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Research on Adoption Strategies of Social E-commerce Recommendation Systems in Dual-Channel Supply Chains

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ABSTRACT

In the context of the rapid rise of social e-commerce, this paper constructs a game-theoretic model for a dual-channel supply chain consisting of a manufacturer and an online retailer. It investigates the manufacturer's strategy for adopting a third-party recommendation system in its direct sales channel. The model innovatively introduces two core variables—social interaction effect intensity and social channel commission rate—to systematically analyze the manufacturer's adoption decisions and the game equilibrium among supply chain members under different payment schemes (Cost-Per-Sale CPS and Cost-Per-Click CPC). By solving a three-stage Stackelberg game across seven scenarios, this study finds that when the retailer has already adopted a recommendation system, the manufacturer's dominant strategy is to forgo adoption and "free-ride." When the retailer does not adopt, the manufacturer's decision depends on the recommendation strength and cost. The social interaction effect amplifies the impact of recommendation strength, thereby increasing the manufacturer's willingness to adopt, while the social channel commission rate increases the cost burden, suppressing adoption willingness. Furthermore, the manufacturer's preference between CPS and CPC shifts dynamically with the adoption context and recommendation cost. The study also clarifies the decision boundaries for achieving a win-win outcome for both the manufacturer and retailer. The conclusions provide a theoretical basis and managerial insights for enterprises formulating recommendation system adoption strategies and channel coordination mechanisms in the social e-commerce environment.

Keywords: Social E-Commerce, Channel Management, Recommendation System, Payment Scheme, Game Theory

Introduction

Over the past decade, the rapid development of e-commerce has been accompanied by increasingly intense competition among online businesses. To succeed in the market, a growing number of companies are leveraging recommendation systems to attract traffic and boost online sales. Recommendation systems capture consumers' purchasing behaviors, identify their preferences and interests through algorithms, and recommend products to target consumers. This not only helps online businesses attract consumers but also significantly promotes sales growth. For example,35% of Amazon's platform sales originate from its recommendation system.

Recommendation systems come in various forms, including those built by retailers themselves, as well as independent recommendation services provided by search engines or third-party comparison websites or software. Self-built systems primarily provide recommendations to consumers within the platform, while independent third-party recommendation systems can recommend products to a broader market of consumers. Notably, third-party recommendation systems are typically fee-based, with payment models mainly including Cost-Per-Sale (CPS) and Cost-Per-Click (CPC). For instance, platforms like Taoke and MaiXuan adopt the CPS model, while Baidu Marketing and Shopping.com use the CPC model. These payment schemes not only affect enterprises' cost structures but also profoundly alter the game relationships among supply chain members.

Although existing literature has explored the impacts of recommendation systems from various angles—such as their effect on increasing consumers' willingness to pay, moderating competition between retailers and manufacturers, and adoption

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strategies in competitive environments—most studies focus on traditional e-commerce settings or self-built recommendation systems. The strategic role of third-party recommendation systems in dual-channel supply chains, especially in the context of the rapid rise of social e-commerce, has not received sufficient attention.

Against the backdrop of the rapid development of social e-commerce, the mechanism and impact pathways of recommendation systems have undergone profound changes. Social e-commerce platforms (e.g., Xiaohongshu, WeChat Mini Programs) not only provide venues for product display and transactions but also build a consumption ecosystem centered on content sharing, community interaction, and trust relationships. Within this ecosystem, user behaviors such as "planting grass" notes, influencer recommendations, and community sharing can significantly amplify the effect of recommendations. We define this market potential enhancement driven by social interaction as the social interaction effect intensity (λ). Meanwhile, the business model of social e-commerce often involves a commission mechanism based on sales sharing; that is, brands or manufacturers need to pay a certain percentage of commission to the platform or content creators for sales generated through social channel referrals. We define this as the social channel commission rate (ρ). The introduction of λ and ρ makes the adoption decision of recommendation systems, the choice of payment scheme, and dual-channel pricing strategies more complex. The manufacturer's decision must not only consider traditional factors like recommendation strength and cost but also assess the market gains brought by social interaction and the additional commission costs incurred. This provides a new theoretical perspective for understanding coordination and competition in dual-channel supply chains in the social e-commerce environment.

In summary, this paper provides a theoretical framework to analyze the strategic interaction between manufacturers and retailers regarding product recommendation strategies in dual-channel supply chains through a game-theoretic model. In this model, the manufacturer can endogenously adopt a recommendation system to increase market share. Through this game-theoretic model, we not only derive the equilibrium pricing of supply chain members but also resolve win-win scenarios for the manufacturer and retailer regarding recommendation adoption strategies. Since third-party recommendations are considered, the payment scheme for the recommendation system becomes a necessary factor. Therefore, modeling the payment scheme of recommendation systems theoretically addresses a gap not yet fully considered in previous empirical research.

In this paper, we consider a dual-channel system where a manufacturer serves consumers through a direct sales channel while also selling products through a wholesale channel operated by a retailer. Under different recommendation strategies of the retailer, the manufacturer decides whether to adopt the recommendation service provided by a recommendation system, which may use either a CPS or CPC payment scheme. Accordingly, we analyze the following seven scenarios:

- Only the retailer adopts a CPS-based recommendation system (SN);
- Both adopt a CPS-based recommendation system (SS);
- Only the retailer adopts a CPC-based recommendation system (CN);
- Both adopt a CPC-based recommendation system (CC);
- Neither adopts a recommendation system (NN);
- Only the manufacturer adopts a CPS-based recommendation system (NS);
- Only the manufacturer adopts a CPC-based recommendation system (NC).

For each scenario, we construct a game-theoretic model for the manufacturer, retailer, and recommendation system, focusing on the manufacturer's strategic choice between adopting and forgoing recommendation systems using CPS or CPC payment schemes. We also study the win-win scenarios for the manufacturer and retailer regarding recommendation strategies under CPS and CPC payment schemes. Notably, in modeling all scenarios, we introduce the social interaction effect intensity and social channel commission rate to capture the profound impact of the social e-commerce environment on recommendation effectiveness, enterprise cost structures, and profit distribution.

The results highlight the importance of recommendation strength and cost in the manufacturer's recommendation system adoption strategy. When the retailer adopts a recommendation system, regardless of whether it is CPS or CPC, the manufacturer's optimal strategy is to forgo using a recommendation system in the direct sales channel. Furthermore, the impact of the payment scheme on the manufacturer's recommendation strategy is as follows: If only one party (manufacturer or retailer) adopts a recommendation system, the manufacturer always prefers the CPS payment scheme. However, if both adopt a recommendation system, the manufacturer tends to prefer CPS when recommendation costs are sufficiently low; otherwise, CPC is preferred. When the retailer does not adopt a recommendation system, high unit recommendation costs lead the manufacturer to not choose a recommendation system, regardless of whether it uses CPS or CPC. However, as recommendation costs become moderate, the manufacturer's decision depends on recommendation strength. In the social e-commerce environment, the social interaction effect intensity strengthens the impact of recommendation strength, potentially prompting the manufacturer to adopt the system at lower recommendation cost thresholds; whereas the social channel commission rate increases the manufacturer's cost burden, potentially suppressing adoption willingness and altering preference for payment schemes, particularly favoring CPC under high commission rates as it transfers the risk of cost structure uncertainty.

We also examine win-win scenarios for the manufacturer and retailer, finding that when recommendation strength is sufficiently low, both can achieve a win-win by not adopting a recommendation system. For medium-to-high recommendation strength and relatively low recommendation costs, both prefer the scenario where only the manufacturer adopts a recommendation system. Interestingly, when only the retailer adopts a recommendation system, a win-win outcome cannot be achieved, indicating that the retailer is unwilling to allow the manufacturer to "free-ride." Regarding the impact of CPS and CPC payment schemes in equilibrium, we observe that the CPC scheme requires a lower recommendation price for enterprises to bear the transfer cost. After introducing social e-commerce variables, the size and location of win-win regions change significantly: higher λ may expand the win-win region for the manufacturer's sole adoption (NS or NC), while higher ρ may expand the win-win region for neither adopting (NN), as commission costs erode the net benefits from the recommendation system. The findings reveal insights related to manufacturer adoption of recommendation systems in dual-channel supply chains, offering new perspectives on pricing strategies, preferences, and recommendation system operations.

