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Competitive Supply Chain Strategy Optimization Based on Game Model and NSGA-II Algorithm

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Abstract: In order to better understand the competitive dynamics between e-commerce platforms and traditional retail outlets, a Stackelberg game model was developed. Subsequently, the Non-dominated Sorting Genetic Algorithm II (NSGA-II) was employed to determine the Pareto solution set for this multi-objective optimization problem. The findings reveal that: a) The effect of consumer reference quality can lead enterprises to adjust their strategy levels downwards, potentially resulting in profit loss under certain conditions. b) When the influence of competitive intensity on market demand is minimal, a reduction in enterprise profits occurs in both centralized and cost-sharing decision-making frameworks, with more significant detriment observed in the cost-sharing mode; conversely, when the influence is substantial, enhancements in competitive intensity can significantly increase overall system profits. c) The model's validity was confirmed through the application of the NSGA-II.

Keywords: Stackelberg game; NSGA-II; Competitive supply chain; Reference quality effect

1 Introduction

With the rapid development of Internet technology, e-commerce has become an important part of the global economy. E-commerce platforms have been gradually changing the traditional mode of business operation with their convenient transaction methods and wide market coverage. According to Heydari and Bakhshi [1], the number of customers accessing e-marketplaces increased by approximately 18% in 2020. In countries such as India, China and the United States, the growth rate of online shopping has exceeded 31.9%, 27.3%, and 14.0%, respectively [2]. With consumers' increasing concern for environmental protection and health, green e-commerce has gradually become an important development trend in the e-commerce field. In this context, as a sustainable business model, the e-commerce supply chain has emerged [3–5]. For physical stores, with the rise of e-commerce, the establishment of online platforms will undoubtedly cut down on store traffic, which in turn has an impact on the offline consumption demand of consumers, making the supply chain operation mode of online-offline integration extremely complex [6–8].

In fact, along with market diversification today, the factor affecting consumers' purchase decisions is not as single as in the past. Several factors, such as brand goodwill, cost-effectiveness, etc., cannot be ignored in influencing consumer decision-making. Research on consumer behavioral factors has found that when consumers make a purchase decision, they refer to the previous brand goodwill, purchase service, etc. to make an expected judgment on the quality of the product, i.e., reference quality [9]. When the quality level of the purchased product is greater than the reference level, it will further stimulate consumer demand, which is known as the reference effect [10, 11]. It can be seen that the expected quality of the product serves as the basis for the establishment of market behavior. The reference effect not only affects the consumer's purchase decision to a large extent but also indirectly affects market demand.

In summary, competitive behavior, reference quality effect and other factors are actually closely related, jointly affecting market changes and corporate profits. Although the existing literature has studied the above factors to varying degrees, it lacks a comprehensive analysis of these factors. In fact, for enterprises in competitive markets, making the right decisions according to different market environments is crucial to their operations and profitability. In addition, suppliers, e-commerce platforms and physical stores need to make decisions with the goal of maximizing their own profits. Therefore, this is a multi-objective optimization problem.

In such a problem, it is usually necessary to satisfy multiple objectives at the same time. However, there may be conflicts between these objectives. For example, optimizing one objective may lead to performance degradation of other objectives. Therefore, in a multi-objective optimization problem, there is usually no single optimal solution that can simultaneously satisfy the optimization requirements of all objective functions but rather a set of solutions. Genetic algorithms have the advantage of being closer to the global optimal solution than other heuristic algorithms. After years of development and evolution, genetic algorithms have produced many branches, among which the NSGA-II is considered by most scholars as a multi-objective evolutionary algorithm with better solution results [12]. Compared with traditional genetic algorithms, the core of the NSGA-II is fast non-dominated sorting, which greatly reduces the complexity and improves the solution performance. The NSGA-II introduces an elite strategy, which helps to retain the good individuals and maintain the diversity of dominant individuals in the population. The algorithm determines the superiority or inferiority of the individuals through the dominance relationship between them and thus solves multiple objectives directly with optimization results, a feature that changes the traditional methods. In addition, the algorithm has fast convergence speed and wider applicability. Therefore, the NSGA-II was used in this study to solve the multi-objective optimization model. The algorithm effectively reduces the computational complexity by evaluating the advantages and disadvantages of the individuals in the population through the fast, non-dominated sorting method. It utilizes the crowding degree distance to evaluate the advantages and disadvantages of individuals under the same non-dominated rank, which enhances the uniformity of the distribution of individuals in the population, thus ensuring the diversity of the population. In addition, the NSGA-II adds an elite retention strategy to expand the sampling space, which improves the existence rate of superior individuals and the accuracy of calculation results. In recent years, the algorithm has achieved good results in different fields of multi-objective optimization problems, and has become one of the classic algorithms for solving multi-objective optimization problems. After comprehensively analyzing the above factors, a Stackelberg game model was constructed in this study to solve the analytical solution of each enterprise under the influence of various market factors. Then the NSGA-II was designed for this multi-objective optimization problem to solve the Parteo solution set of the model. Finally, the effectiveness of the modeling algorithm was proved with examples.

2 Literature Review

In order to highlight the practical significance and theoretical value of this study, the following is a detailed compendium of the research areas that are closely related to this study: competitive behavior, reference quality effect, and the NSGA-II.

The current research literature on competitive behavior mostly focuses on price and service competition between dual channels. After analyzing the changes in pricing strategies of competing retailers operating dual channels, Ofek et al. [13] found that when the differences between competitors are not too high, owning an online channel reduces profits. Dan et al. [14] studied value-added service competition between suppliers and retailers, and found that the stronger the supplier's competitive intensity, the more incentives for suppliers to improve warranty service levels. Brynjolfsson et al. [15] studied how e-retailers can win in channel competition. It was found that e-retailers face brutal competition when they sell mainstream products. However, they are virtually unaffected by competition when they sell niche products. The studies [16, 17] examined the problem of corporate coordination in the presence of competing retailers and derived appropriate strategies. In a series of studies in recent years, competitive behavior has been widely used in the study of pricing strategies, service strategies, and coordination of service providers, but little literature has considered the formulation of logistics-level strategies in the presence of the reference quality effect under competitive behavior. Nowadays, offline and online competition is also gradually expanding to competition between services and marketing efforts. Therefore, this study extends this field of research by richly considering the impact of service competition (logistics level) on strategies and performance.

