\left(\alpha_1 b^2 c+\left(\frac{\alpha 2cdx}{2}+4+\left(T\beta-a\right)\alpha_1\right)b+\frac{\alpha 2dx\left(T\beta-a\right)}{2}\right)\left(\theta-1\right)u+2d^2x^2}{4u\left(\theta-1\right)b+d^2x^2}$$

$$Det(J(E_3))=\frac{\left(2+\left(T\beta+bc-a\right)\alpha_1\right)\left(\alpha_2 x\left(T\beta+bc-a\right)d+4b\right)\left(\theta-1\right)u+2d^2x^2}{8u\left(\theta-1\right)b+2d^2x^2}$$

The characteristic equation of $J(E_3)$ is $\lambda^2-Tr(J(E_3))\lambda+Det(J(E_3))=0$, and according to the Jury criterion, its specific expression is

$$\begin{cases} \left(\alpha_2 x\left(T\beta+bc-a\right)d+8b\right)\left(4+\left(T\beta+bc-a\right)\alpha_1\right)\left(1-\theta\right)u>8d^2x^2 \\ \left(\alpha_1\alpha_2 x\left(T\beta+bc-a\right)^2 d-16b\right)\left(1-\theta\right)u<-4d^2x^2 \\ \left(a-T\beta-bc\right)\alpha_1<2+\dfrac{4\alpha_1 b}{\alpha_2 d} \end{cases} \tag{19}$$

Starting from practical significance, the economic significance of the stability of the three equilibrium points of the system is analyzed. At point $E_1(0,0)$, when the marginal profit and data volume are both 0, the wholesale price is also 0. At this point, both retailers and manufacturers may exit the market and abandon their industries. Therefore, the equilibrium point at this time is unstable. At $E_2(-\frac{T\beta+bc-a}{2b},0)$, the data volume is 0, but the marginal profit is positive. The demand will decrease, and the profits of retailers and manufacturers will also decline as a result. Moreover, the fixed costs invested in the early stage for research and development do not yield returns, which is rarely seen in reality. Therefore, the system is also unstable at this time. At the equilibrium point $E_3(m^*,e^*)$, both parties will aim to maximize their own profits, and at this time, they are in Stackelberg equilibrium, and its stability is simultaneously constrained by the Jury criterion.

5. Numerical simulation

Numerical simulation will be conducted on the dynamic model to explore the impact of adjusting parameters and cost-sharing coefficients on the system stability domain, marginal profit, data processing volume, wholesale price, as well as the profits of manufacturers, retailers, and the supply chain. Let a=150,b=2,x=0.1,d=1.5,u=0.01,T=1,c=10,β=20,F=10. The values of these parameters conform to the assumptions and relevant constraints of this paper.

5.1. The influence of adjusting parameters on the stability domain of the system

Figure 1 shows the Nash equilibrium stable domain presented by the discrete difference equation (15). It demonstrates the corresponding impact of cost allocation on system stability in a dynamic situation. In the figure, $\alpha_i(i=1,2)$ and θ=0.1,0.3,0.5 represent the corresponding adjustment parameters. When the apportionment coefficient is adjusted within a stable region, the Nash equilibrium is locally stable. In terms of the allocation coefficient, since it is assumed that the fixed investment is a one-time investment, it does not directly affect the marginal profit and the volume of data. And as can be seen in Figure 1, when the variable income allocation coefficient is constant, the impact effect of the data volume adjustment rate on system stability is greater than that of the marginal profit adjustment rate. Moreover, it can be clearly seen from Figure 2 that when θ=0.1, the stability region of the system is the largest. Therefore, it can be roughly observed that the allocation coefficient between 0 and 0.1 can maximize the benefits for both parties in the supply chain.