The remainder of this paper is structured as follows. Section 2 provides a literature review. In Section 3, we derive equilibrium results for scenarios SN, SS, CN, and CC when the retailer adopts recommendation systems under CPS and CPC payment schemes. In Section 4, we analyze scenarios NN, NS, and NC where the retailer does not adopt a recommendation system. Then, Section 5 examines win-win scenarios for the manufacturer and retailer regarding recommendation strategies. Section 6 is dedicated to analyzing model extensions. The paper concludes with Section 7.

Literature Review

Recommendation Systems

With the deepening development of the digital economy, recommendation systems have become key intelligent infrastructure connecting supply and demand. The research trajectory has extended from early algorithm optimization to systematic exploration of business ecosystems, user behavior, and social impacts.

Technological evolution and algorithm innovation form the cornerstone of recommendation system research. From traditional methods based on collaborative filtering and content to modern models incorporating deep learning, recommendation technology continues to push the boundaries of personalized services. The empirical study by Adomavicius et al. laid the theoretical foundation for the impact of recommendation systems on consumers' willingness to pay, while the large-scale experiment by Lee and Hosanagar further revealed how product attributes and user reviews moderate recommendation effectiveness, indicating significant situational dependency. Recently, generative artificial intelligence has injected new momentum into recommendation systems [1,2]. The conditional diffusion model proposed by achieves multi-granularity, cross-modal understanding of user preferences by simulating complex data generation processes, significantly enhancing the discovery and recommendation quality of long-tail items [3]. Meanwhile, challenges related to system robustness and security are becoming increasingly prominent. Maden et al. focus on the ability of advanced models to resist targeted attacks by "high-value users," revealing new security threats faced by recommendation systems driven by commercial interests [4]. Giannikis et al. utilize a reinforcement learning framework to effectively mitigate the recommendation challenge for "cold-start users" through a balance of dynamic exploration and exploitation, improving system adaptability in dynamic user environments [5].

Ethical dimensions and social responsibility have become important frontiers in current research. Kazienko and Cambria keenly point out that while algorithms enhance efficiency, they may also harbor risks of exacerbating information cocoons and solidifying social biases, thus strongly advocating for the construction of "responsible recommendation systems" characterized by transparency, fairness, and accountability [6]. This issue is particularly critical in the context of social e-commerce, as social relationships and content dissemination may amplify the homogenization effect of recommendations, necessitating the integration of considerations for diversity and social well-being into algorithm design.

From the perspective of business impact and supply chains, recommendation systems are far more than technical tools; they are forces reshaping market structures. The game analysis by Yang and Gao reveals that retailer-built recommendation systems can serve as coordination mechanisms to alleviate double marginalization caused by channel conflict [7]. Zhou and Zou further focus on the platform ecosystem, analyzing the strategic pricing competition among sellers vying for recommendation positions [8]. However, existing literature pays insufficient attention to the strategic role of independent third-party recommendation systems in cross-channel supply chains, especially lacking in-depth analysis within the framework of dual-channel competition where manufacturers and retailers coexist. As profit-driven independent intermediaries, the objective functions of third-party systems are not naturally aligned with those of supply chain members, potentially leading to new conflicts of interest [9]. The innovation of this paper lies in embedding third-party recommendation systems into dual-channel supply chain games and introducing variables characterizing the core features of social e-commerce—social interaction effect intensity (λ) and social channel commission rate (ρ)—aiming to systematically analyze how social amplification effects and benefit distribution mechanisms jointly influence the recommendation adoption decisions and equilibrium outcomes of all parties.

Recommendation Pricing Models

The commercialization of recommendation services has spurred in-depth research into their pricing models. This field encompasses two interrelated levels: product pricing and service pricing, which together determine the economic benefits and sustainability of recommendation systems.

The synergy between product pricing and recommendations is a core issue. The early work of Jiang et al. shows that significant discounts detached from accurate recommendations may result in "losing money for exposure," while intelligently combining pricing with recommendation algorithms can unify the goals of revenue generation and traffic attraction [10]. Recent research delves into more complex market relationships. Liu et al. go beyond the traditional binary division of complements/substitutes, using graph neural networks to model intricate network relationships among products, providing a novel technical approach for achieving dynamic, synergistic pricing and inventory management in recommendation scenarios [11].

Service pricing and payment scheme choices directly affect the benefit distribution and risk-sharing between recommendation system providers and adopting enterprises. Classic studies such as Chen et al. compare the advantages and disadvantages of

Cost-Per-Click (CPC) and Cost-Per-Sale (CPS), pointing out that CPC is more conducive to traffic expansion, while CPS is more closely tied to final performance [12]. Hu et al. further introduce Cost-Per-Action (CPA) for comparison, finding that it may offer advantages in incentivizing service provider effort but also requires vigilance against adverse selection problems [13]. Current research trends exhibit dynamic and scenario-specific characteristics. Bi et al. construct a theoretical framework encompassing user acquisition costs and lifecycle value, demonstrating that optimal pricing strategies should adjust dynamically with market stages and user segments [14]. Zhou and Zou profoundly point out that recommendations not only affect purchase probability but may also reshape user price sensitivity; therefore, pricing and recommendations should be optimized as integrated decisions [15].

Emerging application scenarios continuously expand the boundaries of pricing models. In the field of green consumption, the optimal usage time recommendation model for household appliances designed by Malakhatka et al. demonstrates how combining price signals with intelligent recommendations can guide user behavior to achieve energy savings [16]. In antitrust, experimental evidence shows that algorithmic recommendations may unintentionally foster collusive pricing behavior in oligopolistic markets, providing important warnings for regulating digital markets.

Despite fruitful results, significant gaps remain in existing research: most assume recommendation service pricing is exogenous or structurally simple, lacking in-depth modeling of complex charging mechanisms of third-party recommendation systems (e.g., tiered pricing, hybrid models); many focus on single entities or intra-platform competition, rarely analyzing joint decisions on product pricing and service pricing within a dual-channel competition framework; more importantly, how the unique variables of the social e-commerce environment (λ and ρ) systematically affect pricing strategies and payment scheme preferences has not been fully explored. This paper aims to fill these gaps by comprehensively analyzing the manufacturer's strategic choices under CPS and CPC schemes in a dual-channel game and thoroughly examining how λ and ρ moderate cost structures and risk preferences, thereby altering the equilibrium choices of payment schemes for all parties, providing new theoretical insights for recommendation service pricing in the era of social e-commerce.

Channel Competition

In today's era where omnichannel retailing has become the norm, channel competition has evolved from simple price and product competition to multidimensional complex games encompassing traffic, experience, data, and relationships. The rise of social e-commerce further integrates social influence and content interaction deeply into the competitive landscape.

Traditional theoretical frameworks primarily revolve around channel conflict and coordination. The pioneering work of Chiang et al. demonstrated that manufacturers introducing direct sales channels can alleviate double marginalization by weakening retailers' monopoly power [17]. However, reality is often more complex; information asymmetry or consumer behavior may diminish its positive effects [18, 19]. The study of the "Buy Online, Pick Up In Store" (BOPS) model by Gao and Su showcases the potential of channel integration in enhancing experience and optimizing operations but also notes its applicability depends on product characteristics [20].

Competition dynamics under emerging models are current research hotspots. The explosive growth of live-streaming e-commerce has spawned new competitive dimensions. The research by Peng et al. shows that in live-streaming scenarios, hosts' social influence, real-time interaction, and trust-building capabilities can reshape traffic distribution logic, making "soft power" competition based on content equally important as "hard power" competition based on price [21]. In the field of content aggregation, Jakhu and Jain analyze the complex game among platforms, content providers, and advertisers in a multi-channel structure, whose model provides insights for understanding revenue sharing and competitive equilibrium in multi-channel environments [22].

However, existing channel competition research has three main limitations: First, channels are often treated as independent entities, with insufficient analysis of synergistic or cannibalization effects arising from recommendations and traffic sharing between channels. Second, they fail to adequately incorporate recommendation systems as endogenous strategic variables, neglecting their key role in changing consumer purchase paths and influencing traffic and profit distribution among channels. Third, they almost never address the reshaping effects of social e-commerce variables (λ, ρ) on channel power structures and cooperative-competitive relationships.

The core innovation of this paper precisely addresses these limitations: constructing a game model integrating manufacturer direct sales and retailer wholesale dual-channels, endogenizing the adoption decision of third-party recommendation systems. It focuses on analyzing: First, the manufacturer's "free-riding" motivation and conditions when the retailer adopts recommendations; Second, how CPS and CPC payment schemes affect profit distribution and competitive dynamics among channel members under different channel power structures and market environments; Third, and most innovatively, systematically exploring how social interaction effects (λ) and commission rates (ρ) act as moderating variables, changing the distribution of value added by recommendation systems among manufacturers, retailers, and the recommendation system, thereby influencing the equilibrium of channel cooperation and competition. This research not only deepens the understanding of the role of technological intermediaries in omnichannel competition but also provides decision support for how enterprises can optimize channel management and synergy through strategic use of recommendation systems in the social e-commerce era.

