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Optimising O2O Supply Chain Strategies Through Cost-Sharing Contracts: Strategic Analysis and Empirical Insights

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Abstract: Manufacturers are increasingly leveraging both online and offline channels to diversify their sales strategies. However, competition between these channels presents challenges in maximising profits for all parties involved. This study investigates the use of cost-sharing contracts by manufacturers to promote marketing in both online and offline channels, with the goal of achieving Pareto improvements in supply chain profitability. The model also accounts for consumers' reference quality perceptions in online channels, offering a comprehensive evaluation of how cost-sharing contracts influence the operational strategies and performance of both online and offline enterprises. An empirical analysis is conducted using the "US Stores Sales" dataset from Kaggle, comprising 4,249 samples with 20 recorded characteristics per sample. The findings indicate that: (1) Cost-sharing in marketing efforts facilitates a Pareto improvement in profits for manufacturers, online enterprises, and offline retailers, with manufacturers experiencing the most significant benefit. (2) When the manufacturer assumes a larger share of marketing costs for one channel (e.g., online or offline) and a smaller share for the other, the party receiving the higher cost-sharing proportion typically sees increased profitability, while the other party's profitability may diminish. (3) Empirical analysis suggests that manufacturers should prioritise supporting online businesses' marketing activities, as this strategy is more likely to result in higher overall profits for the manufacturer. (4) Interestingly, when equal cost-sharing proportions are offered to both online and offline enterprises for the sake of fairness, the manufacturer's profitability is enhanced. Moreover, the profitability of online enterprises tends to increase when the equal cost-sharing proportion is smaller. These findings validate the proposed model and underscore the critical role of strategic cost-sharing contracts in optimising Online to Offline (O2O) supply chain performance. Further research could explore the implications of varying consumer preferences and digitalisation trends on the effectiveness of such strategies.

Keywords: Online to Offline (O2O) supply chain; Cost-sharing contracts; Supply chain coordination; Strategy optimization; Empirical analysis

1 Introduction

Today's rapidly developing information technology can support consumers to pay online and transact after offline experience, which is called O2O channels, such as TripAdvisor and Hipmunk in the tourism industry, and Zipcar and Uber in the transportation industry, etc. [1–4]. In August 2010, Alex Rampell, the founder of TrialPay, published an article on TechCrunch, which overturned people's perception of the traditional commerce model in one fell swoop. In August 2010, Alex Rampell, the founder of TrialPay, published an article on TechCrunch that overturned people's perception of the traditional business model in one fell swoop, and the concept of O2O (the integration of online and offline channels and interoperability) refined in the article became the mainstream of the new generation of business. The U.S. Groupon, Yelp, OpenTable, and other enterprises have realized O2O transformation, and China's retail giants such as Suning, Gree, and Gome have also entered the network field and opened O2O operations. In the information explosion of the "Internet +" era, with the gradual integration of digital technology and retail, enterprises through the use of big data to consumers for precision marketing, so as to accurately understand the needs of consumers to become a new style of network marketing, which as a potential power of a new capital, the value of online platforms to be embodied [5–7]. Offline brick-and-mortar stores also follow the trend, building customer databases based on consumer behavioral trajectories, using store advantages to serve customers, and making intelligent recommendations. However, the challenges faced by marketers include how to analyze massive data and how to gain insights into customer engagement from mobile data, and numerous scholars have solved this problem by developing big data mobile marketing analytics and given certain experimental results [8]. It can be seen that the research on the O2O model and big data marketing as an emerging issue in the business world has also become a hotspot for scholars at home and abroad to study in recent years. Therefore, this paper combines the current popular research background, i.e., O2O supply chain, considers the phenomenon of competition between online and offline enterprises that prevails in O2O supply chain, and deeply analyzes the impact of competitive behavior on the profits of manufacturers and online and offline enterprises, in order to provide managerial suggestions for enterprises. In addition, the reason why this paper chooses to study the O2O supply chain is that although scholars at home and abroad have carried out different degrees of research on the operation and management of the O2O supply chain, most of them are concentrated in the static category. Unlike the previous ones, this paper takes into account the actual operating environment of the enterprises and constructs a dynamic differential game model, which is also the innovation of this paper.

For brick-and-mortar retailers, the introduction of online platforms will inevitably divert the traffic of brick-and-mortar retail stores, thus affecting the offline demand of consumers, and the operation of O2O hybrid channels is still complex [9, 10]. In addition, one of the key issues facing Internet commerce under the O2O model is the nature of competition with traditional brick-and-mortar retailers. Although traditional retailers' sales far exceed those of Internet retailers in most product categories, studies of Internet retailing have largely ignored this fundamental aspect of competition. For example, the rise of takeaway services such as Meituan Takeaway has made its competition with brick-and-mortar stores increasingly white-hot. Although the Internet provides a brand-new means for retailers to reach consumers, it fundamentally changes the competitive landscape of the retail service supply chain, and the integration of online and offline channels adds a new dimension to the competition [11]. Therefore, the operational issues for competitive O2O supply chains deserve further exploration. As a result, this paper incorporates the existence of competitive behavior in the O2O supply chain and takes into account the reference quality effect that exists in online consumption, which is more in line with the actual operation situation.

The coordination of supply chain systems has been a popular issue in the field of operation management in the business world, and the common coordination contracts are revenue sharing and cost sharing. Revenue-sharing contracts have been shown by scholars to be able to coordinate supply chains with quantitatively competing retailers [12]. However, the revenue contract is not always beneficial [13], although it can mitigate the double marginal effect but can not be coordinated for competitive enterprises, which is when the cost sharing contract as an effective tool for coordinating the decentralized supply chain has attracted the general attention of the business community and academics. In summary, this paper not only considers competitive behavior in O2O supply chains and incorporates consumer reference quality effects, but also considers a cost-sharing contract as a way to coordinate the supply chain.

In summary, various factors such as the O2O model, the non-negligible competitive phenomenon between online and offline, and the coordination contract are actually closely related, which jointly affect the consumer's behavioral choices, market changes, and corporate profits. Although the existing literature has studied each of the above factors to varying degrees, it lacks a comprehensive analysis of the above factors. As a matter of fact, for enterprises carrying out O2O operation mode, the correct utilization of the combination and distribution among the factors is especially crucial to increasing profits. In this paper, we consider the above factors in an all-round way to answer the following questions: 1) Can manufacturers' big data marketing cost sharing realize three-party Pareto improvement? For which party is the improvement effect more obvious? 2) What effects will the different combinations of cost-sharing ratios allocated by the manufacturer for online enterprises and offline brick-and-mortar stores have on the enterprises of each party? Based on the research in this paper, can constructive suggestions be given for the future direction of the enterprises?

2 Literature Review

In order to highlight the practical significance and theoretical value of the research in this paper, the following will be a detailed compendium of the various research areas that are closely related to this paper: the O2O model and big data marketing, and the cost-sharing contract.

Currently, in the research field of the O2O model, Gallino and Moreno [9] and Chen et al. [11] verified that the O2O model would have a positive aspect on supply chain performance through the O2O retail service supply chain, respectively. He et al. [14] proposed an O2O model based on subjective competition to study the joint optimal pricing decision of service providers and found that the customers' online follower behaviors would bring the performance risk for service providers. Zheng et al. [15], on the other hand, investigated the effects of positive channel competition and power structure on a two-channel closed-loop supply chain and found that the strength of the power structure depends on the channel substitution rate between the two channels. While most of the research on big data marketing focuses on the analysis of consumers and e-marketplaces, there are few reports in the literature involving business operations and management. Different from the above, this paper combines the current popular research fields and studies the influence of behavioral factors on the consumer side and enterprise side on the big data marketing strategies of online and offline enterprises under the O2O model from a dynamic perspective. Different from the above, this paper combines the current popular research fields and studies the influence of behavioral factors on the consumer side and the enterprise side on the big data marketing strategy of online and offline enterprises under the O2O model from a dynamic perspective.