Most of the existing studies on the reference quality effect focus on optimal pricing and quality investment. For example, He et al. [18], Gavious and Lowengart [19], Chenavaz [20] and He et al. [21] investigated the impact of the reference quality effect on members' decision-making and enterprises' profits from different perspectives, which fills in the research dimensions in the reference quality effect. Liu [22] found that when the reference quality effect is strong, it is more important to consider the impact of members' short- and far-sighted behaviors on strategies and profits. This means that when the reference quality effect is strong, products produced by short-sighted suppliers favor retailers. With the increasing public concern over product quality, exploring the impact of the reference quality effect in different business models has become a common academic focus. However, previous studies have neglected to consider the impact of the reference quality effect when there is competitive behavior among enterprises.

In the study of the NSGA-II, Barman et al. [23] proposed a two-tier supply chain model consisting of a manufacturer and a retailer, and used the NSGA-II to solve the bi-objective planning problem of this supply chain. After listing and analyzing a set of Pareto-optimal solutions, it was found that the retailer's profit increased dramatically in the decentralized marketing decision. The selling price of the product is also lower in the case of non-integrated marketing. By addressing the problem of slow convergence and low probability of accuracy in the process of multi-objective optimization of energy storage materials, Hu et al. [24] proposed a multi-objective optimization model for energy storage materials based on the NSGA-II, and summarized the three types of inventory control. The experiments show that the method can effectively improve the accuracy rate, enhance the ability of scheduling of storage materials, and achieve good performance. Hassangaviar et al. [25] studied a multi-objective, multi-facility, closed-loop supply chain considering a green supply chain in an uncertain environment, and ranked the optimal solutions by the NSGA-II. The results show that the NSGA-II demonstrates good performance in terms of the maximum expansion and the distance measurements. Karimi et al. [26] investigated the effect of the flexibility of the supply chain model on the improvement of system performance. Flexibility and supply chain are linked by applying the NSGA-II and the Multi-Objective Particle Swarm Optimization (MOPSO) algorithm, which were compared based on a number of criteria: spacing metric, computation time, average ideal solution, number of Pareto solutions, and maximum range. The overall results show that the NSGA-II outperforms the MOPSO on most of the criteria. Moghadam et al. [27] proposed a multi-objective mixed integer nonlinear planning model to design a closed-loop supply chain network based on the e-commerce context. The proposed model includes two objectives of optimizing total business profit and customer satisfaction. The given model was validated by the hybrid NSGA-II, which was used in addition to the exact method. It was found that when considering the limitations of the supply chain, the two conflicting objective functions can be improved and can increase the profitability of the enterprise with satisfied customers. Orellana et al. [28] proposed that supply chain optimization enables efficient and effective management of resources. In many cases, the optimization objectives of maximizing profit and maximizing customer service level are usually in conflict with each other. It was found that the NSGA-II achieved the highest service level and maximum profit in the minimum inventory scenario by comparing three evolutionary algorithms, i.e., the NSGA-II, the MOPSO, and the Multi-Objective Mayfly Algorithm (MOMA). Mahjoob et al. [29] devised the transportation sector where excessive greenhouse gas emissions cause enterprises to shift to sustainable supply chain networks, and proposed a new bi-objective nonlinear formulation with an exact methodology and four evolutionary algorithms, i.e., the Pareto Envelope-based Selection Algorithm (PESA)-II, the NGSA-II, the Strength Pareto Evolutionary Algorithm (SPEA)-II, and the Non-dominated Ranking Genetic Algorithm (NRGA), for both small and large scale instances. The results show that at any demand level, the proposed model suggests a set of solutions that can significantly reduce emissions with a slight increase in supply chain costs.

To this end, this study investigates the effects of several factors on the enterprises from the perspectives of dynamic changes, consumer reference quality effects, and competitive behaviors. After exploring the effects of competitive behaviors between e-commerce platforms and physical stores, the NSGA-II was designed. The rest of this study is organized as follows: Section 3 gives a description of the problem and model assumptions; Section 4 is the game model analysis with sensitivity analysis of key parameters and corresponding suggestions for managerial revelation; Section 5 is the numerical example of the model; Section 6 is the design and analysis of the NSGA-II; and finally the conclusions are given in Section 7.

3 Problem Description and Model Assumptions

In this study, it is considered that a competitive supply chain consists of suppliers, online e-commerce platforms, physical stores, and consumers, whose relationships are schematized in Figure 1.

In this system, the supplier is responsible for producing the product, deciding the quality level of the product $q(t)$, and wholesaling it to the e-commerce platforms and the physical stores with a marginal revenue of π_M. The e-commerce platforms continuously improve their logistics service level in order to better promote the product sales and allow consumers to receive the product faster. Therefore, the decision task of the e-commerce platforms is to set the logistics level $A_1(t)$. The marginal revenue is π_o. The marginal earnings of physical stores are π_R, and their decision-making task is to set the marketing level $A_2(t)$. In addition, these stores also make full use of their advantages to provide highquality service introductions to the customers, standard product guides, etc. Therefore, another decisionmaking task of theirs is to set the service level $s(t)$. It can be seen that the e-commerce platforms and the physical stores are independently operated, and there is a competitive behavior. In addition, in order to better represent the actual environment, product goodwill was taken as the state, and the evolution of goodwill was used to describe the dynamic environment. The relevant assumptions are given as follows:

Hypothesis 1. Before purchasing a brand product, online consumers cannot recognize the product quality in advance. Therefore, they form psychological expectations based on the previous product's goodwill.

He et al. [18] argued that consumers form adaptive expectations based on the previous brand goodwill of the product and give a quality judgment, which is called the reference quality level. He et al. [21] and Hellofs and Jacobson [30] suggested that brand goodwill $G(t)$ is the basis for the formation of the reference quality level $R_q(t)$, and there is a positive correlation between the two. The equation is as follows:

$$R_q = \xi G(t) \tag{1}$$

where, $\xi > 0$ indicates the correlation between the reference quality level and brand goodwill.