Model When the Retailer Adopts a Recommendation System

This paper considers an online operating system consisting of a manufacturer, retailer, and recommendation system, where the recommendation system may adopt CPS or CPC payment schemes. The manufacturer sells products to consumers in the market through an online direct sales channel and an online wholesale channel. In the direct sales channel, the manufacturer sells directly to consumers at a unit retail price p_m ; in the wholesale channel, the manufacturer sells products to the online retailer at a unit wholesale price w, and the retailer then sells them to consumers at a unit retail price p_r .

The notation used in this paper is described in Table 1 below.

Symbol	Description
U	Consumer utility in the traditional market
$\hat{U}$	Consumer utility in the recommendation market when only one party uses a recommendation system
$\tilde{U}$	Consumer utility in the recommendation market when both parties use recommendation systems
$\hat{a}$	Potential market size of the traditional market
a	Potential market size of the recommendation market
p_m	Direct sales price set by the manufacturer
p_r	Retail price set by the retailer
w	Wholesale price set by the manufacturer
p_e	Unit service price set by the recommendation system
u	Note: This symbol appears in the table but not in subsequent text; likely a typo for w or unused
$D_i, i \in \{m,r\}$	Demand in the traditional market for the direct sales channel or wholesale channel
$\hat{D}_i, i \in \{m,r\}$	Demand in the recommendation market for the corresponding channel when only one party uses a recommendation system
$\tilde{D}_i, i \in \{m,r\}$	Demand in the recommendation market for the corresponding channel when both parties use recommendation systems
θ	Substitutability between the direct sales channel and the wholesale channel
c	Unit recommendation cost of the recommendation system
k	Conversion efficiency coefficient
$\pi_i, i \in \{m,r,e\}$	Profits of the manufacturer, retailer, and recommendation system
λ	Social interaction effect intensity
ρ	Social channel commission rate

Given the variety of payment schemes for recommendation systems, this paper considers both CPS and CPC cases. This section explores the following four recommendation scenarios when the retailer adopts a recommendation system:

- The retailer adopts a CPS or CPC-based recommendation system in the wholesale channel, while the manufacturer does not adopt one in the direct sales channel, denoted as scenarios "SN" and "CN," respectively;
- Both manufacturer and retailer adopt CPS or CPC-based recommendation systems, denoted as scenarios "SS" and "CC," respectively.

In each scenario, we consider the following game sequence: First, the recommendation system decides the unit service price (p_e); second, the manufacturer decides the direct sales price (p_m) and wholesale price (w); finally, the retailer decides the retail price (p_r). By studying these issues, we will reveal the deep impact of the retailer's adoption of a recommendation system on the manufacturer's strategic choices in the context of social e-commerce, providing a theoretical basis for enterprises' decision-making in an omnichannel retail environment.

Scenario One: SN (Only the Retailer Uses a Recommendation System, CPS Payment)

In this scenario, the retailer adopts a recommendation system (using CPS payment) in its retail channel, while the manufacturer does not use a recommendation system in its direct sales channel.

In the traditional market, each consumer can purchase the manufacturer's product from either the direct sales channel or the retail channel, indicating substitutability between the two channels. Following the classical modeling approaches of we construct the consumer utility function in the following form:

$$U = \sum\nolimits_{i=m,r} \left(\alpha D_r - p_i D_i - \frac{1}{2} D_i^2 \right) - \theta D_m D_r \tag{1}$$

where α represents consumers' basic preference for purchasing in the traditional market, D_m and D_r represent the demand quantities in the direct sales and retail channels, respectively [8]. By maximizing the utility function U, we obtain the demand functions for the two channels in the traditional market as:

$$D_m = \frac{(1-\theta)\alpha - p_m + \theta p_r}{1-\theta^2}, Dr = \frac{(1-\theta)\alpha - p_r + \theta p_m}{1-\theta^2}$$

In the recommendation market, consumers discover products through the recommendation system and complete purchases. Considering the interactive effects of social e-commerce platforms (e.g., Xiaohongshu, WeChat Mini Programs), such as "planting grass" notes and community sharing, can significantly enhance consumers' purchase willingness, we introduce the social interaction effect intensity λ(λ≥1) into the potential size of the recommendation market. The consumer utility function in this market is:

$$\hat{U} = (\lambda \hat{\alpha})\hat{D}_r - p_r \hat{D}_r - \frac{1}{2}\hat{D}_r^2 \tag{2}$$

Maximizing the utility function $\hat{U}$ yields the demand function for the recommendation market:

$$\hat{D}_r = \lambda \hat{\alpha} - p_r$$

The recommendation system provides recommendation services for the retail channel, and the retailer pays the service fee according to the CPS scheme $p_e f(\hat{D}_r)$, where $f(\hat{D}_r) = \hat{D}_r$. In the context of social e-commerce, for sales generated through recommendation links (often embedded in social platforms), the manufacturer needs to pay additional or the traffic referrer. We introduce the variable social channel commission rate ρ(0≤ρ<1) to capture this cost.

Manufacturer's profit: $\pi_m = w(D_r + \hat{D}_r) + p_m D_m - p p_r \hat{D}_r$

Retailer's profit: $\pi_r = (p_r - w)(D_r + \hat{D}_r) - p_e D_m + p p_r \hat{D}_r$

Recommendation system's profit: $\pi_e = (p_e - c)\hat{D}_r$

Solving this Stackelberg game by backward induction, we obtain the following equilibrium solution:

$$p_m^{SN} = \frac{1}{4}(\alpha(2-\theta) + \theta\lambda\hat{\alpha})$$

$$w^{SN} = \frac{-c(1-\theta^2) + \alpha(5-\theta-2\theta^2) - \lambda\hat{\alpha}(3-\theta^2-4\rho(2-\theta^2))}{4(2-\theta^2)}$$

$$p_r^{SN} = \frac{\alpha(3-\theta-\theta^2) + \lambda\hat{\alpha}(5-2\theta^2-4\rho(1-\theta^2)) - c(1-\theta^2)}{4(2-\theta^2)}$$

$$p_e^{SN} = \frac{\alpha(3-2\theta-\theta^2) + \lambda\hat{\alpha}(11+2\theta-5\theta^2-4\rho(3+\theta)(1-\theta)) - c(1-\theta^2)}{8(1-\theta^2)}$$

To ensure non-negativity of the equilibrium solution, we require $\frac{c}{2} < \alpha \leq 1$.

Proposition 1

In scenario SN, recommendation strength $\hat{\alpha}$ and social interaction effect λ drive up retail price p_r^{SN} and recommendation service price p_e^{SN}. When the social channel commission rate ρ is low, wholesale price w^{SN} decreases with increases in $\hat{\alpha}$ and λ; when ρ is high, wholesale price w^{SN} increases with increases in $\hat{\alpha}$ and λ.

From Proposition 1, it can be seen that as recommendation strength and social interaction effects increase, the recommendation system raises its service price to gain more revenue. The increased cost is passed from the recommendation system to the retailer, who then raises the retail price to maintain profits. Simultaneously, the manufacturer also increases the direct sales channel price to maximize overall profit and maintain price consistency across channels.

It is noteworthy that changes in the wholesale price are moderated by the social commission rate ρ. When ρ is low, the manufacturer tends to lower the wholesale price as a form of "compensation" to the retailer, incentivizing continued use of the recommendation system and sharing some of the cost. When ρ is high, the manufacturer's own commission burden is already heavy,so they increase the wholesale price to shift part of the cost back to the retailer.

Scenario Two: SS (Both Manufacturer and Retailer Adopt Recommendation Systems, CPS Payment)

In this scenario, both the retailer in the retail channel and the manufacturer in the direct sales channel adopt recommendation systems, and both systems use the CPS payment scheme. This represents both parties actively competing for the market through recommendations.