For the research field of cost sharing, Lu et al. [16] and Bai et al. [17] demonstrated that cost sharing contracts can coordinate the effectiveness of the system. Liu and Yi [18] studied a three-stage supply chain and showed that the big data investment threshold of a data company is determined by the cost improvement factor. Wu and Yang [19] conducted a study of cost-sharing contracts for a two-stage supply chain based on carbon emission control and found that it is possible to identify a range of cost-sharing ratios that lead to a Pareto improvement in the profits of both parties. Unfortunately, although the above literature has studied the cost-sharing contract at different levels, it lacks reference to the quality effect, the competitive behavior that exists in the O2O model, and a comprehensive study on the cost-sharing contract. Unfortunately, although the above literature has examined the cost-sharing contract for different dimensions, all of them lack reference to the quality effect, the competitive behavior that exists in the O2O model, and comprehensive studies on the cost-sharing contract.

For this reason, this paper examines the impact that each factor has on firms from the perspectives of dynamic change and manufacturer's big data marketing cost sharing and identifies the effectiveness of manufacturer's cost sharing contract. The rest of the paper is organized as follows: Section 3 gives the problem description and model assumptions; Section 4 is the model analysis, giving the sensitivity analysis of the key parameters and the corresponding managerial revelation suggestions; Section 5 is the comparative analysis of the different decision-making models; Section 6 is the numerical arithmetic example; Section 7 is the empirical analysis; and finally, the conclusion is given.

3 Problem Description and Model Assumptions

In this paper, we consider an O2O supply chain system consisting of a manufacturer, an online business, an offline retailer, and a consumer, whose relationships are schematized in Figure 1.

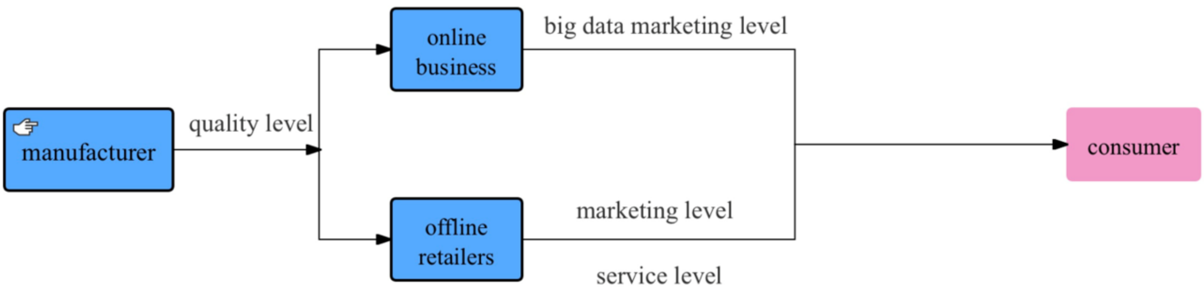


Figure 1. Schematic diagram of the system

In this dynamic system, the manufacturer, as a channel leader, produces a branded product and wholesales it to online enterprises and brick-and-mortar stores for dual-channel sales, with a marginal return of π_M, and optimizes the return by deciding the quality level of the product $q(t)$. Online enterprises, on the other hand, play to their strengths and conduct precision marketing with the help of massive big data, i.e., they rely on big data technology to precisely locate consumers and market their products based on the massive amount of data in numerous platforms [5], with a marginal return of π_O, and the decision variable is the level of big data marketing $A_1(t)$. Offline retailers, on the other hand, sell products directly to consumers through their offline physical stores, with a marginal revenue of π_R, and in addition to deciding their own marketing level $A_2(t)$, they will also make full use of the advantages of their physical stores to provide customer services, such as detailed product introductions, standardized product guides, and so on, and thus they also need to decide the level of service $s(t)$. Without loss of generality, set the same price for online and offline products, and both online businesses and offline retailers operate independently. It is worth noting that the market is in a dynamically changing environment, and in order to better describe the dynamic environment, the evolution of the state of goodwill is used to portray this phenomenon. Based on this, the hypothesis of this paper is given:

Hypothesis 1. As the consumer market iterates and becomes more sophisticated, consumers are no longer buying products blindly, but are considering many factors before purchasing, with quality being one of the key purchasing criteria. Consumers who choose to buy green products from offline retailers can make purchasing decisions by experiencing the products in the physical store, including checking the product packaging and asking the attendant about the product's indicator system. If consumers who choose to buy products through online enterprises can not perceive the quality of the product in advance, then there will be a psychological behavioral phenomenon, consumers will be based on the brand's products in the past cumulative formation of the goodwill to psychological prejudgment of the product to a quality level of the product, that is, the reference quality level $R_q(t)$ [20, 21], this phenomenon is known as the reference quality effect. This is very common in real life, some consumers are keen to buy products without leaving home, so they choose to shop online, however, online consumers can only go through the picture as well as the text description to judge the quality of the product, which is often not enough. This time there is a group of consumers who will go through the product's previous purchase evaluation or brand value analysis, in order to judge the product. According to the studies [22, 23], the reference quality level can be expressed as the following equation:

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

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

Hypothesis 2. As the core competence of a product, goodwill plays a key role in the product's foothold in the market. The service experience consumers receive when purchasing a product in an offline physical store can be a key influence on goodwill, and the existence of consumer reference quality effects in the market can also have a dynamic impact on goodwill. In addition, consumer forgetfulness or competition from brands in the same industry can lead to the erosion of brand goodwills [24]. In summary, the dynamic evolution of goodwill $G(t)$ 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, and $\delta > 0$ denotes the attenuation factor of the brand goodwill. $G_0 > 0$ 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. For consumers who choose to shop online, they will rely more on the reference quality level of the product and the goodwill of the product to make a purchase decision [25]. Therefore, the reference quality level is one of the factors affecting the online market demand. In addition, online enterprises will also use the huge amount of big data to carry out big data marketing, accurate targeting of consumers who like the brand's products for advertising. Consumers who choose to shop offline are more likely to make decisions based on on-site inspections of product quality and goodwill. In addition, offline retailers will also actively develop marketing strategies to promote offline market demand. Inevitably, there is competition between online and offline channels. In summary, the functions of online demand $D_O(t)$ and offline demand $D_R(t)$ can be obtained separately. i.e.:

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

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 $\mu_2\left(A_2(t) - A_1(t)\right)$ portray the competitive behavior between online and offline channels. It can be seen that good product quality, high quality expectations, favorable competitive position, and 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. Assume that each firm is a rational agent with a discount rate r , all pursuing their own profit maximization over an infinite period of time and making decisions based on complete information. The subscripts denote the manufacturer, the online business, and the offline brick-and-mortar store, respectively. The manufacturer decides its quality level strategy, the online enterprise decides its big data marketing strategy, and the offline brick-and-mortar store formulates its big data marketing strategy and service level strategy, so the objective function of each enterprise is:

$$\begin{aligned} &\max_{q(\cdot)} J_M = \int_0^\infty e^{-rt}\left[\pi_M\left(D_O(t) + D_R(t)\right) - \frac{1}{2}k_M q^2(t)\right]\mathrm{d}t \\ &\max_{A_1(\cdot)} J_O = \int_0^\infty e^{-rt}\left[\pi_O D_O(t) - \frac{1}{2}k_1 A_1^2(t)\right]\mathrm{d}t \\ &\max_{A_2(\cdot), s(\cdot)} J_R = \int_0^\infty e^{-rt}\left[\pi_R D_R(t) - \frac{1}{2}k_2 A_2^2(t) - \frac{1}{2}k_s s^2(t)\right]\mathrm{d}t \end{aligned} \tag{6}$$

where, $k_M > 0, k_1 > 0, k_2 > 0, k_s > 0$ denote the cost coefficients, respectively.