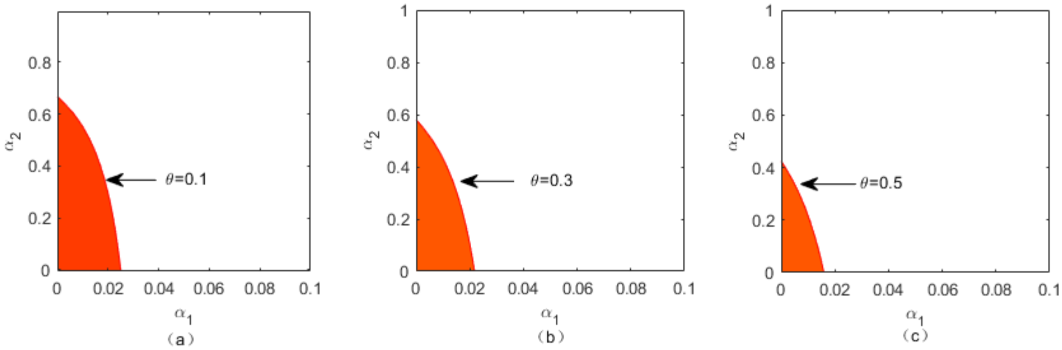
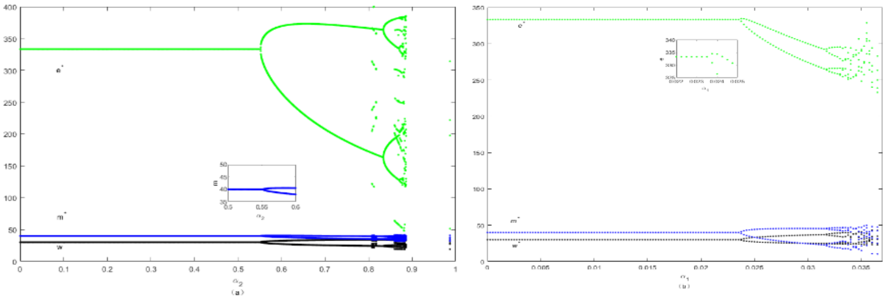


Fig. 1 The influence of the apportionment coefficient on the stability domain of the system

Conclusion 1. The impact of data volume adjustment parameters on system stability is greater than that of marginal profit adjustment parameters. The variable cost allocation coefficient can reach the optimal value point within the range of 0 to 0.1.

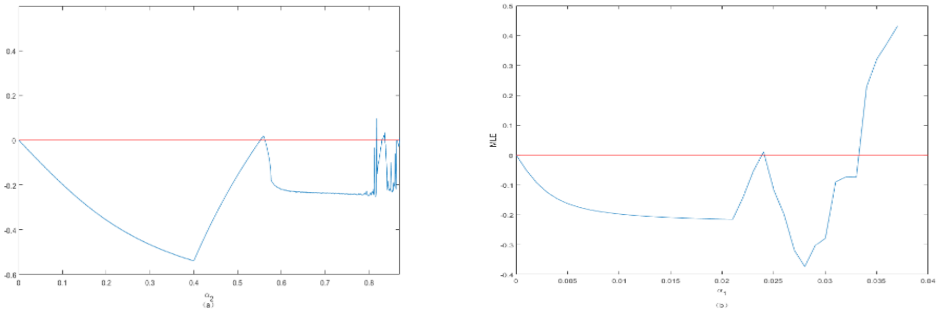
5.2. The subgraph of the system, the maximum Lyapunov exponent graph and the chaotic attractor

The following will explore the impact of adjusting parameter $\alpha_i (i=1,2)$ on system stability. At this point, take θ=0.1 to further explore the current system. At this point, based on the parameter values, the Stackelberg equilibrium point can be determined as $E_3(40,333.33)$. Figures 3 and 4 respectively show the subgraphs and attractors of the system as the adjustment parameters change. Figures 3 (a) and (b) and 4 (a) and (b) respectively show the changes when the fixed adjustment parameters α_1=0.01 and α_2=0.1 are adjusted. It can be seen from the figures that the decision variables e, m and w are stable in the initial period of system adjustment, and then enter a chaotic state. When α_1=0.01, the decision variables start to bifurcate successively after α_2 exceeds 0.55. When α_2=0.1, the decision variables in the system start to enter a chaotic bifurcation state when α_1=0.0237559. All of them enter the two-fold bifurcation region, the four-fold bifurcation region and then the eight-fold bifurcation region from the steady state of the system, which reflects that the system has corresponding periodic characteristics. From the attractor diagram in Figure 5, it can be more clearly demonstrated that as time progresses and the adjustment parameters increase, the system will enter the corresponding chaotic state. Chaos implies uncertainty, and the stronger the chaos, the greater the uncertainty. Therefore, only when the adjustment parameters are within a certain range can the system enter a stable state, and then the optimal solutions for each decision variable under the corresponding conditions can be obtained.



(a) (b)

Fig. 3 The bifurcation diagram of the decision variable varying with the adjustment parameters



(a) (b)