The demand functions in the traditional market are the same as in scenario SN:

$$D_m = \frac{(1-\theta)\alpha - p_m + \theta p_r}{1-\theta^2}, D_r = \frac{(1-\theta)\alpha - p_r + \theta p_m}{1-\theta^2}$$

In the recommendation market, since both parties use recommendation systems, the two channels compete within this market. Considering the universal enhancement of social interaction on recommendation effectiveness, the consumer utility function for the recommendation market is constructed as follows:

$$\widetilde{U} = (\lambda\hat{\alpha})\widetilde{D}_m - p_m\widetilde{D}_m - \tfrac{1}{2}\widetilde{D}_m^2 + (\lambda\hat{\alpha})\widetilde{D}_r - p_r\widetilde{D}_r - \tfrac{1}{2}\widetilde{D}_r^2 - \theta\widetilde{D}_m\widetilde{D}_r \quad (3)$$

where $\widetilde{D}_m$ and $\widetilde{D}_r$ represent the demand for the manufacturer and retailer in the recommendation market, respectively. By maximizing the utility function $\widetilde{U}$, we obtain the aggregate demand functions for the two channels in the recommendation market as:

$$\widetilde{D}_m = \frac{(1-\theta)\lambda\hat{\alpha} - p_m + \theta p_r}{1-\theta^2}, \widetilde{D}_r = \frac{(1-\theta)\lambda\hat{\alpha} - p_r + \theta p_m}{1-\theta^2}$$

In this scenario, both the manufacturer and retailer need to pay fees to the recommendation system for sales generated through it. Simultaneously, the social channel commission mechanism remains in effect: the manufacturer needs to pay commissions to the social platform (or operator) for sales converted through social referrals.

Manufacturer'sprofit: $\pi_m = w(D_r + \widetilde{D}_r) + p_m(D_m + \widetilde{D}_m) + p_e\widetilde{D}_m - \rho p_m\widetilde{D}_m$

Retailer's profit: $\pi_r = (p_r - w)(D_r + \widetilde{D}_r) - p_e\widetilde{D}_r + \rho p_r\widetilde{D}_r$

Recommendation system's profit: $\pi_e = (p_e - c)(\widetilde{D}_m + \widetilde{D}_r)$

The game sequence is consistent with scenario SN. Solving this Stackelberg game by backward induction yields the following equilibrium solution:

$$p_m^{ss} = \frac{\alpha + 3\alpha\theta + c(3+\theta) + \lambda\hat{\alpha}(17+3\theta-4\rho(3+\theta))}{8(3+\theta)}$$

$$w^{ss} = \frac{\alpha(11+\theta) - c(3+\theta) + \lambda\hat{\alpha}(-5+\theta+4\rho(3+\theta))}{8(3+\theta)}$$

$$p_r^{ss} = \frac{\alpha(12-4\theta-\theta^2) + c(3+4\theta+\theta^2) + \lambda\hat{\alpha}(29+12\theta-\theta^2+4\rho(3+\theta)(3-\theta))}{16(3+\theta)}$$

$$p_e^{ss} = \frac{\alpha(-5+\theta) - c(3+\theta) + \lambda\hat{\alpha}(11+\theta-4\rho(3+\theta))}{2(3+\theta)}$$

Similarly, to ensure non-negativity of the equilibrium solution, we require $\frac{c}{2} < \alpha \leq 1$.

Proposition 2

In scenario SS, demand in the recommendation market $\widetilde{D}_m^{ss}$ and $\widetilde{D}_r^{ss}$ increases with recommendation strength $\hat{\alpha}$ and social interaction effect λ; while demand in the traditional market D_m^{ss} and D_r^{ss} decreases accordingly.

Proposition 2

Indicates that the enhanced social interaction effect and recommendation systems work synergistically to effectively shift consumers from the traditional market to the recommendation market. This reveals the powerful ability of social e-commerce to guide consumer traffic and reshape purchase paths.

We further analyze the impact of recommendation strength $\hat{\alpha}$ and social commission rate ρ on the profits of each party, summarized in Table 2 below.

Table 2: Impact of Recommendation Strength and Commission Rate on Profits in Scenario SS

Profit	When $\hat{\alpha}$ or λ increases	When ρ increases
π_m^{ss}	↑if $\hat{\alpha} \in (0, \hat{a}_1^{ss}) \cap (\hat{a}_2^{ss}, \hat{a}_h^{ss})$; ↓otherwise。	↓if ρ is low; ↑ if ρ is high and $\hat{\alpha}$ is large (due to wholesale price increase)
π_r^{ss}	↑if $\hat{\alpha} \in (0, \hat{a}_3^{ss}) \cap (\hat{a}_4^{ss}, \hat{a}_h^{ss})$; ↓otherwise。	↑(Retailer directly benefits from commission revenue)
π_e^{ss}		↓(High commissions may suppress demand, affecting recommendation system revenue)

The results in Table 2 show: The manufacturer's profit faces a double squeeze: paying recommendation service fees and social commissions. Only when the additional revenue from the recommendation market is sufficiently high can they benefit from stronger social interaction. The retailer emerges as a clear beneficiary, profiting from increased demand and directly gaining an additional revenue stream through commission rate ρ, enhancing their bargaining power in the supply chain. Although the recommendation system benefits from the expanded recommendation market, excessively high social commission rates may force manufacturers to raise prices, suppressing demand and indirectly negatively impacting the recommendation system.

Scenario Three:CN (Only the Retailer Adopts a Recommendation System, CPC Payment)

In this scenario, the retailer adopts a recommendation system in its retail channel using the CPC payment scheme, while the manufacturer does not use one in its direct sales channel. The core feature of the CPC scheme is that the recommendation system's revenue depends on consumer clicks rather than final sales, making the payment logic and conversion efficiency crucial.

The demand functions in the traditional market are the same as in scenario SN:

$$D_m = \frac{(1-\theta)\alpha - p_m + \theta p_r}{1-\theta^2}, D_m = \frac{(1-\theta)\alpha - p_r + \theta p_m}{1-\theta^2}$$

In the recommendation market, the social interaction effect λ similarly amplifies the role of recommendation strength, and the demand function is:

$$\hat{D}_r = \lambda \hat{\alpha} - p_r$$

Under the CPC payment scheme, the recommendation system's revenue depends on click volume. We define the recommendation conversion rate as the ratio of clicks converted to purchases, which is positively correlated with recommendation strength $\hat{\alpha}$. Let N represent the number of clicks generated through the recommendation system; then the conversion rate can be expressed as $\hat{D}_r$/N=k$\hat{\alpha}$, where k>0 is a parameter measuring conversion efficiency. Therefore, click volume N=$\hat{D}_r$/k$\hat{\alpha}$. The retailer pays the recommendation system $p_e f(\hat{D}_r)=p_e \hat{D}_r/(k\hat{\alpha})$.

Simultaneously, the social channel commission mechanism remains in effect: the manufacturer needs to pay commissions for sales generated through this social recommendation channel.

Manufacturer's profit: $\pi_m = w(D_r + \hat{D}_r) + p_m D_m - \rho p_r D_r$

Retailer's profit: $\pi_r = (p_r - w)(D_r + \hat{D}_r) - p_e \frac{\hat{D}_m}{k\hat{\alpha}} + \rho p_r D_r$

Recommendation system's profit: $\pi_e = (p_r - c)\frac{\hat{D}_r}{k\hat{\alpha}}$

$$p_m^{CN} = \frac{1}{4}(\alpha(2-\theta) + \theta\lambda\hat{\alpha}$$

$$w^{CN} = \frac{-c(1-\theta^2) + k\hat{\alpha}[\alpha(5-\theta-2\theta^2) + \lambda\hat{\alpha}(-3+\theta^2-4\rho(2-\theta^2))]}{4k\hat{\alpha}(2-\theta^2)}$$

$$p_r^{CN} = \frac{c(1-\theta^2) + k\hat{\alpha}[\alpha(3-\theta-\theta^2) + \lambda\hat{\alpha}(11-6\theta^2-4\rho(1-\theta^2))]}{8k\hat{\alpha}(2-\theta^2)}$$

$$p_e^{CN} = \frac{1}{2}\left[c + \frac{k\hat{\alpha}(-\alpha(3-\theta-\theta^2) + \lambda\hat{\alpha}(5-2\theta^2-4\rho(1-\theta^2)))}{1-\theta^2}\right]$$

Based on the equilibrium results, we analyze the impact of $\hat{\alpha}$ and c on firms' pricing decisions, summarized in Table 3.