It is worth noting that the model is constructed based on the Stackelberg differential game model, taking into account the consumer reference quality effect and the competitive behaviour between online and offline enterprises. This approach is more aligned with the actual operating environment. However, the model is also applicable to other contexts, such as e-commerce supply chains and green supply chains, where green suppliers use both online and offline channels to sell their products. In these cases, cost-sharing contracts can also be utilised to achieve Pareto improvements in supply chain profits.

4 Model Analysis

4.1 Centralized Decision-Making Model (C)

In the centralized decision-making model (C), the three parties work together as an organic whole with the goal of maximizing the total profit of the system, and jointly formulate various strategies. Although the centralized decision-making model is almost impossible to achieve in reality, it can be regarded as a benchmark for decision-making and a target template for enterprises to develop coordinated strategies. The centralized decision-making model is denoted by the superscript. The optimal control problem at this point can be summarized as:

$$\max_{q(\cdot),A_1(\cdot),A_2(\cdot),s(\cdot)} J^C =$$

$$\int_0^\infty e^{-rt}\left[(\pi_M+\pi_O)\,D_O(t)+(\pi_M+\pi_R)\,D_R(t)-\frac{1}{2}k_M q^2(t)-\frac{1}{2}k_1A_1^2(t)-\frac{1}{2}k_2A_2^2(t)-\frac{1}{2}k_s s^2(t)\right]\mathrm{d}t$$

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

Proposition 1 (1) The various optimal strategies for the O2O supply chain are:

$$q^C=\frac{(\pi_M+\pi_R)\,a_2+\alpha f_1}{k_M}$$

$$A_1^C=\begin{cases}\frac{(\gamma_1+\mu_1)(\pi_M+\pi_O)-\mu_2(\pi_M+\pi_R)}{k_1} & (\gamma_1+\mu_1)(\pi_M+\pi_O)>\mu_2(\pi_M+\pi_R)\\ 0 & (\gamma_1+\mu_1)(\pi_M+\pi_O)\le\mu_2(\pi_M+\pi_R)\end{cases}$$

$$A_2^C=\begin{cases}\frac{(\gamma_2+\mu_2)(\pi_M+\pi_R)-\mu_1(\pi_M+\pi_O)}{k_2} & (\gamma_2+\mu_2)(\pi_M+\pi_R)>\mu_1(\pi_M+\pi_O)\\ 0 & (\gamma_2+\mu_2)(\pi_M+\pi_R)\le\mu_1(\pi_M+\pi_O)\end{cases}$$

$$s^C=\frac{f_1\beta}{k_s}$$

(2) The time evolution paths of goodwill, reference quality, and total system profit are respectively.

$$\begin{aligned}&G^C(t)=G_\infty^C+\left(G_0-G_\infty^C\right)e^{-\chi G}\\&R_q^C(t)=\xi\left(G_\infty^C+\left(G_0-G_\infty^C\right)e^{-\chi G}\right)\\&V^C=f_1G^C+f_2\end{aligned}$$

where,

$G_\infty^C=\frac{1}{\chi}\left[\frac{(\pi_M+\pi_R)\alpha a_2-\alpha^2 f_1}{k_M}+\frac{\beta^2 f_1}{k_s}\right]$; $f_1=\frac{(\pi_O+\pi_M)a_1\xi+(\pi_O+\pi_R+2\pi_M)\theta}{\chi+r}$;

$$f_2=\frac{1}{r}\left[\begin{array}{l}f_1\alpha q+\frac{(a_2\pi_M+a_2\pi_R)^2-(\alpha f_1)^2}{2k_M}+\frac{(\beta f_1)^2}{2k_s}+\frac{[(\pi_M+\pi_O)\gamma_1+(\pi_M+\pi_O)\mu_1-(\pi_M+\pi_R)\mu_2]^2}{2k_1}\\+\frac{[(\pi_M+\pi_R)\gamma_2-(\pi_M+\pi_O)\mu_1+(\pi_M+\pi_R)\mu_2]^2}{2k_2}\end{array}\right]$$

Property 1 The sensitivity analysis of the key parameters to each strategy in the centralised decision-making model can be obtained from Proposition 1, and can be collated in Table 1.

Table 1. Sensitivity analysis of key parameters in C-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^C	+	+	+	+	×	×	×	×	×	+	+	+	-	×	×	×	*	-
A_1^C	+	+	-	×	×	+	×	+	-	×	×	×	×	-	×	×	×	×
A_2^C	+	-	+	×	×	×	+	-	+	×	×	×	×	×	-	×	×	×
$_sC$	+	+	+	-	+	×	×	×	×	+	×	+	×	×	×	-	*	-

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

By analysing Table 1 we can get: 1) Throughout this result, the increase in the marginal revenue of the manufacturer's product will prompt it to increase the investment in quality level, the online enterprise and the offline retailer will improve their respective marketing levels accordingly, and it will incentivize the offline retailer to improve the level of service, which will form a positive cycle. 2) When the marginal revenue of the online enterprise is increased, it means that at this time, the online enterprise is more profitable or the cost is smaller, the manufacturer will inevitably increase investment in quality level, and the online firm's big data marketing will be incentivized as a result, at which point the online firm is at a sales advantage. Offline retailers will be impacted by this and will reduce their marketing levels to avoid unnecessary losses. At the same time, the retailer should also increase its service level investment to gain additional potential resources. 3) Similarly, when the offline retailer's marginal revenue from its products increases, the online enterprise is at a sales disadvantage, and the reduction of big data marketing will be in its favor at this time. The retailer's marketing as well as service level will be encouraged to further improve on this basis. 4) As the reference quality effect increases on the evolution of the goodwill state, the manufacturer will correspondingly increase the quality level of the green product, which will raise the product expectation; and since the reference quality will promote the consumer's online demand, which will frustrate the service level of the brick-and-mortar store, the retailer will correspondingly reduce the service level at this time. 5) Further horizontal observation of the analysis results of the manufacturer's product quality strategy, when the impact of reference quality on online demand increases, the impact of quality on offline market demand increases, and the impact of goodwill on the market demand increases, all of which will incentivize the manufacturer to further increase the level of quality investment. 6) As the impact of the respective marketing strategy of online and offline on the demand of their own market increases, the more actively online and offline firms will market their products, thus further driving the increase in demand in their respective markets. 7) Since a firm's marketing strategy cannot be infinite, $\mu_1\mu_2$ in the centralized decision-making model can be regarded as the coefficient of interaction between the two parties' marketing levels. Online firms' big data marketing will increase online demand, while offline retailers' marketing efforts will decrease online market demand, so when μ_1 increases, it indicates that the greater the strength of the positive influence of online firms' big data marketing on online demand, the more it will motivate online firms to improve their big data marketing. Whereas, when the marketing effort of online firms is too high, it will harm the demand of offline retailers. When μ_2 increases, it implies that the greater the intensity of the negative impact of online firms' big data marketing on offline demand, the more the level of big data marketing should be appropriately weakened. Similarly, when μ_1 increases, the more offline retailers are urged to increase their marketing efforts, and when μ_2 increases, retailers should weaken their marketing levels.