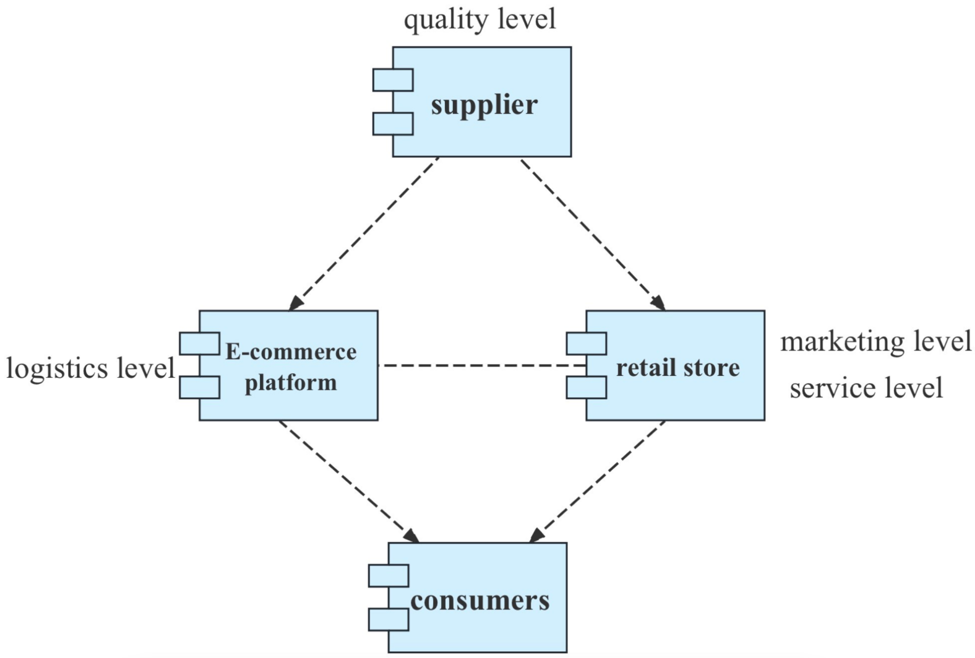


Figure 1. Schematic diagram of the system

Hypothesis 2. In a dynamic supply chain system, brand goodwill changes all the time, in which the reference quality effect of consumers has a dynamic impact on goodwill; the purchasing experience of consumers in the physical stores is the key to the formation of goodwill. Therefore, the service level of the physical stores is also an effective guarantee for the establishment of brand goodwill. In addition, consumer forgetfulness or competition from other brands in the same industry can lead to the erosion of brand goodwill.

Drawing on the improved Nerlove-Arrow goodwill model [31], the kinetic equation for the state variable $G(t)$ can be described as follows:

$$\dot{G} = \alpha\left(q(t) - R_q(t)\right) + \beta s(t) - \delta G(t), G(0) = G_0 > 0 \tag{2}$$

where, $q(t) - R_q(t)$ denotes the reference quality effect, $s(t)$ is the service level of the physical store, $\alpha > 0$ denotes the impact of the reference quality effect on goodwill, $\beta > 0$ is the coefficient of the impact of the service level on goodwill, $\delta > 0$ denotes the attenuation factor of the brand goodwill, and $G_0 > 0$ denotes the brand goodwill at the initial moment. Further combined with Eq. (1), the change of brand goodwill can be expressed as follows:

$$\dot{G}(t) = \alpha q(t) + \beta s(t) - \chi G(t), G(0) = G_0 \tag{3}$$

Hypothesis 3. Nowadays, products have become more and more diversified, and consumers pay more attention to the quality and goodwill of products when purchasing a product [14]. The efficient logistics service level promotes market demand.

Considering the fact that some consumers can shop online without leaving their homes, they choose to spend money online. Since they can't personally perceive the quality of the product, the reference quality plays a key role in this case. Offline consumers, who are keen to know the quality of the product in person before making a purchase decision, rely on the actual quality of the product to make their decisions. In fact, for many e-commerce models, e.g., Business-to-Consumer (B2C), Consumer-to-Consumer (C2C), brand goodwill has become one of the key factors constraining their development [32], and there is no exception in competitive supply chains. In addition, e-commerce platforms and physical stores inevitably generate competitive behaviors, and competitive strengths and weaknesses affect their own market demand. Based on this, the online demand function $D_O(t)$ and the offline demand function $D_R(t)$ were constructed by drawing on the demand function affected by the reference quality effect in two related studies [11, 19]. The equations are as follows:

$$\begin{aligned} D_O(t) &= a_1 R_q(t) + \gamma_1 A_1(t) + \mu_1\left[A_1(t) - A_2(t)\right] + \theta G \\ D_R(t) &= a_2 R_q(t) + \gamma_2 A_2(t) + \mu_2\left[A_2(t) - A_1(t)\right] + \theta G \end{aligned} \tag{4}$$

where, $a_1 > 0, a_2 > 0, \gamma_1 > 0, \gamma_2 > 0, \mu_1 > 0, \mu_2 > 0, \theta > 0$ represent the corresponding influence coefficients, and $\mu_1\left(A_1(t) - A_2(t)\right)$ and $\mu_2\left(A_2(t) - A_1(t)\right)$ denote the competitive behavior between online and offline channels.

It can be seen that good product quality, high quality expectations, favorable competitive position and a good brand reputation are the long-term ways to ensure market demand.

$$D(t) = \Phi\sqrt{G(t)} - \beta p(t) \tag{5}$$

where, $\Phi = \theta + \beta\xi$.

Hypothesis 4. Assuming that the cost function is quadratic [33], the supplier quality cost function is $k_M q^2(t)/2$, the logistics cost function of the e-commerce platform is $k_1 A_1^2(t)/2$, the marketing cost function of the physical store is $k_2 A_2^2(t)/2$, the service cost function is $k_s s^2(t)/2$, and $k_M > 0, k_1 > 0, k_2 > 0, k_s > 0$ denote the cost coefficients, respectively.

4 Analysis of the Stackelberg Game Model

For the competitive supply chain, all three parties, i.e., suppliers, e-commerce platforms, and physical stores, make decisions independently with the goal of maximizing their own profits, which is common in real life. Since each member of the channel makes strategies and rationally formulates strategies at the same time, the decision-making process is a Nash non-cooperative differential game. The Stackelberg game model was chosen because the problem studied in this research is a dynamic decision-making process and the Stackelberg game model is suitable for describing strategy interactions in a dynamic decision-making environment. For example, in a supply chain, a manufacturer may first decide on the quantity to be produced, and then retailers adjust their ordering based on this decision. This dynamic interaction can be modeled and analyzed by the Stackelberg game model. In the Stackelberg game, the leader has a first mover advantage. This means that the leader can make decisions before the followers and his/her decisions influence the choices of the followers. Therefore, the leader must use this advantage to ensure that he or she maximizes his or her benefits. Therefore, in the model of this study, the supplier is the leader. The superscript represents decentralized decision-making, and the subscripts M, O, and R represent suppliers, e-commerce platforms, and physical stores, respectively.