Table 3: Impact of Recommendation Strength and Cost on Prices in Scenario CN

Price	When $\hat{\alpha}$ increases	When c increases
p_m^{CN}	↑	-
w^CN	↑if $c \in (c_1^{CN}, 1) \cap (c_1^{CN}, c_h^{CN})$ ↓otherwise.	↓
p_r^{CN}	↑if $c \in (0, c_2^{CN}) \cap (c_2^{CN}, c_h^{CN})$ ↓otherwise.	↑
p_e^{CN}	↑if $\hat{\alpha} \in (\hat{\alpha}_1^{CN}, 1)$ and $c \in (c_1^{CN}, c_h^{CN})$ ↓otherwise。	↑

From Table 3, we find that the manufacturer's direct sales price increases with recommendation strength, consistent with the trend under CPS. However, under CPC, the impact of recommendation strength on wholesale price and recommendation service price shows non-monotonicity. This may be because when the recommendation market is small, the recommendation system needs to lower its service price to attract retailer adoption; when the market is sufficiently large, it can leverage its influence to raise prices.

Table 4: Impact of Recommendation Strength and Cost on Profits in Scenario CN

Price	When $\hat{\alpha}$ increases	When c increases
π_m^{CN}	↑if $c \in (c_3^{CN}, c_4^{CN}) \cap (c_3^{CN}, c_h^{CN})$ ↓otherwise.	↑if $c \in (c_5^{CN}, 1) \cap (c_5^{CN}, c_h^{CN})$ ↓otherwise.
π_r^{CN}	↑if $c \in (c_6^{CN}, c_7^{CN}) \cap (c_6^{CN}, c_h^{CN})$ otherwise.	↑if $c \in (c_8^{CN}, 1) \cap (c_8^{CN}, c_h^{CN})$ ↓otherwise.
π_e^{CN}	↑if $\hat{\alpha} \in (\hat{a}_2^{CN}, 1)$ $c \in (0, c_9^{CN}) \cap (c_9^{CN}, c_h^{CN})$ ↓otherwise.	↑if $c \in (c_{10}^{CN}, 1) \cap (c_{10}^{CN}, c_h^{CN})$ ↓otherwise.

Table 4 reveals that under the CPC payment scheme, firm profits also exhibit complex non-monotonic relationships with recommendation strength and cost. Only when unit recommendation cost is within a moderate range can the manufacturer and retailer benefit from higher recommendation strength. This is because when costs are too low, wholesale price decreases while service price increases, harming both parties; when costs are too high, high service prices suppress profit margins for all. The recommendation system may also suffer profit loss when both cost and recommendation strength are high, as excessive pricing weakens the retailer's willingness to use the service.

Scenario Four:CC (Both Manufacturer and Retailer Adopt Recommendation Systems, CPC Payment)

In this scenario, both the retailer in the retail channel and the manufacturer in the direct sales channel adopt recommendation systems, and both systems use the CPC payment scheme. This represents both parties actively investing resources to compete for consumer traffic flowing through social recommendation channels under a pay-per-click model.

The demand functions in the traditional market are the same as in scenario SS:

$$D_m = \frac{(1-\theta)\alpha - p_m + \theta p_r}{1-\theta^2}, D_r = \frac{(1-\theta)\alpha - p_r + \theta p_m}{1-\theta^2}$$

In the recommendation market, since both use recommendation systems, the two channels compete. The social interaction effect λ similarly amplifies the market potential, and the demand function is constructed as follows:

$$\widetilde{U} = (\lambda\hat{\alpha})\widetilde{D}_m - p_m\widetilde{D}_m - \frac{1}{2}\widetilde{D}_m^2 + (\lambda\hat{\alpha})\widetilde{D}_r - p_r\widetilde{D}_r - \frac{1}{2}\widetilde{D}_r^2 - \theta\widetilde{D}_m\widetilde{D}_r$$

Maximizing $\widetilde{U}$ yields the aggregate demand functions for the two channels in the recommendation market:

$$\widetilde{D}_m = \frac{(1-\theta)\lambda\hat{\alpha} - p_m + \theta p_r}{1-\theta^2}, \widetilde{D}_r = \frac{(1-\theta)\lambda\hat{\alpha} - p_r + \theta p_m}{1-\theta^2}$$

In this scenario, both the manufacturer and retailer pay the recommendation system for clicks generated through it (CPC scheme). Simultaneously, the social channel commission mechanism remains in effect.

Manufacturer's profit: $\pi_m = w(D_r + \widetilde{D}_r) + p_m(D_r + \widetilde{D}_r) - p_e\dfrac{\widetilde{D}_m}{k\hat{\alpha}} - \rho p_m\widetilde{D}_m$

Retailer's profit: $\pi_r = (p_r - w)(D_r + \widetilde{D}_r) - p_e\dfrac{\widetilde{D}_r}{k\hat{\alpha}} - \rho p_r\widetilde{D}_r$

Recommendation system's profit: $\pi_e = (p_e - c)\left(\dfrac{\widetilde{D}_m + \widetilde{D}_r}{k\hat{\alpha}}\right)$

The game sequence is consistent with previous scenarios. Solving by backward induction yields the following equilibrium solution:

$$p_m^{CC} = \frac{\alpha(1-\theta^2) + c(3+\theta) + k\hat{\alpha}[\lambda\hat{\alpha}(17+3\theta) - 4\rho(3+\theta)(\alpha+\lambda\hat{\alpha})]}{8k\hat{\alpha}(3+\theta)}$$

$$w^{CC} = \frac{\alpha(11+\theta) + c(3+\theta) + k\hat{\alpha}[\lambda\hat{\alpha}(-5+\theta) + 4\rho(3+\theta)(\alpha+\lambda\hat{\alpha})]}{8k\hat{\alpha}(3+\theta)}$$

$$p_r^{CC} = \frac{\alpha(12-4\theta-\theta^2) + c(3+4\theta+\theta^2) + k\hat{\alpha}[\lambda\hat{\alpha}(29+12\theta-\theta^2) - 4\rho(3+\theta)(3-\theta) + \lambda\hat{\alpha}(3+\theta)]}{16k\hat{\alpha}(3+\theta)}$$

$$p_e^{CC} = \frac{\alpha(-5+\theta) + c(3+\theta) + k\hat{\alpha}[\lambda\hat{\alpha}(11+\theta) - 4\rho(3+\theta)(\alpha+\lambda\hat{\alpha})]}{2k\hat{\alpha}(3+\theta)}$$

To ensure non-negativity, we require $c \in (c_1^{CN}, c_h^{CN})$

For scenario CC, we obtain results on the impact of $\hat{\alpha}$ and c on firm pricing decisions, summarized in Table 5.

Table 5: Impact of Recommendation Strength and Cost on Prices in Scenario CC

Price	When $\hat{\alpha}$ increases	When c increases
p_m^{CC}	↑if $c \in (0, c_1^{CN}) \cap (c_1^{CN}, c_h^{CN})$; ↓otherwise.	↓
w^{CC}	↑if $c \in (0, c_2^{CN}) \cap (c_2^{CN}, c_h^{CN})$; ↓otherwise.	↓
p_r^{CC}	↑if $c \in (0, c_3^{CN}) \cap (c_3^{CN}, c_h^{CN})$; ↓otherwise.	↑
p_e^{CC}	↑if $\hat{a} \in (\hat{a}_1^{CN}, 1)$ and $c \in (c_1^{CN}, c_h^{CN})$; ↓otherwise.	↑

From Table 5, we find that the impact of recommendation cost on prices is consistent with the conclusion in Proposition 1. However, the impact of recommendation strength on prices exhibits different characteristics under CPC compared to CPS (scenario SS). The recommendation service price p_e^{CC} changes non-monotonically with recommendation strength: when strength is low, the system may lower its price to incentivize adoption; when sufficiently high, it raises prices to maximize profit. When unit recommendation cost is sufficiently low, the manufacturer not only raises the direct sales price but also lowers the wholesale price. This suggests that under CPC, facing strong social recommendation demand, the manufacturer may prefer to stimulate end sales by conceding profits to the retailer to offset its dual expenditures on click fees and social commissions.