The managerial insights and recommendations that this brings are: 1) Since goodwill affects firms' profits throughout, firms should always make the establishment and maintenance of product goodwill a top priority, with establishment and maintenance going hand in hand. In addition, manufacturers should enhance the marginal returns of their products by, for example, improving skill levels. Online and offline can be combined to carry out interactive marketing, through joint product launches, etc., to improve the sales effect. 2) Online and offline enterprises should strive to expand the influence of the enterprise and, at the same time, pay attention to good after-sales service, so as to win the trust of the customers. 3) The centralized decision-making mode should pay attention to narrowing the marketing gap between the online and offline enterprises so as to stabilize and seek development together. For example, in the initial stage of raw material procurement, the two sides can negotiate with multiple manufacturers to select the best quality and price of the best materials, to determine all aspects of the manufacturer that meet the standards, and should establish a long-term cooperative relationship with them to win the price concessions. 4) The centralized decision-making mode of each channel in the marketing of the product should be balanced between its own positive impact and the negative impact on the partners. Both parties can send each other specialists, conduct regular special meetings, and jointly discuss and formulate marketing strategies to establish a long-term and stable cooperative relationship.

4.2 Manufacturer's Cost-Sharing Decision Model (D)

Taking into account the fact that the centralized decision-making situation is difficult to achieve in reality, many firms will choose to use the centralized decision-making situation as a target template to formulate coordination strategies for Pareto improvement. This section considers a cost-sharing contract, which is common in reality, in which the manufacturer, in order to incentivize firms to make efforts to market their products, will share a certain percentage of the marketing costs for the online firms and the offline retailers, respectively, and the downstream firms will formulate their strategies based on this. The order of the game is as follows: the manufacturer first decides on its quality level strategy, the proportion of big data marketing costs to be shared by online enterprises and the proportion of marketing costs to be shared by offline retailers, and then the online enterprises and offline retailers, as channel followers, formulate their own marketing strategies on this basis, and the offline retailers formulate their service level strategies accordingly. At the same time, because of the competition between online and offline firms and their simultaneous strategies, the process includes the Nash game and the Stackelberg master-slave game, which can be summarized as follows:

$$\max_{q(\cdot),\varphi_1(\cdot),\varphi_2(\cdot)} J_M=\int_0^{\infty} e^{-rt}\left[\pi_M\left(D_O(t)+D_R(t)\right)-\frac{1}{2}k_M q^2(t)-\frac{1}{2}\varphi_1 k_1 A_1^2(t)-\frac{1}{2}\varphi_2 k_2 A_2^2(t)\right]\mathrm{d}t$$

$$\begin{cases}\max_{A_1(\cdot)} J_O=\int_0^{\infty} e^{-rt}\left[\pi_O D_O(t)-\frac{1}{2}k_1\left(1-\varphi_1\right)A_1^2(t)\right]\mathrm{d}t\\ \max_{A_2(\cdot),s(\cdot)} J_R=\int_0^{\infty} e^{-rt}\left[\pi_R D_R(t)-\frac{1}{2}k_2\left(1-\varphi_2\right)A_2^2(t)-\frac{1}{2}k_s s^2(t)\right]\mathrm{d}t\\ \text{s.t. } \dot{G}=\alpha q+\beta s-\chi^G\end{cases}$$

Proposition 2 (1) The optimal strategies for each of the O2O supply chains and the manufacturer's share of the online and offline big data marketing costs were:

$$q^D=\frac{\pi_M a_2+\alpha m_1}{k_M};A_1^D=\frac{\pi_O\left(\gamma_1+\mu_1\right)}{\left(1-\varphi_1^D\right)k_1};A_2^D=\frac{\pi_R\left(\gamma_2+\mu_2\right)}{\left(1-\varphi_2^D\right)k_2};s^D=\frac{o_1\beta}{k_s};$$

$$\varphi_1^D=\begin{cases}\frac{2\pi_M(\gamma_1+\mu_1-\mu_2)-\pi_O(\gamma_1+\mu_1)}{2\pi_M(\gamma_1+\mu_1-\mu_2)+\pi_O(\gamma_1+\mu_1)} 2\pi_M\left(\gamma_1+\mu_1-\mu_2\right)>\pi_O\left(\gamma_1+\mu_1\right)\\ 0 2\pi_M\left(\gamma_1+\mu_1-\mu_2\right)\leq\pi_O\left(\gamma_1+\mu_1\right)\end{cases};$$

$$\varphi_2^D=\begin{cases}\frac{2\pi_M(\gamma_2-\mu_1+\mu_2)-\pi_R(\gamma_2+\mu_2)}{2\pi_M(\gamma_2-\mu_1+\mu_2)+\pi_R(\gamma_2+\mu_2)} 2\pi_M\left(\gamma_2-\mu_1+\mu_2\right)>\pi_R\left(\gamma_2+\mu_2\right)\\ 0 2\pi_M\left(\gamma_2-\mu_1+\mu_2\right)\leq\pi_R\left(\gamma_2+\mu_2\right)\end{cases}$$

(2) The time evolution paths of goodwill, and reference quality are respectively:

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

where, $G_\infty^D=\frac{1}{\chi}\left[\frac{\alpha(\pi_M a_2+\alpha m_1)}{k_M}+\frac{o_1\beta^2}{k_s}\right]$.

(3) The profits of M, O, R are respectively:

$$V_M^D=m_1 G^D+m_2;\quad V_O^D=n_1 G^D+n_2;\quad V_R^D=o_1 G^D+o_2$$

where,

$$m_1=\frac{\pi_M(a_1\xi+2\theta)}{\chi+r};n_1=\frac{\pi_O(a_1\xi+\theta)}{\chi+r};o_1=\frac{\pi_R\theta}{\chi+r};$$

$$m_2=\frac{1}{r}\left[\begin{array}{l}\frac{(\pi_M a_2+\alpha m_1)^2}{2k_M}+\frac{o_1 m_1\beta^2}{k_s}+\frac{\pi_M\pi_o(\gamma_1+\mu_1)(\gamma_1+\mu_1-\mu_2)}{\left(1-\varphi_1^D\right)k_1}+\frac{\pi_M\pi_R(\gamma_2+\mu_2)(\gamma_2-\mu_1+\mu_2)}{\left(1-\varphi_2^D\right)k_2}\\ +\frac{\varphi_1(\pi_o)^2(\gamma_1+\mu_1)^2}{2k_1\left(1-\varphi_1^D\right)^2}+\frac{\varphi_2(\pi_R)^2(\gamma_2+\mu_2)^2}{2k_2\left(1-\varphi_2^D\right)^2}\end{array}\right]$$

$$n_2=\frac{1}{r}\left[\frac{n_1\alpha(a_2\pi_M+\alpha m_1)}{k_M}+\frac{n_1 o_1\beta^2}{k_s}+\frac{(\pi_o(\gamma_1+\mu_1))^2}{2k_1\left(1-\varphi_1^D\right)}-\frac{\mu_1\pi_o\pi_R(\gamma_2+\mu_2)}{\left(1-\varphi_2^D\right)k_2}\right]$$

$$o_2=\frac{1}{r}\left[\frac{(\pi_M a_2+\alpha m_1)(a_2\pi_R+o_1\alpha)}{k_M}+\frac{(o_1\beta)^2}{2k_s}-\frac{\mu_2\pi_o\pi_R(\gamma_1+\mu_1)}{\left(1-\varphi_1^D\right)k_1}+\frac{(\pi_R(\gamma_2+\mu_2))^2}{2\left(1-\varphi_2^D\right)k_2}\right]$$

Property 2 From proposition 2, we can obtain the sensitivity analysis of key parameters to each strategy in the manufacturer's cost-sharing decision-making model, and by collating them we can obtain Table 2.