In addition, π denotes the respective profit function. The game problem is expressed as follows:

$$\begin{aligned}
&\max_{q(\cdot)} J_M = \int_0^\infty e^{-rt}\left[\pi_M\left(D_O(t)+D_R(t)\right) - \frac{1}{2}k_M q^2(t)\right]\mathrm{d}t \\
&\max_{A_1(\cdot)} J_O = \int_0^\infty e^{-rt}\left[\pi_O D_O(t) - \frac{1}{2}k_1 A_1^2(t)\right]\mathrm{d}t \\
&\max_{A_2(\cdot),s(\cdot)} J_R = \int_0^\infty e^{-rt}\left[\pi_R D_R(t) - \frac{1}{2}k_2 A_2^2(t) - \frac{1}{2}k_s s^2(t)\right]\mathrm{d}t \\
&\text{s.t. } \dot{G} = \alpha q(t) + \beta s(t) - \chi G(t), G(0) = G_0 > 0
\end{aligned}$$

Proposition 1. The proposition is as follows:

(a) The various optimal strategies for the Online-to-Offline (O2O) supply chain are given below.

$$q^N = \frac{\pi_M a_2 + \alpha g_1}{k_M}; A_1^N = \frac{\pi_o\left(\gamma_1+\mu_1\right)}{k_1}; A_2^N = \frac{\pi_R\left(\gamma_2+\mu_2\right)}{k_2}; s^N = \frac{l_1\beta}{k_s}$$

(b) The time evolution paths of goodwill, reference quality, and total system profit are given below.

$$G^N(t) = G_\infty^N + \left(G_0 - G_\infty^N\right)e^{-\chi G}; R_q^N(t) = \xi\left(G_\infty^N + \left(G_0 - G_\infty^N\right)e^{-\chi G}\right)$$

where, $G_\infty^N = \frac{1}{\chi}\left[\frac{\alpha(\pi_M a_2 + \alpha g_1)}{k_M} + \frac{l_1\beta^2}{k_s}\right]$.

(c) The profits of suppliers, e-commerce platforms, and physical stores are given below.

$$V_M^N = g_1 G^N + g_2; V_O^N = h_1 G^N + h_2; V_R^N = l_1 G^N + l_2$$

where,

$$\begin{aligned}
g_1 &= \frac{\pi_M\left(a_1\xi + 2\theta\right)}{\chi + r}; h_1 = \frac{\pi_O\left(a_1\xi + \theta\right)}{\chi + r}; l_1 = \frac{\pi_R\theta}{\chi + r}; \\
g_2 &= \frac{1}{r}\left[\frac{\left(\pi_M a_2 + \alpha g_1\right)^2}{2k_M} + \frac{l_1 g_1\beta^2}{k_s} + \frac{\pi_M\pi_o\left(\gamma_1+\mu_1\right)\left(\gamma_1+\mu_1-\mu_2\right)}{k_1} + \frac{\pi_M\pi_R\left(\gamma_2+\mu_2\right)\left(\gamma_2-\mu_1+\mu_2\right)}{k_2}\right]; \\
h_2 &= \frac{1}{r}\left[\frac{\alpha\left(a_2\pi_M + \alpha g_1\right)h_1}{k_M} + \frac{h_1 l_1\beta^2}{k_s} + \frac{\left(\pi_O\left(\gamma_1+\mu_1\right)\right)^2}{2k_1} - \frac{\mu_1\pi_o\pi_R\left(\gamma_2+\mu_2\right)}{k_2}\right]; \\
l_2 &= \frac{1}{r}\left[\frac{\left(a_2\pi_R + \alpha l_1\right)\left(\pi_M a_2 + \alpha g_1\right)}{k_M} + \frac{\left(l_1\beta\right)^2}{2k_s} - \frac{\mu_2\pi_O\pi_R\left(\gamma_1+\mu_1\right)}{k_1} + \frac{\left(\pi_R\left(\gamma_2+\mu_2\right)\right)^2}{2k_2}\right].
\end{aligned}$$

Property 1. The sensitivity analysis of key parameters to each strategy in the centralized decision-making model was obtained from Proposition 1, as shown in Table 1.

Table 1. Sensitivity analysis of key parameters in N-mode

	π_M	π_O	π_R	α	β	γ_1	γ_2	μ_1	μ_2	a_1	a_2	θ	k_M	k_1	k_2	k_s	ξ	δ
q^N	+	×	×	+	×	×	×	×	×	+	+	+	-	×	×	×	*	-
A_1^N	×	+	×	×	×	+	×	+	×	×	×	×	×	-	×	×	×	×
A_2^N	×	×	+	×	×	×	+	×	+	×	×	×	×	×		×	×	×
s^N	×	×	+		+	×	×	×	×	×	×	+	×	×	×	-	×	-

Note: + indicates a positive correlation with the parameter, - indicates a negative correlation, × indicates no correlation, and * indicates a case-by-case basis.

Comprehensive nature was obtained as follows: a) This situation belongs to the decentralized decision-making mode, in which, due to the independent decision-making of each enterprise, the supplier's quality level strategy is only related to its own product marginal revenue. The supplier's quality level is positively correlated with marginal returns. When the marginal returns on its own products increase, it promotes confidence in investing in the supplier's product quality level. b) The logistics level of the e-commerce platform, the physical stores' marketing level and service level are all positively correlated with their own marginal revenue. c) The logistics level of e-commerce platforms, the marketing level of physical stores and the service level are all positively related to their own marginal revenue, which reflects the decentralized decision-making mode in which both parties only maximize their own profits for the purpose of decision-making. d) When enterprises independently carry out rational decision-making, they are only concerned about the impact of their own competitive factors on their own market demand. When the competitive factor increases, the best strategy is to make full use of the current favorable situation to improve the strategy. e) Due to the independent decision-making of each enterprise, the service level and the reference quality of physical stores have no influence on the online market demand.

The managerial insights and recommendations arising from the above nature are: a) The establishment and maintenance of goodwill remains an important factor that cannot be ignored in a decentralized decision-making model. Firstly, at the initial stage of creating a brand, it is necessary to establish quality and brand advantages through innovative advertising and promotion, with a view to obtaining a higher level of awareness. Secondly, enterprises should create a full range of enterprise-customer relations, set up a special department responsible for the maintenance of relations with customers, provide personalized services for different customers, and maintain long-term friendly relations with customers. In addition, the enterprise should also set up a professional marketing department responsible for tapping new consumer groups, aiming to maintain good old customers while attracting more customers. b) Suppliers should always focus on product quality, improve product expectations, and make full use of the positive impact of the reference quality effect for their own. Enterprises can improve the technical level of employees and establish higher product testing standards under the premise of ensuring a stable product quality system by means of periodic inspection and regular testing, etc. c) Online e-commerce platforms should make every effort to improve the level of logistics, select appropriate consumer groups for in-depth analysis, and carry out diversified marketing such as online e-commerce platforms to optimize the consumer search channels for the products. As for product introduction pages, the functional quality of the products should be improved so as to maintain old customers while attracting more customers. In addition, the functional quality of the products should be introduced in detail, and consumers' attention should be attracted by adding pictures and setting coupons in order to purchase the products. Offline stores should make full use of their advantages of face-to-face communication with customers, improve the quality of employees, enhance the level of service, select the target consumers, and conduct a comprehensive quantitative analysis. For example, enterprises can set up a standard shopping guide, add on-site experience links, establish customer data manuals, establish a VIP system for long-term customers, and regularly give back gifts. d) Online and offline enterprises should pay extra attention to their own competitive positions, respond quickly to market changes, and make full use of big data to improve the marketing level.