Fig. 4 The maximum Lyapunov index chart

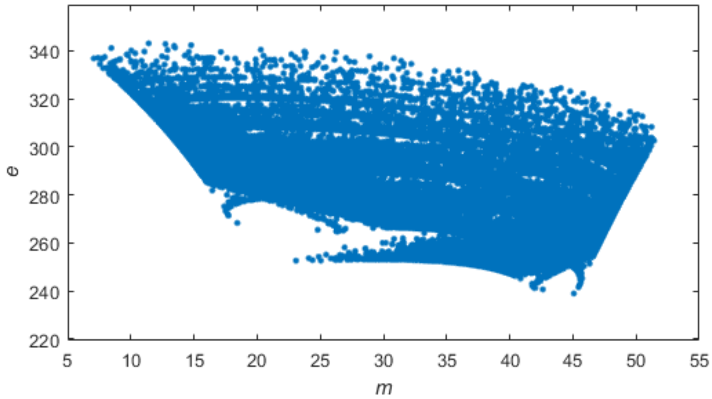
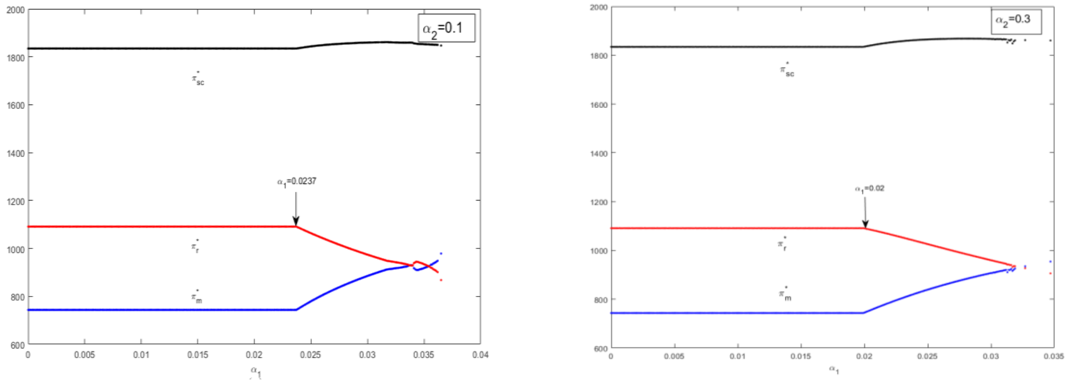


Fig. 5 Chaotic attractors in the supply chain system

5.3. The impact of adjusting parameters on profits

From the influence of the above-mentioned adjustment parameters on the decision variables, it can be inferred that they must also have a corresponding impact on the profits of the supply chain system. So, let's assume that α_1 is fixed and α_2 is changed to observe the changes in the profits of each part of the supply chain system. As shown in Figure 6 (a), when α_2=0.1, the profit of the supply chain system changes with the variation of α_1. When α_1=0.0237, the profit of the supply chain system begins to change. Among them, the average profit of retailers began to decline, the average profit of manufacturers started to increase, and the overall profit of the supply chain also began to rise. As can be seen from Figure 6 (b), when α_2=0.3, the profit of the supply chain system changes with the variation of α_1. When α_1=0.02, the profit of the supply chain system begins to change. Similarly, the profits of manufacturers rise as the profits of retailers decline, but the overall profits of the supply chain are on the rise. It can be seen that when the system exceeds the stable state, within a certain range, the overall profit of the supply chain will increase slightly as the adjustment parameters rise. However, the profit changes of retailers and suppliers are opposite, which can lead to abnormal competition among members in a chaotic supply chain system. This does not often occur in real economic activities. Moreover, there is an opposite variable relationship between α_1 and α_2. That is, when retailers blindly increase marginal profits and simultaneously increase the usage of data volume, it will cause the supply chain system to become disordered. Therefore, when retailers deal with the benefits of their own dynamic decisions, they should not blindly expand the adjustment parameters of their decision variables. This may cause the entire system to enter a chaotic state, resulting in the opposite effect of the entire adjustment.

Conclusion 2. If retailers fail to correctly adjust the parameters of decision variables, the entire system will enter a chaotic state, and at the same time, their own profits will be damaged.



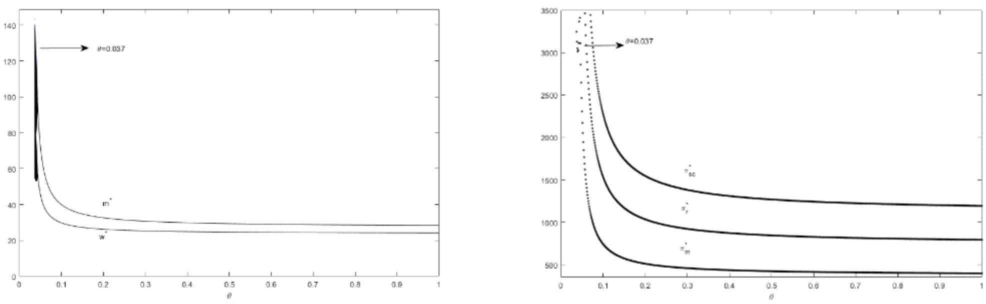
(a) (b)

Fig. 6 Chart of changes in profits of retailers and manufacturers with adjustment parameters

5.4. The impact of cost allocation on the supply chain system

Figure 7 (a) and (b) show the impact of cost allocation on the marginal profit and wholesale price of the system in a stable state. In a dynamic situation (multi-period case), it can be seen that as θ increases, m^*, w^* and the average profits π_{sc}^*, π_r^* and π_m^* of the supply chain gradually decrease and eventually tend to a fixed value. m^*, w^*, π_{sc}^*, π_r^* and π_m^* all reach their maximum values at θ=0.037, which is the same as the conclusion previously inferred that the supply chain system reaches its optimum when $0<\theta<0.1$. Under the condition of economic benefits, retailers and manufacturers will reach a cooperation agreement when θ=0.037 and sign a cost-sharing contract, thereby enabling both parties to obtain more economic benefits.