Table 2. Sensitivity analysis of key parameters in D-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^D	+	×	×	+	×	×	×	×	×	+	+	+		×	×	×	*	
A_1^D	×	+	×	×	×	+	×	+		×	×	×	×		×	×	×	×
A_2^D	+	×	+	×	×	×	+		+	×	×	×	×	×		×	×	×
φ_1^D	+		×	×	×		×	+		×	×	×	×	×	×	×	×	×
φ_2^D	+	×		×	×	×			+	×	×	×	×	×	×	×	×	×
s^D	×	×	+		+	×	×	×	×	×	×	+	×	×	×			

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

Through Table 2, it was found that: 1) Manufacturers sharing marketing costs for online firms and offline retailers do not affect their own quality level strategy, nor do they have an impact on the service level strategy of offline retailers. 2) Manufacturers are motivated to increase their cost sharing when the marginal returns to their products become higher and the marginal returns to the online firms and offline retailers are lower, i.e., the marginal profit is the incentive for the manufacturers to invest in cost sharing. This is reflected in the fact that, firstly, when the manufacturer's own benefit is high, it can put the surplus benefit on helping downstream enterprises; secondly, when the marginal benefit of online enterprises and offline retailers decreases, in order to encourage their operation, the manufacturer will also increase cost sharing. 3) When the marketing influence factor of the offline retailers becomes larger, as the retailers are in an advantageous position in the competitive process, the manufacturer will reduce the cost sharing ratio of the online enterprises accordingly, and vice versa. cost-sharing ratio, and vice versa. 4) The marketing strategies of both online and offline firms are positively related not only to their respective marginal returns, but also to the manufacturer's marginal returns. This is manifested in the fact that when the manufacturer shares part of the marketing costs for the offline and online enterprises, it will consume part of its assets, and if the manufacturer's marginal revenue of its products still grows at this time, it indicates that it has great potential for development, which will further stimulate the online and offline enterprises to invest in marketing. 5) Under the cost-sharing model, the competing online and offline enterprises not only pay attention to their own competitive factors, but also pay attention to their rivals' competitive factors, and when their competitive factors increase, they will also pay attention to their competitors' competitive factors. In addition to their own competitive factors, competing online and offline enterprises will also pay extra attention to their rivals' competitive factors, and when their own competitive factors increase, it is the best strategy to further enhance their marketing efforts; conversely, when their rivals' competitive factors increase, it is better to reduce their marketing levels. 6) The larger the proportion of cost sharing a manufacturer bears for the online enterprise, the more it will be encouraged to engage in big data marketing; the same is also true for the offline retailers.

The management insights and suggestions that this brings are: 1) When manufacturers share marketing costs for online businesses and offline retailers, manufacturers face greater cost pressure, and in order to reasonably respond to the issue of how to minimize costs, companies should make efforts to reduce fixed costs and variable costs. For example, enterprises can set up a specialized department to carry out job cost management, so as to detail every cost expenditure. Increase technical investment, master the latest product technology, and improve product quality while reducing unit costs, so as to improve marginal returns while reducing costs. 2) In addition, manufacturers should always pay attention to market changes, always observe the competitive advantages and disadvantages of online and offline enterprises, and reasonably allocate the proportion of cost sharing. 3) Whether it is an online enterprise or an offline retailer, at this time, the cost pressure has been eased, and should be Make full use of this excellent environment to actively market their products and enhance consumers' willingness to buy, so as to expand market demand. For example, enterprises should make accurate optimizations of decision-making data, effectively screen consumer groups on the basis of scientific big data, and constantly explore the potential needs of consumers, in addition to the use of peer-to-peer intelligent advertising, consultative marketing and other ways to carry out personalized marketing.

5 Contrast Analysis

In order to analyze the impacts of the above two different decision-making models on the various strategies of the enterprises, and to verify whether the manufacturer's cost-sharing decision-making model can effectively coordinate the supply chain, this chapter carries out a steady-state solution and a comparison of the size relationship on top of the theoretical foundation of the previous section.

Proposition 3 The relationship between the size of the strategies of the supply chain under the two decision-making models are $q^C > q^D, A_1^C > A_1^D, A_2^C > A_2^D, s^C > s^D$.

Proposition 3 shows that the synergy of members in the centralized decision-making model can effectively improve the quality level of the product, the service level of the retailer, and the marketing efforts of the offline and online firms. The manufacturer's marketing cost sharing does not change the manufacturer's quality level as well as the retailer's service level, but it can effectively improve the marketing level of the online and offline firms and sufficiently stimulate the market demand, which in turn can help them to make Pareto improvements in their performance.

Proposition 4 The relationship between the goodwill steady state and the reference quality steady state for the two decision models is $G_\infty^C > G_\infty^D, R_{q\infty}^C > R_{q\infty}^D$.

Proposition 4 shows that goodwill is highest in the centralized decision-making model. This shows that the cooperative model is effective in eliminating competition and achieving Pareto improvement in performance.

Proposition 5 The results of the comparative analysis of the market demand function under the two decision-making models are $D_O^C > D_O^D, D_R^C > D_R^D$.

Proposition 5 shows that analyzing the market demand functions of online and offline retailers separately, we can find that the market demand is highest in the centralized decision-making model, followed by the cost-sharing decision-making model, because the manufacturer's cost sharing to online and offline companies does not affect the goodwill change, but it can motivate the companies to raise their marketing level, which is effective in promoting the market demand. All of the above propositions fully illustrate the effectiveness of manufacturer cost sharing, although it does not affect the brand goodwill, the reference quality level, the manufacturer's quality level strategy, and the offline retailer's service level strategy, it can raise the marketing level and promote market demand to increase the profit effectively.

6 Numerical Calculation Examples

In order to make the previous results clearer, this section will further verify the conclusions obtained in the previous section through numerical examples, analyze the equilibrium strategies and supply chain performance of firms under different decision-making modes, and study the Pareto improvement effect of manufacturers' cost sharing on firms. Drawing on literature [26], the parameters of the example are set as follows:

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

6.1 Brand Goodwill and Reference Quality in Different Decision Models

Figure 2 shows the time trajectory of product goodwill when different initial goodwill is given for different decision models.