5 Numerical Calculation Example

In order to make the previous results clearer, this section further verifies the conclusions obtained through a numerical example by analyzing the equilibrium strategies and supply chain performance of enterprises under different decision-making modes and studying the Pareto improvement effect of manufacturers' cost sharing on enterprises. Drawing on the study by Karimi et al. [26], the parameters of the example were set as follows:

$$\alpha = 1; \xi = 0.9; \delta = 0.9; \pi_M = 2.0; \pi_O = 2.0; \pi_R = 2.0; a_1 = 1.0; a_2 = 1.0; \beta = 1.0; \theta = 1.0; r = 0.1;$$
$$k_M = 1.5; k_1 = 1.2; k_2 = 1.2; k_s = 1.5; \gamma_1 = 2; \gamma_2 = 2; \mu_1 = 1; \mu_2 = 1$$

5.1 Brand Goodwill and Reference Quality in Different Decision Models

Figure 2 shows the time trajectory of the reference quality level with different initial goodwill.

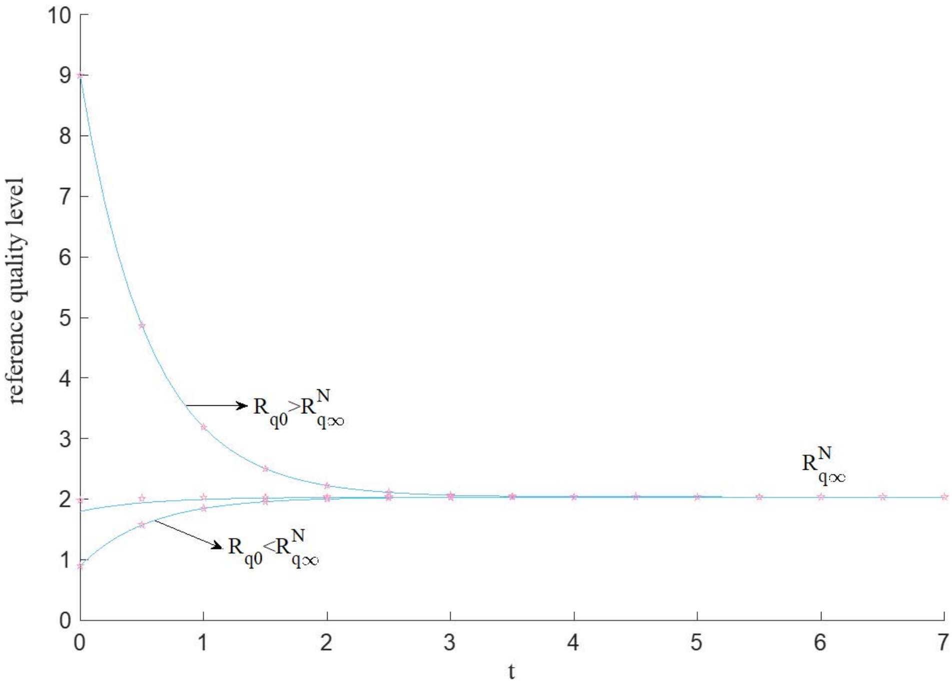


Figure 2. Reference quality level

In Figure 2, when different initial reference levels are given, the reference quality level of the product eventually converges to a globally stable state. It is clear that when the initial reference level is large, although it decreases over time and eventually stabilizes, a higher initial reference level still brings more benefits to the enterprise upfront than a lower one. It shows that although the reference quality level eventually stabilizes, establishing good self-generated goodwill at the beginning is still the best decision for the enterprise.

Therefore, several management measures were recommended. Since the reference quality level is directly influenced by goodwill, enterprises should first build up brand goodwill in the preparatory phase of their founding. For example, enterprises can make full use of big data to target customers and advertise in advance by broadcasting colorful promotional videos on shopping mall screens to create a sense of mystery and attract consumers' attention before they see the product. Secondly, enterprises should establish goodwill at the initial stage, choose famous enterprises with goodwill for cooperation, and enhance their initial goodwill through association with other enterprises. In addition, when an enterprise has established good initial goodwill, it should pay attention to the maintenance of goodwill decay when formulating various strategies. For example, goodwill decay can be effectively alleviated through real-time logistics. If the enterprise's initial goodwill is low, it should pay attention to improving its goodwill as soon as possible when formulating strategies, aiming to reach a stable state as soon as possible.

5.2 Corporate Profits and Supply Chain Performance

Taking the initial goodwill, subgraphs (a)–(d) of Figure 3 give the time trajectory graphs of corporate profits and supply chain performance.

As shown in Figure 3, with the passage of time, corporate profits are all globally stable. However, it is obvious from the public figures that in the early stage, the profits of both the e-commerce platforms and the physical stores are in a linear downward trend. Therefore, as for the e-commerce platforms, in addition to improving the level of logistics services, they can also make use of big data to accurately locate the consumer preferences through the consumers' search records, and reasonably arrange the product classification of the push interface to effectively attract online consumers. For the physical stores, the actual sales data can be used to develop customer preference records and reasonable maintenance of old customers and cultivate new customers. As the improvement of logistics level drives the market demand, which can effectively enhance the profits of enterprises, it can be seen that the reduction of costs and the increase of demand can drive the profits of e-commerce platforms and physical stores.