Table 6: Impact of Recommendation Strength and Cost on Profits in Scenario CC

Profit	When $\hat{\alpha}$ increases	When c increases
π_m^{CC}	↑if $\hat{\alpha} \in \Omega_1$ and $c \in (c_4^{CN}, c_5^{CN}) \cap (c_5^{CN}, c_h^{CN})$ ↓otherwise.	↓if $c \in (c_7^{CN}, 1) \cap (c_7^{CN}, c_h^{CN})$ ↓otherwise.
π_r^{CC}	↑if $c \in (c_8^{CN}, c_9^{CN}) \cap (c_6^{CN}, c_h^{CN})$ ↓otherwise.	↓if $c \in (c_{10}^{CN}, 1) \cap (c_{10}^{CN}, c_h^{CN})$ ↓otherwise.
π_e^{CC}	↑	↓

Table 6 shows that the manufacturer's profit benefits from increased recommendation strength only when strength is moderate and channel competition is limited. Under intense channel competition, the manufacturer may be forced to lower prices, leading to unfavorable outcomes. The retailer's profit increases with recommendation strength when recommendation cost is moderate. The recommendation system always benefits from higher recommendation strength, but its profit monotonically decreases with rising recommendation cost. Moreover, when recommendation cost is sufficiently high, the profits of both manufacturer and retailer may increase with cost, possibly because high costs push up overall industry price levels, and if demand elasticity is low, firms may benefit.

Manufacturer's Strategic Choice Between Adoption and Abandonment of Recommendation Services

To explore whether the manufacturer should adopt a recommendation system in its direct sales channel, we need to compare the manufacturer's profits under two strategies—adoption vs. non-adoption—given that the retailer has already adopted one. Specifically, under the CPS payment scheme, we compare the manufacturer's profits in scenarios SN and SS; under CPC, we compare scenarios CN and CC. To ensure non-negative prices and demands, we require recommendation strength $(\hat{a} \in F_a \equiv (\hat{a}_1^{SN}, \hat{a}_h^{SN}) \cap (\hat{a}_1^{SN}, \hat{a}_h^{SN}))$, recommendation cost $(c \in F_c(c_1^{CN}, c_h^{CN}) \cap (c_1^{CN}, c_h^{CN}))$.

Theorem 1

We find that, regardless of whether the recommendation system uses CPS or CPC, when the retailer adopts a recommendation system, it is always optimal for the manufacturer not to adopt one, i.e.:

$$\pi_m^{SN} > \pi_m^{SS} \text{ and } \pi_m^{CN} > \pi_m^{CC}$$

Theorem 1 indicates that when the retailer has already adopted a recommendation system in the retail channel, the manufacturer's optimal strategy is to forgo adopting the service in the direct sales channel. This stems mainly from dual cost pressures: adopting a recommendation system in the direct sales channel requires direct payment of recommendation service fees and incurs associated social channel commissions. This leads to an increase in the direct sales channel's retail price, potentially intensifying inter-channel competition and eroding the manufacturer's overall profit. Conversely, by not adopting, the manufacturer can focus on the retail channel and incentivize the retailer to more actively utilize the recommendation system by lowering the wholesale price. Essentially, the manufacturer tends to "free-ride," leveraging the retailer's investment in the recommendation system to indirectly promote wholesale business growth, rather than directly bearing additional costs.

Manufacturer's Preference for CPS vs. CPC Payment Schemes

Given that recommendation systems may offer different payment schemes like CPS or CPC, we further explore under what conditions the manufacturer prefers which scheme.

Theorem 2

When the retailer adopts a recommendation system and the manufacturer does not (i.e., comparing scenarios SN and CN), the manufacturer always prefers the CPS payment scheme:

$$\pi_m^{SN} > \pi_m^{CN}$$

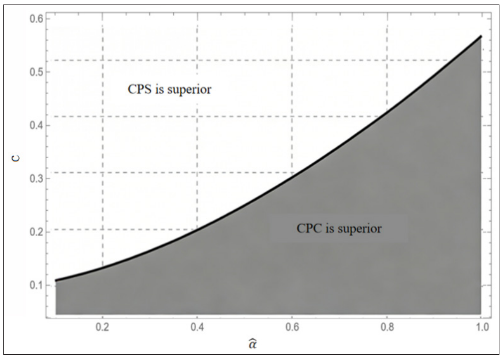

Figure 1: Manufacturer's Preference for the Two Payment Schemes when Both Adopt Recommendation Systems

Theorem 2 states that when only the retailer uses a recommendation system, the manufacturer obtains higher profit from the CPS scheme than from CPC. Even though the manufacturer does not directly adopt the system, they can indirectly benefit from the retailer's adoption (i.e., "free-ride"). The CPS scheme, with payments tied to actual sales, provides the manufacturer with higher certainty and risk protection. It avoids the risk of ineffective marketing expenditures under CPC due to click fraud or low conversion rates, uncertainties that indirectly affect the manufacturer's wholesale business through the retailer's cost structure. Therefore, a healthy, sales-result-oriented retail channel is more beneficial for the manufacturer, making CPS the default preference.

Theorem 3

When both the manufacturer and retailer adopt recommendation systems (i.e., comparing scenarios SS and CC), the manufacturer's payment scheme preference depends on recommendation cost (c):

- If recommendation cost $\left(c < c_m^{SC}\right)$(a specific cost threshold), then $\left(\pi_m^{SS} > \pi_m^{CC}\right)$, and the manufacturer prefers CPS.
- If recommendation cost $\left(c > c_m^{SC}\right)$, then $\left(\pi_m^{SS} < \pi_m^{CC}\right)$, and the manufacturer prefers CPC.

Theorem 3 reveals a shift in manufacturer preference in the complex scenario where both adopt. When recommendation costs are low, the predictability of CPS and its direct link to sales manifest their advantages, and the manufacturer is willing to pay for certain sales outcomes. However, when recommendation costs rise above a certain threshold, CPC becomes more attractive. This is because under high cost pressure, the pay-per-click CPC scheme transfers part of the uncertainty of traffic acquisition to the recommendation system, providing the manufacturer with greater operational flexibility and potential cost control. Furthermore, in environments with high commission rates (ρ), the manufacturer's preference for CPC may be even more pronounced, as the CPC model allows for more granular management of unit sales costs generated from social referrals.

Model When the Retailer Does Not Adopt a Recommendation System

In the previous section, we explored in depth the complex strategic choices faced by the manufacturer when the retailer adopts a recommendation system. However, in practice, not all retailers adopt such systems. Many traditional retailers or those focused on specific market segments may choose not to rely on third-party recommendation systems due to cost considerations, technological capabilities, or strategic positioning. Therefore, to gain a more comprehensive understanding of the manufacturer's recommendation strategy, this section systematically analyzes the manufacturer's optimal decision when the retailer does not adopt a recommendation system. This analysis is crucial as it represents another picture of supply chain power structure and competitive dynamics. With the retailer not participating in recommendations, the manufacturer loses the possibility of "free-riding" through the retail channel but gains greater autonomy and differentiation space in the direct sales channel. In this case, the impact mechanisms of the two key social e-commerce features—social interaction effect intensity and social channel commission rate—on the manufacturer's decision will differ significantly from those in Section 3.

This section focuses on the following three core sub-scenarios:

- Scenario NN: Neither manufacturer nor retailer adopts a recommendation system;
- (ii) Scenario NS: Only the manufacturer adopts a recommendation system in its direct sales channel, using CPS;
- Scenario NC: Only the manufacturer adopts a recommendation system in its direct sales channel, using CPC.

Scenario Five: NN (No Firm Adopts a Recommendation System)

In this scenario, neither the retailer nor the manufacturer adopts any recommendation system. This constitutes a benchmark situation, allowing us to assess the basic operation of the supply chain in a purely traditional dual-channel competitive environment, without direct intervention from recommendation systems and social e-commerce.

Since there is no recommendation system, the entire market consists of the traditional market. Consumers only learn about and purchase products through conventional channels. The demand functions for the traditional market are consistent with previous chapters, but note: In the absence of a recommendation system, the social interaction effect λ and social channel commission rate ρ do not directly act on market demand because there is no "recommendation link" or "social referral scenario" to trigger these mechanisms. Therefore, the demand functions retain their basic form:

$$D_m = \frac{(1-\theta)\alpha - p_m + \theta p_r}{1-\theta^2}, D_r = \frac{(1-\theta)\alpha - p_r + \theta p_m}{1-\theta^2}$$

Without recommendation systems and corresponding social referrals, the manufacturer's profit comes solely from wholesale and direct sales, and the retailer's profit solely from retail margin. Neither party's profit function involves recommendation service fees p_e or social commissions ρ.