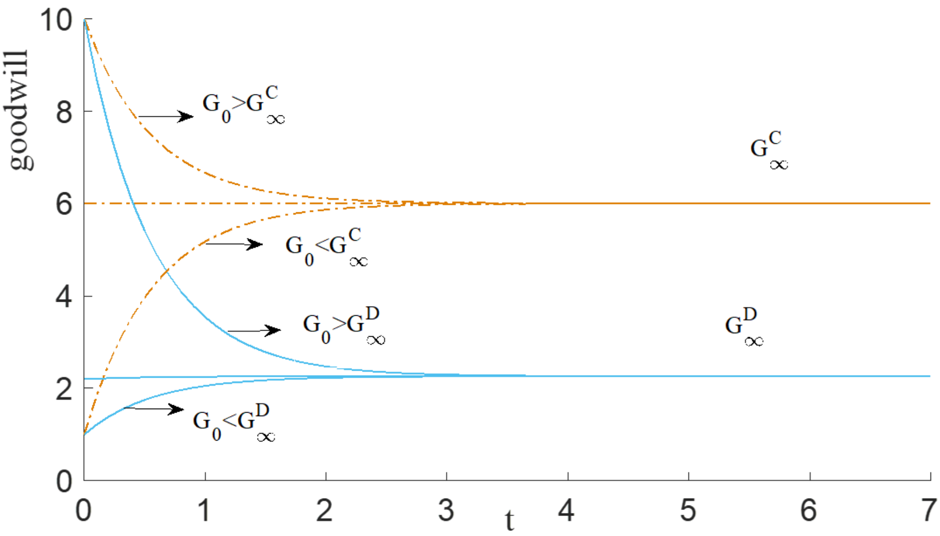


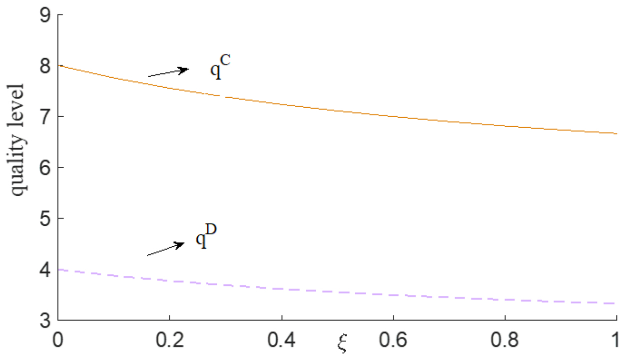
Figure 2. Product brand goodwill

Figure 2 shows that the brand goodwill of a product eventually converges to a global steady state when given different initial goodwill, regardless of the decision mode. After reaching the steady state, the product brand goodwill is globally highest in the centralized decision-making mode. It is clear that when the initial goodwill is large, although it decreases over time and eventually reaches the steady state, it still brings more benefits to the firm in the early stage compared to a lower initial goodwill. It can be shown that although goodwill will eventually stabilize, establishing good initial goodwill at the beginning of the business is still the best decision for the business.

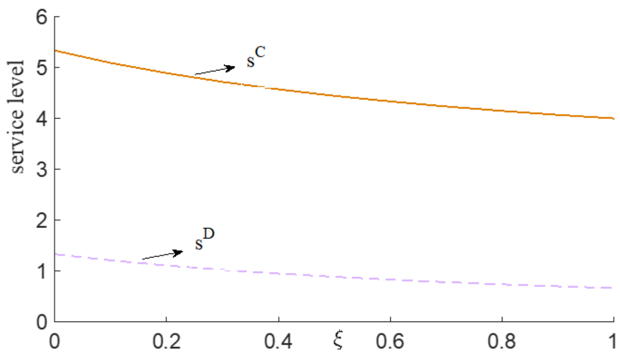
This leads to the suggestion of management measures: firstly, goodwill should be built up during the preparatory stage of the company's founding. For example, a company can make full use of big data to target customers and advertise in advance by playing colorful promotional videos on the screen in shopping malls, creating a sense of mystery and attracting consumers' attention before they see it. Secondly, enterprises should establish goodwill at the initial stage, and can choose famous enterprises with goodwill for cooperation, and enhance their initial goodwill through association with other enterprises. In addition, when an enterprise establishes good initial goodwill, it should pay attention to the maintenance of goodwill decay when formulating various strategies, for example, through real-time big data marketing to effectively mitigate the decay of goodwill; and if the initial goodwill of the enterprise is low, it should pay attention to improving goodwill as soon as possible when formulating strategies to reach a stable state as soon as possible.

6.2 Sensitivity Analysis of the "Brand Goodwill-Reference Quality" Correlation Coefficient ξ

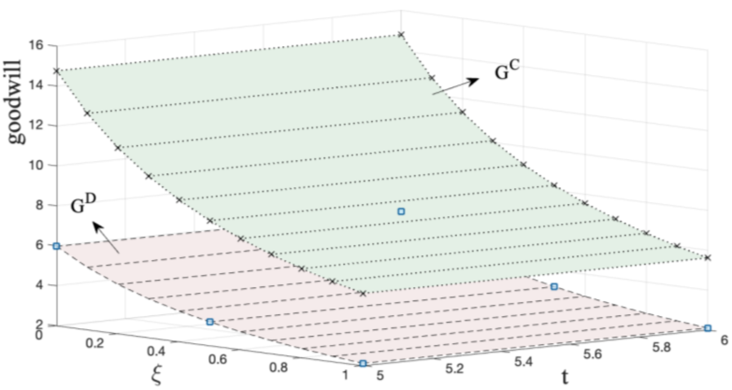
The association coefficient ξ represents the dependence of the reference quality on goodwill, which is particularly important because it plays an important role in market demand and supply chain performance. Figure 3 shows the sensitivity analysis of corporate strategy and supply chain performance under different decision-making modes from 0 to 1, respectively.



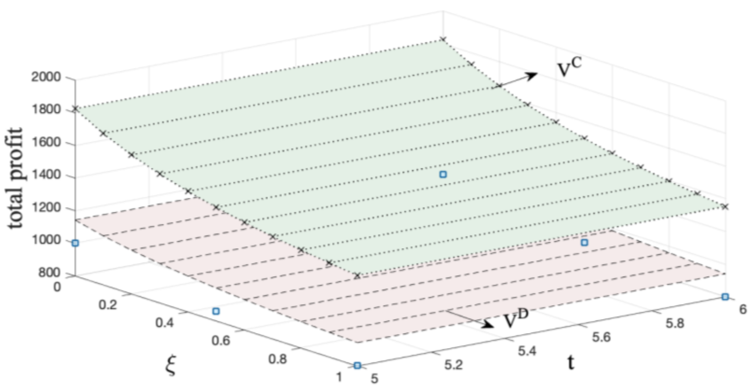
(a) Manufacturer quality level



(b) Retailer service level strategy



(c) Goodwill



(d) Total pofit

Figure 3. Impact of ξ on supply chain performance

Figure 3 demonstrates that the manufacturer's cost-sharing contract effectively increases total system profit, which aligns with the previous analysis. As the coefficient of "Goodwill-Reference Quality" increases, consumers tend to rely more on goodwill to assess the quality of green products, which negatively impacts strategies and profits. This suggests that an over-reliance on goodwill when evaluating green product quality leads companies to reduce their investments in quality and service levels. The underlying issue is that consumers often have limited information about the quality of green products, and excessive dependence on goodwill elevates product expectations, thereby creating information asymmetry between companies and consumers. To lower these expectations, companies may reduce their investment in both quality and service levels, diminishing goodwill and ultimately harming profits. To mitigate this, companies should work to reduce the correlation between goodwill and reference quality. Both online and offline enterprises should focus on promoting and highlighting the environmental attributes, quality, and performance of green products, enabling consumers to make purchasing decisions based on accurate product information and thereby reducing profit losses caused by information asymmetry.

6.3 The Effect of Cost Coefficients on the Pareto Improvement of Cost Sharing

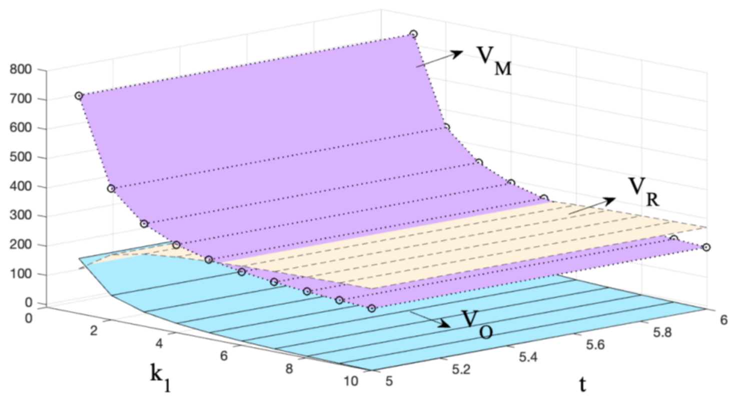


Figure 4. Plot of the effect of cost coefficients on the effectiveness of cost-sharing covenants

Figure 4 shows that the manufacturer's marketing cost-sharing contract has a more pronounced Pareto improvement effect on its own profits. As the big data marketing cost coefficient k_1 of the online enterprise increases, the less significant the incentive effectiveness of the manufacturer is, i.e., the profit of the online enterprise will be reduced, then the online enterprise will reduce the investment in the level of big data marketing, and the retailer competing with it will have more market demand, and the profit will be improved. Similarly, an increase in k_2 will result in a decrease in the retailer's profits and an increase in the online company's profits.