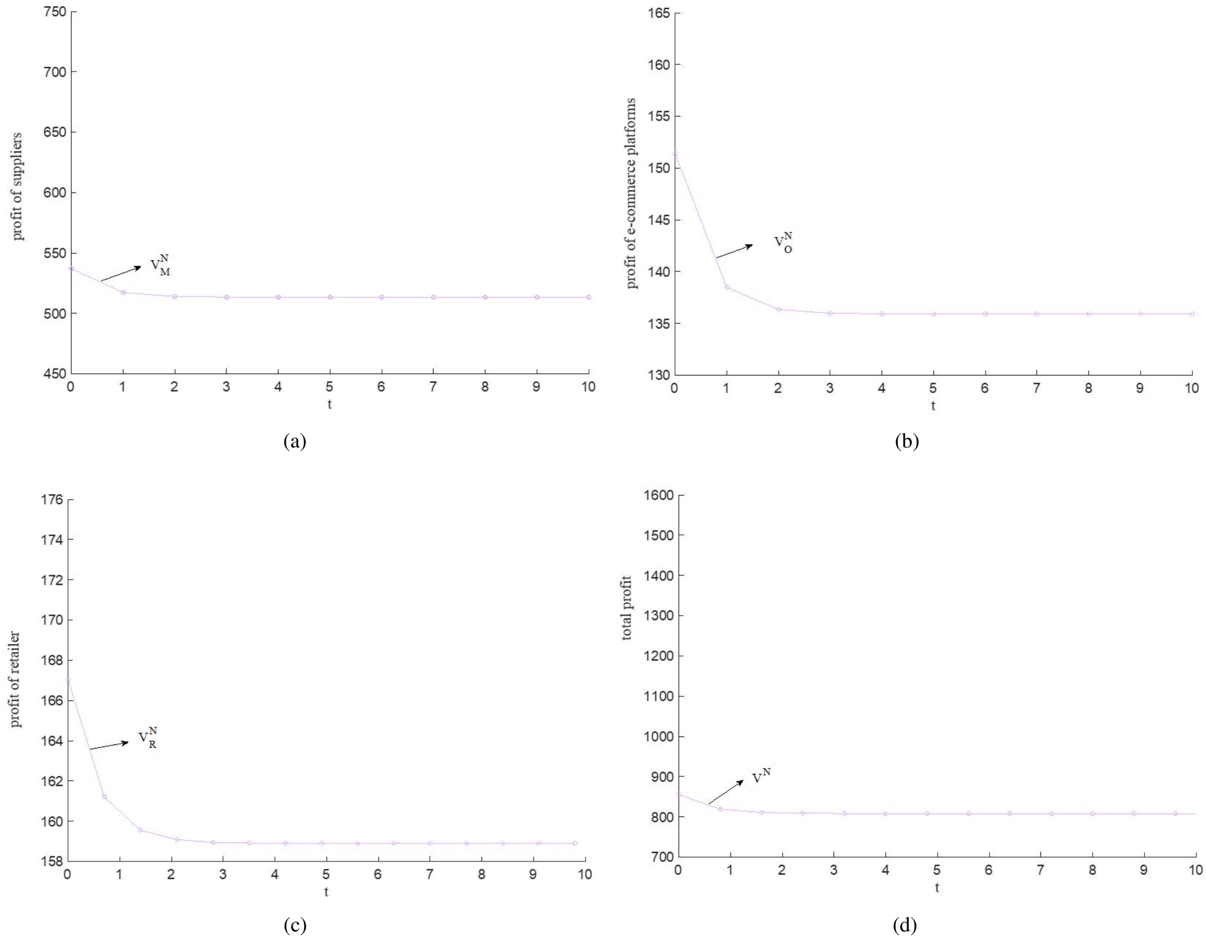


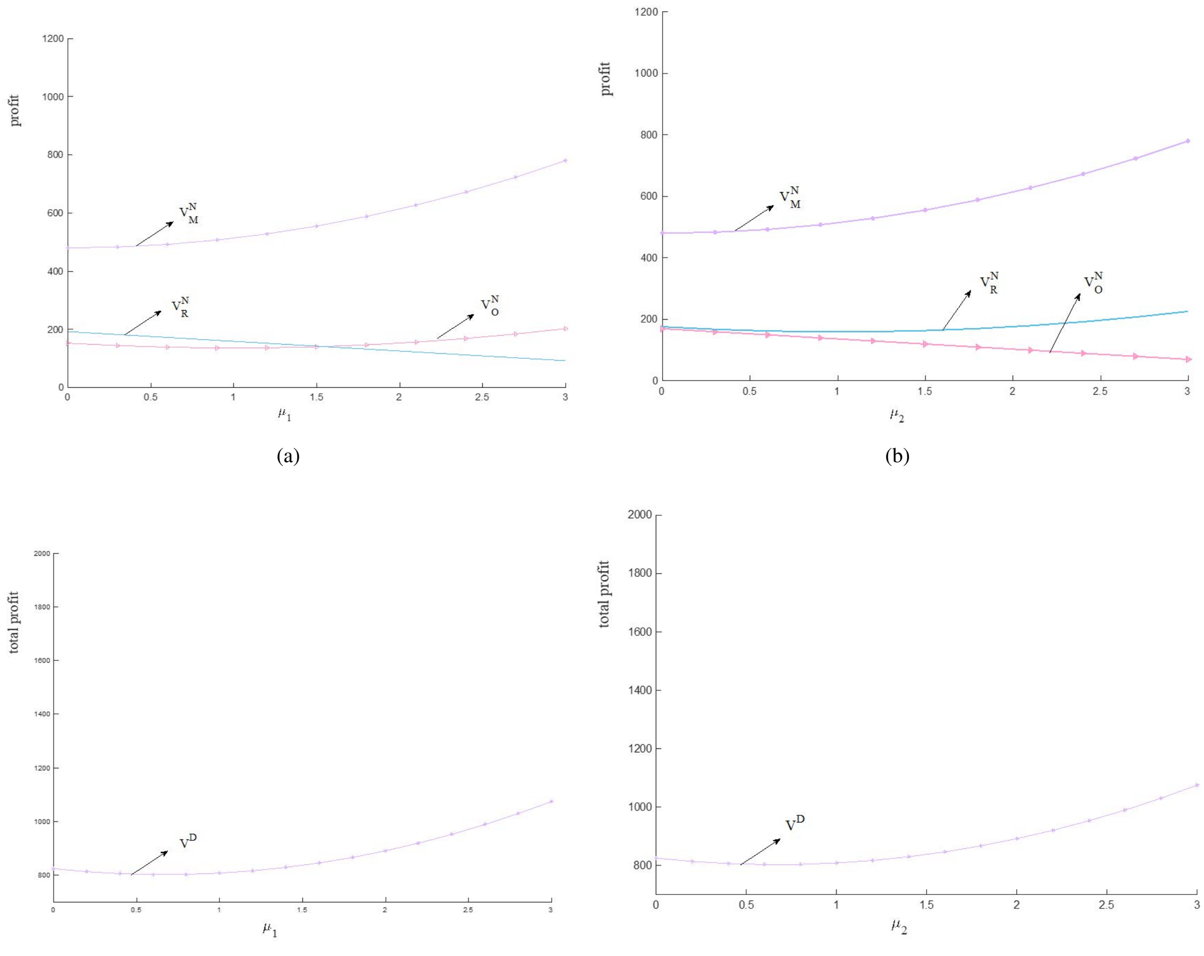
Figure 3. Profit trajectory chart. (a) Profit of suppliers; (b) Profit of e-commerce platforms; (c) Profit of retailers; (d) Total profit

5.3 Impact of Competitive Factors μ_1 and μ_2 on Membership Strategies and Supply Chain Performance

Subgraphs (a)–(d) of Figure 4 show the effect of parameters μ_1 and μ_2 on the corporate profits and the total profit of the supply chain, respectively.