Manufacturer's profit: $\pi_m = wD_r + p_m D_m$

Retailer's profit: $\pi_r = (p_r - w)D_r$

In the game, the manufacturer, as the leader, first determines its direct sales price p_m and wholesale price w; the retailer, as the follower, then determines its retail price p_r. Solving this "leader-follower" game by backward induction yields the following equilibrium solution:

$$p_m^{NN} = w^{NN} = \frac{\alpha}{2}, p_m^{NN} = \frac{\alpha(3+\theta)}{4}$$

The corresponding profits for the two firms are:

$$\pi_m^{NN} = \frac{(3+\theta)\alpha^2}{8(1+\theta)}, \pi_m^{NN} = \frac{(1-\theta)\alpha^2}{16(1+\theta)}$$

An increase in channel competition intensity θ forces the retailer to lower prices, thereby compressing the manufacturer's direct sales channel demand and profit. This indicates that in traditional dual-channels, the cost of channel conflict is shared by both parties, but the retailer typically bears greater pressure. Even though λ and ρ do not explicitly appear in this scenario, their opportunity cost and avoidance benefits are implicit in the decision. The manufacturer forgoes the market amplification opportunity brought by λ but also avoids the additional commission expenditure caused by ρ. In market environments where the social interaction effect λ is weak and platform commission rates ρ are high, maintaining the traditional dual-channel model NN may constitute a robust dominant strategy, avoiding channel conflicts and profit erosion in the digital ecosystem.

Scenario Six:NS (Only the Manufacturer Adopts a CPS-Based Recommendation System)

The retailer does not adopt a recommendation system in the wholesale channel, while the manufacturer uses a CPS-based recommendation system service in the direct sales channel. The demand in the recommendation market can be easily derived as $\widehat{D}_m = \lambda\widehat{\alpha} - p_m$.The profit functions for the manufacturer, retailer, and recommendation system are as follows:

Manufacturer profit: $\pi_m = wD_r + p_m(D_m + \widehat{D}_m) - p_e\widehat{D}_m - \rho p_m \widehat{D}_m$

Retailer profit: $\pi_r = (p_r - w)D_r$

Recommendation system profit: $\pi_e = (p_e - c)\widehat{D}_m$

The Stackelberg equilibrium prices for scenario NS are:

$$p_m^{NS} = \frac{c + 5\lambda\widehat{\alpha} + \alpha}{8}$$

$$w^{NS} = \frac{\alpha(4-3\theta) + \theta(c + 5\lambda\widehat{\alpha})}{8}$$

$$p_r^{NS} = \frac{\alpha(6-5\theta) + \theta(c + 5\lambda\widehat{\alpha})}{8}$$

$$p_e^{NS} = \frac{c + 3\lambda\widehat{\alpha} + \alpha}{2}$$

Using the equilibrium prices, we calculate the profits of the three firms:

$$\pi_m^{NS} = \frac{\alpha^2(5-3\theta)+c^2(1+\theta)-23(\lambda\hat{\alpha})^2(1+\theta)-2c(3\lambda\hat{\alpha}-\alpha)(1+\theta)+52\lambda\hat{\alpha}\alpha(1+\theta)}{32(1+\theta)}$$

$$\pi_r^{NS} = \frac{\alpha^2(1-\theta)}{16(1+\theta)}$$

$$\pi_e^{NS} = \frac{(c+3\lambda\hat{\alpha}-\alpha)^2}{16}$$

Proposition 3

For scenario NS, the direct sales price p_m^{NS} wholesale price w^{NS} and retail price p_r^{NS} all increase with social interaction effect intensity λ and unit recommendation cost c. Proposition 3 indicates that both enhanced social interaction and rising recommendation costs drive up prices throughout the supply chain. The manufacturer passes part of the increased cost to the retailer via the wholesale price, and the retailer ultimately passes it to consumers through higher retail prices.

Proposition 4

For scenario NS: (i) If $c \in (0, c_1^{NS}) \cap (c_1^{NS}, c_h^{NS})$, then the manufacturer's profit π_m^{NS} increases with λ ; otherwise, π_m^{NS} decreases with λ. Additionally, the retailer's profit π_r^{NS} is independent of λ, while the recommendation system's profit π_e^{NS} always increases with λ . (ii) The manufacturer's profit π_m^{NS} and the recommendation system's profit π_e^{NS} decrease with c, while π_r^{NS} is independent of c.

Analysis of Proposition 4

When recommendation cost c is low, enhanced social interaction can significantly expand the recommendation market size. The revenue the manufacturer gains from incremental sales is sufficient to cover the increase in recommendation service fees and social commission ρ, so profit rises. When c is high, the recommendation system substantially raises its price, and coupled with social commission costs, the manufacturer's total cost growth outpaces revenue growth, leading to decreased profit. The retailer's profit is unaffected by λ, while the recommendation system always directly benefits from an increase in λ.

Analysis of Proposition 4

An increase in recommendation cost c forces the manufacturer to raise direct sales price p_m^{NS} and wholesale price w^{NS} to pass on costs. However, price increases suppress price-sensitive recommendation market demand $\hat{D}_m$, and social commission ρ amplifies cost pressure, causing manufacturer profit to decline. Although the retailer does not directly bear recommendation costs, a higher wholesale price compresses its profit margin, so its profit may also suffer as c increases.

Scenario Seven: NC (Only the Manufacturer Adopts a Recommendation System, CPC Payment)

In this scenario, the retailer does not adopt a recommendation system, while the manufacturer adopts one in its direct sales channel using the CPC payment scheme. This represents the manufacturer choosing a pay-per-click model to acquire social e-commerce traffic, where costs are directly linked to clicks rather than final sales.

The demand functions for the traditional market are the same as in scenario NS:

$$D_m = \frac{(1-\theta)\alpha - p_m + \theta p_r}{1-\theta^2}, D_r = \frac{(1-\theta)\alpha - p_r + \theta p_m}{1-\theta^2}$$

The demand function for the recommendation market is consistent with scenario NS:

$$\hat{D}_m = \lambda\hat{\alpha} - p_m$$

Under the CPC payment scheme, the recommendation system's revenue depends on click volume. Define the recommendation conversion rate as the ratio of clicks converted to purchases, positively correlated with recommendation strength $\hat{a}$. Let N be the number of clicks; then the conversion rate $\hat{D}_m / N = k\hat{a}$, where k>0 is the conversion efficiency parameter. Therefore, click volume $N = \hat{D}_m / (k\hat{a})$. The manufacturer pays the recommendation system based on clicks.

Manufacturer's profit: $\pi_m = wD_r + p_m(D_m + \hat{D}_m) - p_e \cdot \frac{\hat{D}_m}{k\hat{a}} - \rho \cdot_m \hat{D}_m$

Retailer's profit: $\pi_r = (p_r - w)D_r$

Recommendation system's profit: $\pi_e = (p_e - c) \cdot \frac{\hat{D}_m}{k\hat{a}}$

Solving by backward induction yields equilibrium prices:

$$p_m^{NC} = \frac{c + k\hat{a}(5\lambda\hat{\alpha} + \alpha)}{k\hat{a}}$$

$$w^{NC} = \frac{c\theta + k\hat{\alpha}[\alpha(4-3\theta) + 5\lambda\hat{\alpha}\theta]}{8k\hat{a}}$$

$$p_r^{NC} = \frac{c\theta + k\hat{\alpha}[\alpha(6-5\theta) + 5\lambda\hat{\alpha}\theta]}{8k\hat{a}}$$

$$p_e^{NC} = \frac{c + k\hat{\alpha}(3\lambda\hat{\alpha} - \alpha)}{2}$$

The equilibrium profits for the three parties are:

$$\pi_m^{NC} = \frac{c^2(1+\theta) - 2ck\hat{\alpha}(3\lambda\hat{\alpha}-\alpha)(1+\theta) + k^2\hat{\alpha}^2[\alpha^2(5-3\theta) - 23(\lambda\hat{\alpha})^2(1+\theta) + 52\lambda\hat{\alpha}\alpha(1+\theta)}{32k^2\hat{\alpha}^2(1+\theta)}$$

$$\pi_r^{NC} = \frac{\alpha^2(1-\theta)}{16(1+\theta)}$$

$$\pi_e^{NC} = \frac{[c + k\hat{\alpha}(3\lambda\hat{\alpha} - \alpha)]^2}{16k^2\hat{\alpha}^2}$$

To ensure non-negative equilibrium solutions, we require recommendation cost c to satisfy $c \in (c_1^{NC}, c_h^{NC})$,where:

$$c_1^{NC} \equiv \max\{k\hat{\alpha}(\alpha - 3\lambda\hat{\alpha}), 0\}, c_h^{NC} \equiv \min\left\{k\hat{\alpha}\left[\frac{\alpha(7+5\theta)}{1+\theta} - 5\lambda\hat{\alpha}\right], k\hat{\alpha}(3\lambda\hat{\alpha} - \alpha), 1\right\}$$

Proposition 5

For scenario NC, the direct sales price p_m^{NC}, wholesale price w^{NC}, and retail price p_r^{NC} all increase with social interaction effect intensity λ and unit recommendation cost c. Additionally, the recommendation service price p_e^{NC} increases with c, but exhibits non-monotonicity with respect to λ: when $\lambda\hat{\alpha} > \alpha / 6$, p_e^{NC} increases with λ; otherwise, it decreases with λ.