Table 3. Effect of different ratio combinations on members' strategies and performance

Profit Mode		G_∞	$R_{q\infty}$	q	A_1	A_2	s	$V_{M\infty}$	$V_{O\infty}$	$V_{R\infty}$	V
C	-	6.00	5.40	6.74	6.67	4.07	-	-	-	-	1375.01
	(φ_1, φ_2)						-				
	$(0.8, 0.8)$	2.26	2.04	3.37	25	25	0.70	8113.42	335.93	358.90	8808.25
	$(0.8, 0.5)$	2.26	2.04	3.37	25	10	0.70	4813.42	635.93	-91.10	5358.25
	$(0.8, 0.3)$	2.26	2.04	3.37	25	7.14	0.70	4490.97	693.07	-176.82	5007.22
	$(0.8, 0.0)$	2.26	2.04	3.37	25	5	0.70	4313.42	735.93	-241.10	4808.25
	$(0.5, 0.8)$	2.26	2.04	3.37	10	25	0.70	4813.42	-114.07	658.90	5358.25
D	$(0.5, 0.5)$	2.26	2.04	3.37	10	10	0.70	1513.42	185.93	208.90	1908.25
(φ_1, φ_2)	$(0.5, 0.0)$	2.26	2.04	3.37	10	5	0.70	1013.42	285.93	58.90	1358.25
	$(0.3, 0.8)$	2.26	2.04	3.37	7.14	25	0.70	4490.97	-199.79	716.04	5007.22
	$(0.3, 0.5)$	2.26	2.04	3.37	7.14	10	0.70	1190.97	100.21	266.04	1557.22
	$(0.0, 0.8)$	2.26	2.04	3.37	5	25	0.70	4313.42	-264.07	758.90	4808.25
	$(0.0, 0.5)$	2.26	2.04	3.37	5	10	0.70	1013.42	35.93	308.90	1358.25
	$(0.0, 0.3)$	2.26	2.04	3.37	5	7.14	0.70	690.97	93.07	223.19	1007.23
	$(0.0, 0.0)$	2.26	2.04	3.37	5	5	0.70	513.42	135.93	158.90	808.25

6.4 Impact of Cost Sharing Ratio on Membership Strategies and Performance

Table 3 illustrates that there is no effect of the manufacturer's marketing cost share ratio on goodwill, reference quality, quality level, or service level. In the macro view, the manufacturer's profit rises as the cost share increases, which is also consistent with the previous validation results. It is worth noting that when the manufacturer provides a larger proportion of big data marketing cost sharing for the online business, and at the same time gives a smaller proportion of marketing cost sharing to the retailer, the profit of the online business will be effectively improved accordingly, and if the manufacturer provides a large proportion of cost sharing for the online business, and doesn't give the same proportion of cost sharing to the retailer, but instead gives the retailer a smaller proportion of cost sharing than the proportion of cost sharing provided for the online business, and the retailer's profits will be severely lost. The reason for this is that the manufacturer shares more of the big data marketing costs with the online company, which boosts the online company's big data marketing efforts, and the online company captures more of the market, so profits are effectively boosted, which at the same time results in the retailer not being able to make ends meet, and not gaining a proportionate share of the market after investing in the marketing effort, which results in a loss of revenue. At this point, the management advice given is that retailers should always pay attention to market changes, and should adjust their status as soon as possible after the occurrence of such a situation. For example, retailers can sell complementary products of hot-selling products, and sell their complementary products with the help of the favorable situation of online enterprises; or retailers can switch to the sale of other types of products to reduce competition with online enterprises; in addition, retailers can take advantage of their ability to directly face the customers to increase the level of service. In addition, retailers can increase their service levels by taking advantage of their direct access to customers. Similarly, the situation is the same as above when the manufacturer provides a larger share of marketing costs to the retailer and a smaller share of big data marketing costs to the online business. Therefore, analyzing from the perspective of each business, it should be encouraged to increase the impact of their respective competitive intensities on market demand, and to strive for a larger cost-sharing percentage in order to increase their own profits and avoid losses.

7 Empirical Analysis of Online Businesses

The data used to validate the model for this research example comes from the "US Stores Sales" dataset on the Kaggle website (https://www.kaggle.com/datasets/dsfelix/us-stores-sales). This is an exhaustive retail sales dataset containing a total of 4,249 samples. Each sample records 20 features that cover various business metrics of the company. See Table 4 for descriptions of specific variables in the dataset:

Table 4. Description of retail sales data

Form	Attribute Variable	Property Description
Store Information	Area Code	Code of the store
	State	State where the store is located
	Market	Market area where the store is located
	Market Size	Size of the store
Product Information	Product ID	Product ID
	Product	Product Description
	Product Type	Commodity category
	Type	Product Type
	Date	Date of sale
Financial data	Sales	Total income from sales
	Profit	Margins
	COGS	Cost of sales
	Total Expenses	Total cost of the merchandising process
	Marketing	Marketing cost
	Inventory	Inventory value of goods at the time of sale
Budget data	Budget Profit	Budget Profit
	Budget COGS	Budgeted cost of sales
	Budget Margin	The sum of budgeted profit and budgeted total expenses, or budgeted sales minus budgeted cost of goods sold (COGS)
	Budget Sales	Budgeted sales
Profit and costing	Margin	Sum of profit and total expenses, or sales minus cost of goods sold (COGS)

In this study, we focus on two characteristics in particular:

Margin (Margin): we use it as a proxy for the marginal cost of the e-commerce platform.

Marketing expenses (Marketing): we use it as a proxy for the platform cost coefficient.

In order to deeply analyze the profitability of online businesses, we set different combinations of cost-sharing ratios. By using the Python programming language, we performed a detailed calculation of the profit of the online business under these parameters. We recorded the profit data of the online businesses under different settings and visualized it using Matplotlib to generate the corresponding graphs and charts for a more intuitive understanding of the changes in the profit situation. As a result, we plotted the profit comparison of online businesses under different combinations of sharing ratios, as shown in Figure 5. For ease of analysis, we have excerpted the profit comparison for rows 5-15, as shown in Figure 6.

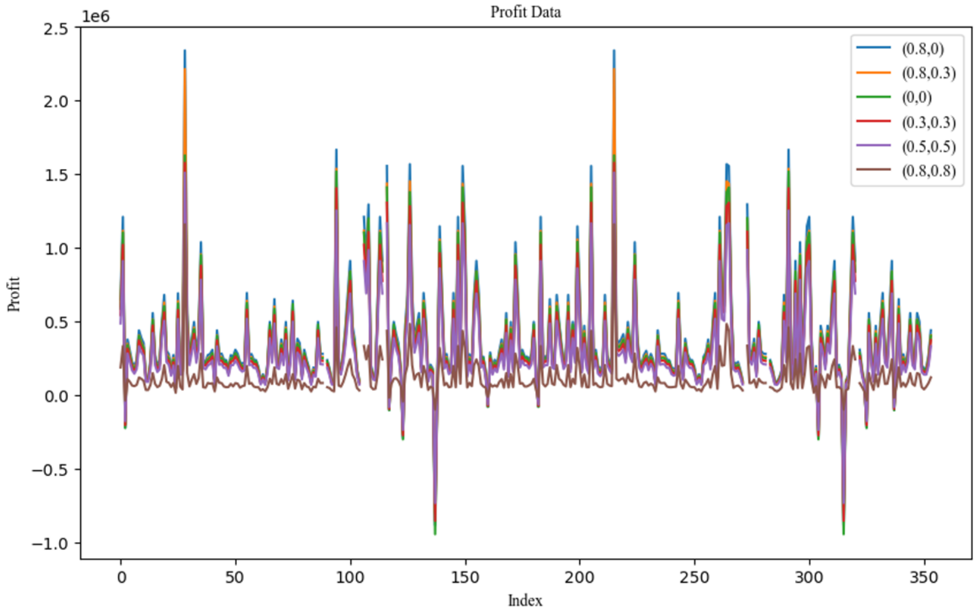


Figure 5. Comparison of profits of online businesses under different combinations of sharing ratios