As shown in Figure 4, under this numerical example, the impact of μ_1 and μ_2 on the strategy and profit is symmetric. Therefore, only the impact of μ_1 was analyzed in this study. As μ_1 increases, the impact of the competition between the two on the online market demand becomes stronger, which means that there is more demand in the online market, and the profit of the enterprise is increased. Therefore, in order to ensure the continuation of this positive cycle, the e-commerce platform should concentrate its resources on improving the logistics level, seizing the first opportunity with the help of the competitive advantage, and promoting market demand, thus increasing its profit. At this time, consumers are more eager to consume online, which reduces the offline demand. Therefore, the physical store should correspondingly reduce the level of marketing to avoid unnecessary losses. The service level of the physical store is not affected by μ_1. If an online or offline enterprise occupies the competitive advantage, it has little impact to enhance the supplier's profit and does not affect its own profit. In addition, it brings profit loss to its competitors. When the impact of competition on market demand is more intense, the effect of profit enhancement on suppliers and the enterprises is obvious, and the loss of profits to competitors is also obvious.

The results of the above analyses fully confirm that the impact of competition on enterprises is significant. Enterprises should face up to the existence of competitive behaviors, improve the intensity of the impact of competition on market demand, and constantly innovate their marketing. For example, suppliers should improve the level of technology, production of diversified products, and delivery of a variety of homogeneous products, and utilize information tools to foster competition among enterprises, thereby intensifying competition's influence on market demand.



(a) (b) (c) (d)

Figure 4. Impact of competitive intensity on strategies and supply chain performance. (a) Impact of μ_1 on the profit of each enterprise; (b) Impact of μ_2 on the profit of each enterprise; (c) Impact of μ_1 on the total profit; (d) Impact of μ_2 on the total profit

6 Design and Analysis of the NSGA-II

The design of the NSGA-II can be divided into the following steps:

Step 1: Encoding and initializing the population. The parameters were first generated by real number encoding to act on the fitness function. Subsequently, the population was generated based on the encoding operation to provide the initial solution set for the subsequent crossover and mutation operations. The population size of 100 was chosen in this study.

Step 2: Fitness evaluation. The algorithm was used to measure the merit of the solution through fitness evaluation, which maps the genes of an individual to one or more target values, thus enabling the algorithm to select a better individual for evolution. In this study, the fitness was calculated by calculating the three objective functions $q(A1)$, G and $JM(JO)$.

Step 3: Non-dominance sorting and calculation of crowding degree. The NSGA-II sorts the individuals according to dominance relationships and generates the next generation of the population on this basis. During each generation of evolution, the algorithm preferentially selects non-dominated individuals. If two individuals have the same dominance rank, the one with a higher crowding degree should be selected.

Step 4: Selection. By selecting high-quality individuals from the current population, these individuals can pass their genes to the next generation. The selection is mainly based on the comparison of non-dominated ranking and the crowding degree.

Step 5: Crossover and mutation. They are two important parts of genetic operations. This study uses simulated binary crossover and chooses 0.8 as the crossover probability $cxpb$. The mutation operation generates a new solution by randomly changing the genes of an individual. This study adopts a polynomial mutation method, where the mutation probability $indpb$ is 1/13.

Step 6: Iterative update. The algorithm evolves by repeating the execution of the above steps, which constantly makes the population close to the optimal solution. The number of iterations $gen = 100$ was chosen in this study.

According to the principle of the NSGA-II, this algorithm deals with multiple objective functions at the same time, and it does not need to convert the multi-objective problem into a single-objective problem through weighted summation as some traditional algorithms do. Therefore, this algorithm was chosen in this study. In addition, compared to other multi-objective optimization algorithms, the NSGA-II maintains the diversity of solutions through the crowding degree distance, avoiding the situation where the solution set is over-concentrated in one part. The study by Karimi shows that the NSGA-II works better when dealing with interacting multi-objective problems. In this study, several factors need to be optimized simultaneously, i.e., the investment decision level q, goodwill level G, and the supplier's profit JM, as well as the decision level $A1$, goodwill level G, and the profit JO for the e-commerce enterprise, respectively. By using non-dominated ordering, the NSGA-II can find multiple Pareto optimal solutions that satisfy all objectives in a single debugging.

The NSGA-II was used to solve the model, obtaining evolutionary generation $gen = 100$, population size $INDIV = 100$, crossover probability $cxpb = 0.8$, variation probability $indpb = 1.0/13$, and Parteo optimal solution in the 100th generation. Figures 5 and 6 show the profit trends of the supplier and the e-commerce platform.

As shown in Figure 5, the level of quality and goodwill of the green supplier jointly affect its profit. The size of goodwill and the level of quality show a positive correlation in terms of their impact on the profit of the supplier, with the supplier with a higher level of goodwill being keen to invest more in quality decisions. When the goodwill level is low, an increase in the quality level does not lead to an increase in profit. This suggests that the size of the initial goodwill has a significant impact on the profit earned by the supplier and even an increase in the quality level fails to significantly improve the profit. When the supplier's profit increases significantly with the levels of goodwill and quality, this suggests that at this point the supplier has secured its position in the market through higher goodwill, attracted more consumption, and gained higher market share and profit by investing in increasing the level of quality. After the levels of goodwill and quality reach a certain threshold, the growth of profit begins to level off, indicating that the marginal effect of goodwill gradually decreases and too high investment decisions yield limited improvements in profit.