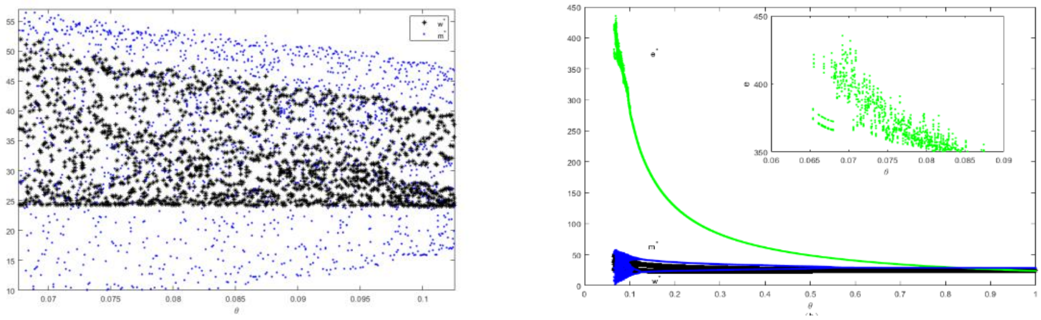
Conclusion 3. Generally speaking, the profit of the supply chain will decrease as it increases and reach its maximum value at 0.037 on θ. Therefore, retailers and manufacturers can determine the cost allocation and achieve the optimal profit when θ=0.037.



(a) (b)

Fig. 7 The impact of cost allocation on the system when it is in a stable state

Figure 8 (a) and (b) show that in the chaotic state (α_1=0.0343 , α_2=0.01), it can be seen from Figure (a) that the impact of cost allocation on marginal profit and wholesale price fluctuations is relatively consistent. In the dynamic situation, both are in a fluctuating state when the allocation coefficient is small, but as the allocation coefficient increases, their magnitudes tend to be consistent and remain stable. It can be seen from Figure (b) that the data volume e is greatly affected by the apportionment coefficient in the chaotic state, and it decreases significantly as the apportionment coefficient increases. This further indicates that retailers and manufacturers need to select the most appropriate apportion coefficient within a stable area for cooperation. Only in this way can the long-term stability of the supply chain system be maintained and a win-win situation be achieved.



(a) (b)

Fig. 8 The impact of cost allocation on the system when it is in an unstable state

6. Summary

This article integrates knowledge from multiple disciplines such as economics, management, and computer science, providing a powerful case for interdisciplinary research and promoting the exchange and integration of knowledge among various fields. From the perspective of artificial intelligence natural language processing, we explore its application potential in supply chain enterprises, helping people both inside and outside the industry to have a more comprehensive understanding of the application scope of AI technology. By introducing complex dynamic theory to analyze multi-cycle issues in the supply chain, this paper provides a new theoretical perspective for supply chain management, especially in the development of data-driven AI models. We emphasized the crucial role of data in supply chain decision-making, especially during the iteration and optimization of AI models, thereby helping enterprises utilize data assets more efficiently. In addition, this paper also analyzes how retailer-led supply chains can drive the optimization of the entire supply chain by controlling marginal profits and leveraging data, demonstrating the close interaction between technological progress and supply chain management. The research results show that:

(1) In a single-cycle static game, cost allocation has always brought positive benefits to large retailers. For manufacturing, the variable cost allocation coefficient only brings positive benefits within a certain range, while fixed cost allocation has always brought negative benefits to them. In a multi-period dynamic game, the variable cost allocation coefficient only brings positive benefits to large online retailers and manufacturers within a certain range.

(2) In multi-period dynamic games, retailers' adjustment of the information richness and marginal profit of generative language large models is not necessarily the greater the better. Only within a certain range can the system remain in a stable state and achieve stable positive returns. The same is true for manufacturers' adjustment of wholesale prices. Therefore, compared with the gains in a single cycle, to obtain more profits and maintain stability in a long-term dynamic game. Decision-makers must appropriately adjust the changes in decision-

making parameters and not overdo it; otherwise, it will lead the system into a chaotic state, which in turn will cause various uncertainties in the operation process.

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