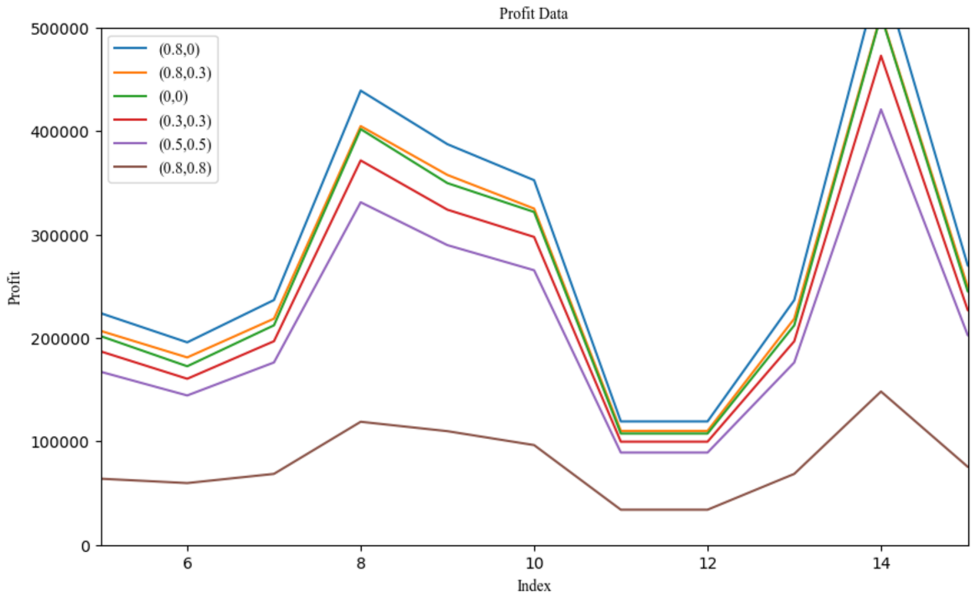


Figure 6. Comparison of profits of online firms in rows 5-15 of the excerpts

Figure 5 and Figure 6 show that: 1) When the manufacturer provides different proportions of cost sharing for online businesses and physical stores, it will have an important impact on the profits of online businesses. Obviously, when the combination of the proportion of cost sharing provided by the manufacturer for the online business and the physical store is (0.8, 0), the profit of the online business is better than the other cases, and we verify the validity of the model in this paper. 2) When the manufacturer provides different proportions of cost sharing for the online business and the physical store, the results of the comparison of the size of the profit of the online business are (0.8, 0) > (0.8, 0.3) > (0, 0) > (0.3, 0.3) > (0.5, 0.5) > (0.8, 0.8). It can be seen that when the manufacturer's cost share for the online firm is fixed, the lower the cost share for the brick-and-mortar store, the more profitable the online firm is. Interestingly, we find that if the manufacturer chooses to provide the same proportion of cost sharing for both online businesses and physical stores, the relationship between the size of profit values in different scenarios is (0, 0) > (0.3, 0.3) > (0.5, 0.5) > (0.8, 0.8). It can be seen that if the manufacturer chooses to provide the same proportion of cost sharing to the online business and the brick-and-mortar store for the sake of fairness, then the smaller the value of the proportion, the higher the profit of the online business instead.

8 Conclusions

This study has focused on an O2O supply chain consisting of a manufacturer, an online enterprise, and an offline retailer, investigating the potential for Pareto improvements through the manufacturer's marketing cost-sharing between online and offline channels. The impact of these factors on the operational strategies and performance of enterprises has been comprehensively examined. Optimal strategies for supply chain members and overall supply chain performance under different decision-making models have been derived. Additionally, a comparative static analysis of key parameters was conducted, offering management insights and recommendations.

A steady-state analysis of the strategies was undertaken through comparative analysis, and sensitivity analysis of key parameters, such as the correlation between reference quality and goodwill, was carried out using numerical examples. The main conclusions drawn from this research are as follows:

(1) Based on the model analysis, it was found that the manufacturer's big data marketing cost-sharing mechanism does not fully coordinate the supply chain but achieves a Pareto improvement for all three parties. The improvement is more pronounced for the manufacturer. Full Pareto optimisation of the system can be realised under centralised decision-making; however, given the practical difficulties of centralised decision-making, a coordination mechanism based on the manufacturer's marketing cost-sharing was proposed. It was shown that the individual profits of all three parties, as well as the total system profits, are enhanced under the cost-sharing decision-making model, confirming that marketing cost-sharing is an effective mechanism for achieving Pareto improvement across the supply chain.

(2) Analysis of numerical examples revealed that the manufacturer achieves the highest profits when providing a uniform and high percentage of cost-sharing to both online and offline enterprises. When a higher cost-sharing percentage is allocated to online businesses and a lower percentage to offline retailers, the profits exceed those achieved when the reverse distribution occurs. This indicates that manufacturers should prioritise support for online enterprises. The lowest profits are observed when no cost-sharing is provided to either channel. It is evident that a carefully structured cost-sharing strategy for both online and offline enterprises can significantly enhance the manufacturer's profitability, with the improvement for the manufacturer being particularly substantial. In addition, manufacturers should actively support the marketing efforts of online enterprises, as this is more conducive to increasing their own profits.

(3) When the manufacturer allocates a larger share of big data marketing costs to the online enterprise and a smaller share to the retailer, the online enterprise's profitability is significantly improved. If the manufacturer provides a very high share to the online enterprise but a proportionately smaller share to the retailer, the retailer's profits are likely to suffer. Conversely, the reverse distribution will result in reduced profitability for the online enterprise. To mitigate profit loss, it is recommended that firms explore countermeasures such as selling complementary products or diversifying their marketing efforts to include other product categories.

(4) Empirical analysis confirms that competition between online and offline enterprises intensifies when the manufacturer provides a larger cost-sharing proportion to the online business. This results in higher profits for online enterprises. The model developed in this study has been validated through empirical testing. Interestingly, when the manufacturer adopts an equal cost-sharing strategy for both online and offline enterprises, the relationship between the size of the profit in different scenarios follows this pattern: (0, 0) > (0.3, 0.3) > (0.5, 0.5) > (0.8, 0.8). This suggests that when the manufacturer chooses to allocate the same proportion of cost-sharing to both online and offline channels, the smaller the proportion, the higher the profits of the online enterprise.

In conclusion, this research contributes new managerial insights based on differential game theory. Specifically, if the manufacturer opts for an equal cost-sharing strategy between online businesses and brick-and-mortar stores, a smaller proportion of cost-sharing leads to higher profits for online enterprises. These insights can provide substantial guidance for companies in their operational and managerial decision-making processes.

It is important to acknowledge some limitations in this study. For instance, the model does not account for product pricing strategies, as incorporating such strategies would result in a significantly more complex model structure, complicating the analysis of competitive dynamics. Future research could explore additional factors, such as the logistics service strategies employed by online enterprises.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflict of interest.

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