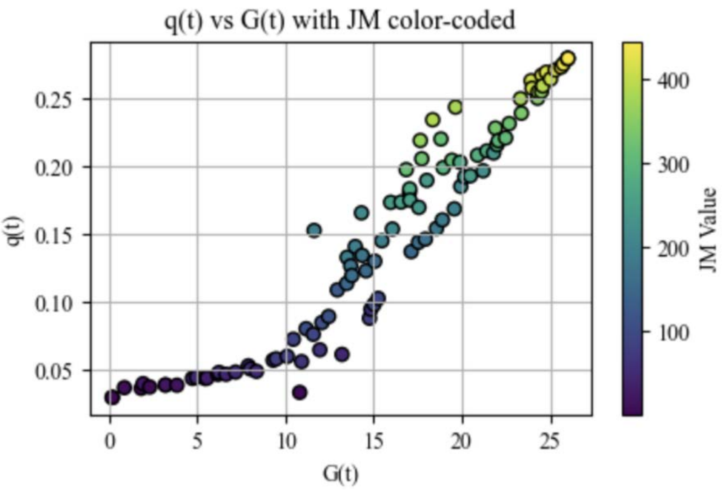


Figure 5. Profit trend chart of the supplier

As shown in Figure 6, the decision-making level A and the goodwill level G of the e-commerce platform jointly affect its profit JO. The positive effect of goodwill G on the profit JO of the e-commerce platform can be analyzed. With the enhancement of goodwill G, the profit JO shows an upward trend. This indicates that the improvement of goodwill can effectively promote the growth of profit, and good goodwill can bring more customers and business opportunities for the e-commerce platform, which in turn can improve sales and profit. The range of changes in decision level A affects its impact on goodwill G and profit JO. It can be analyzed from the figure that some specific range of the decision level can bring profit maximization, but high goodwill can also bring good profit under different decision levels. Therefore, in this decision level interval, the size of the decision level does not have a significant impact on profit. In addition, reasonable decision-making not only needs to consider how to improve profit quickly but also pays attention to the long-term impact of goodwill. In some cases, strategies to enhance goodwill may lead to higher long-term returns even if profits decline in the short term. It can be seen that for e-commerce platforms, it is important to make sound decisions based on a combination of market factors with reference to quality effects, competitive phenomena, etc. Apart from short-term, temporary profit returns, the long-term impact of each decision and goodwill should also be paid attention. Although in some cases (increased competition or external uncertainties in the market), profits may fall in the short term, strategies to enhance goodwill may also lead to higher long-term returns.

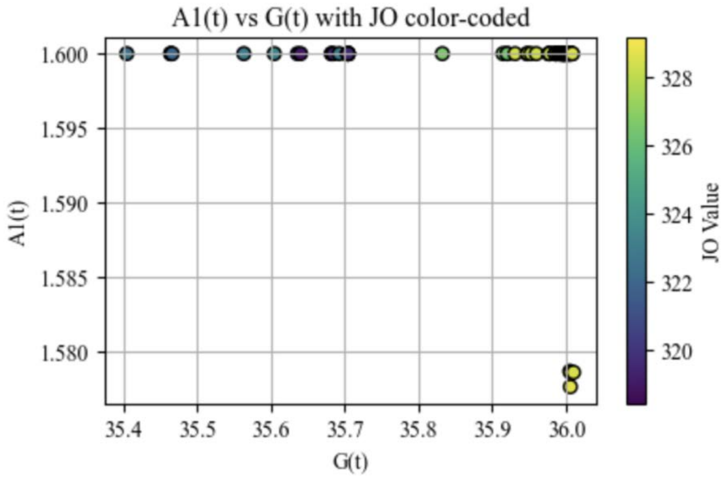


Figure 6. Profit trend chart of the e-commerce platform

7 Conclusions

Taking suppliers, e-commerce platforms and physical stores that have competitive behaviors with each other as the research objects, this study combines the logistics level of the e-commerce platforms and the marketing and service level of the physical stores as the background of the research. This study incorporates the reference quality effect that depends on the brand's goodwill, which also affects the dynamic evolution of the brand's goodwill and influences the market demand on the e-commerce platform, and taps the competitive behaviors between online and offline enterprises. After exploring the competitive behaviors between online and offline enterprises, this study comprehensively explores the impacts of the above factors on the operation strategies and performance of enterprises. After solving the optimal strategies of the members and the performance of the supply chain and conducting the comparative static analyses of the key parameters, this study provides the managerial insights and suggestions accordingly and a numerical example. In addition, the NSGA-II was designed to solve the Parteo solution set of the model for this multi-objective optimization problem. The main conclusions drawn from the study are as follows:

(a) The consumer's reference quality effect can, under certain circumstances, cause enterprises to reduce their strategy level accordingly and bring about profit loss. That is, over-reliance on brand goodwill to judge the quality of products discourages members from investing in quality and service levels, which is not only detrimental to the development of brand goodwill but also results in the loss of profits. Therefore, all parties should show more product quality and performance in marketing promotion, attract consumers' attention to the quality of the product itself, and reduce the dependence on brand goodwill.

(b) This study considers that the intensity of competitive behavior between enterprises affects their respective demand, which is noteworthy. Some new findings were obtained. Firstly, as the intensity of the impact of their own competitive factors on their own market demand increases, this makes the enterprises correspondingly increase the level of their own strategies and profits. Simultaneously, the strategy levels and profits of competing parties are subjected to disruption. Secondly, the overall profit of the system should be considered. When the intensity of competition has a smaller impact on market demand, the profit under the centralized and cost-sharing decision-making mode is reduced, and the damage is greater under the cost-sharing decision-making mode. When the intensity of competition has a larger impact on the market demand, the overall profit is improved effectively. In summary, constructive advice was given to the enterprises for their future direction. The enterprises can use the cost-sharing contract to coordinate the supply chain, and increase the intensity of the impact of competitive behavior on market demand, with a view to maximizing the supply chain profits.

(c) By solving the model using the NSGA-II, it was found that the size of goodwill and the investment decision level show a positive correlation on the impact of the supplier's profit, which again validates the model. However, when the levels of goodwill and quality reach a certain threshold, the supplier's profit tends to level off. At this time, excessively high investment decisions yield limited improvements in profits. As for the e-commerce platform, reasonable decisions based on a combination of market factors with reference to quality effects, competitive phenomena, etc. should not only consider short-term, temporary profit returns but should also pay attention to the long-term impact of the decisions and goodwill. Although in some cases (increased competition or external uncertainties in the market), profits may fall in the short term, strategies to enhance goodwill may also lead to higher long-term returns.

This study has some limitations, such as uncertainty in practical applications, where many external factors (e.g., policy changes, emergencies, etc.) may affect the final decision outcome. It is difficult to accurately capture and quantify these uncertainties in the model, which affects its practicality and reliability. Future research could be extended to study the Stackelberg game model with incomplete information, exploring how to optimize the behaviors of leaders and followers through decision-making strategies under this condition. Information updating mechanisms and learning processes could be introduced to simulate the process of information acquisition and processing in the real world.

Data Availability

Not applicable.

Conflicts of Interest

The authors declare no conflict of interest.

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