Proposition 5 shows that under CPC, the impact of social interaction effect and recommendation cost on traditional price variables is consistent with CPS (Proposition 3). However, the recommendation system's own pricing strategy exhibits more complex behavior: when the social interaction effect is weak, it may lower the service price to incentivize manufacturer adoption; only when the effect is sufficiently strong does it raise prices to capture more profit.

Proposition 6

For scenario NC: (i) If $\lambda\hat{\alpha} < \hat{\alpha}^{NC}$ and $(c \in (0, c_2^{NC}) \cap (c_1^{NS}, c_h^{NS}))$ then the manufacturer's profit π_m^{NC} increases with λ; otherwise, π_m^{NC} decreases with "λ" . Additionally, the retailer's profit π_r^{NC} is independent of "λ" , while the recommendation system's profit π_e^{NC} always increases with "λ" . (ii) The manufacturer's profit π_m^{NC} and the recommendation system's profit π_e^{NC} decrease with c, while the retailer's profit π_r^{NC} is independent of c.

The findings of Proposition 6 are similar to Proposition 4 but with a key distinction: the condition for the manufacturer to benefit from the social interaction effect depends on the absolute level of λ and $\hat{\alpha}(i.e., \lambda\hat{\alpha} < \hat{\alpha}^{NC})$. This indicates that under CPC, the absolute size of the recommendation market (not just the relative amplification effect) is crucial for manufacturer profitability. When the recommendation market itself is small, even with a strong amplification effect, the manufacturer may struggle to profit because the click costs under CPC may not be adequately covered by limited sales.

Manufacturer's Strategic Choice When the Retailer Does Not Adopt a Recommendation System

To study whether the manufacturer should adopt a recommendation system when the retailer does not, we compare the manufacturer's profit under adoption vs. non-adoption. Specifically, under CPS, we compare profits in scenarios NS and NN; under CPC, we compare scenarios NC and NN.

Theorem 4

When the retailer does not adopt a recommendation system, we find that regardless of whether the system uses CPS or CPC, the manufacturer should adopt the recommendation system if the unit recommendation cost c is below a certain threshold $(i.e., c < c_M^{NS}\ for\ CPS, c < c_M^{NC}\ for\ CPC)$; otherwise, the manufacturer should not adopt.

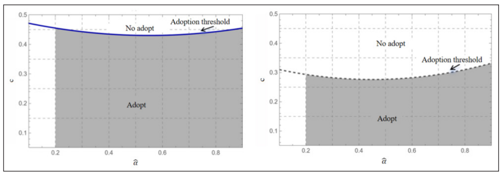

Figure 2: Manufacturer's Strategic Choice when the Retailer Does Not Adopt a Recommendation System

When unit recommendation cost exceeds a certain threshold, the recommendation system sets a higher service price and passes the cost to the adopting manufacturer. Faced with high service fees, the manufacturer may choose not to adopt. Additionally, the manufacturer's decision is influenced by recommendation strength. When recommendation strength increases, more consumers purchase based on recommendations, so the manufacturer is more inclined to adopt. However, if recommendation strength is sufficiently large, the manufacturer faces the risk of paying a high recommendation service price. Thus, although the manufacturer may gain more sales from higher recommendation strength, a significant increase in service price may reduce the incentive to adopt.

We further explore the manufacturer's preference between CPS and CPC when it decides to adopt a recommendation system and the retailer does not. To do this, we compare the manufacturer's profits in scenarios NS (only manufacturer adopts CPS) and NC (only manufacturer adopts CPC).

Theorem 5

When the manufacturer adopts a recommendation system and the retailer does not, the manufacturer always prefers the CPS payment scheme, i.e., $\pi_m^{NS} > \pi_m^{NC}$.

Theorem 5 indicates that in the scenario where the manufacturer alone adopts a recommendation system, CPS is always superior to CPC. This conclusion remains robust after introducing social e-commerce variables. The underlying economic logic can be explained from the following aspects:

Cost Certainty and Risk Aversion

Under CPS, the manufacturer's recommendation service fee is directly tied to actual sales $p_e D_m$. providing higher cost certainty. Under CPC, the manufacturer's recommendation cost depends on click volume $p_e \cdot \frac{\hat{D}_m}{k\hat{\alpha}}$ with uncertainty in the conversion rate $k\hat{a}$ between clicks and sales. Given that the social interaction effect intensity λ is typically significant λ≥1, click volume through recommendation systems is often large. In such cases, the manufacturer faces a typical risk: paying for a large number of clicks that may not convert into actual sales.

Dual Risks in the Social E-commerce Environment

Amplified Click Fraud Risk:The open nature of social e-commerce platforms (e.g., Xiaohongshu, WeChat Mini Programs) may exacerbate click fraud. Under CPC, the manufacturer pays not only for genuine consumer clicks but potentially for fake clicks or invalid traffic. CPS ties costs to final sales outcomes, effectively avoiding such risks.

Social Commission Cost Linkage Effect:The manufacturer needs to pay commissions ρ for sales generated through social referral channels. Under CPS, both recommendation service fees and social commissions are based on the same benchmark (actual sales), creating consistency in the cost structure. Under CPC, the manufacturer's cost structure is split: recommendation fees are based on clicks, social commissions on sales. This mismatch can lead to cost-revenue misalignment, where the manufacturer pays for clicks that generate insufficient sales to cover social commission costs.

Analysis of Win-Win Scenarios for Recommendation Service Adoption

In the previous two sections, we analyzed recommendation system adoption strategies from the respective perspectives of the manufacturer and retailer. However, in a dual-channel supply chain, their strategic decisions interact; analyzing from a single perspective may not achieve overall optimality. This section takes a cooperative win-win perspective to explore strategic combinations under which the manufacturer and retailer can achieve mutual benefits from recommendation service adoption in the social e-commerce environment.

Analytical Framework and Method
We consider four possible strategic combinations, denoted as (N,N), (N,S), (S,N), (S,S), where the first letter represents the retailer's strategy and the second the manufacturer's strategy, with "N" meaning does not adopt a recommendation system and "S" meaning adopts a CPS-based recommendation system. For each combination, we compare the profits of the manufacturer and retailer in the corresponding scenario.

Analysis of Win-Win Scenarios Under CPS Payment Scheme
Proposition 7.Under the CPS payment scheme, two possible win-win scenarios exist:

- When $(c \in (c_{r1}^{NN}, c_{r2}^{NN}) \cap (c_{m1}^{NN}, c_{m2}^{NN})$, scenario (N,N) is win-win.
- When $(c \in (c_{r1}^{NS}, c_{r2}^{NS}) \cap \{(0, c_{m2}^{NN}) \cup (c_{m2}^{NN}, 1)\}$, scenario (N,S) is win-win.

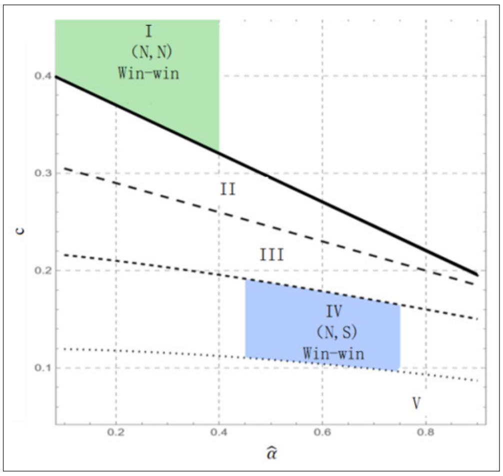

Figure 3: Win-Win for Manufacturer and Retailer Under CPS Scheme

We visually present these win-win regions through Figure 3 (parameter values: (α=1,θ=0.8,k=0.2,λ=1.5,ρ=0.1)).The space of recommendation strength a ̂ and unit recommendation cost c is divided into five regions; shaded areas represent win-win scenarios:

Region I
Recommendation strength is sufficiently low. In this case, adopting recommendation services cannot bring significant sales growth for either party; neither has an incentive to adopt, so scenario (N,N) is win-win.

Regions II and III
Recommendation strength is at a medium-low level. Here, the retailer prefers scenario SN (retailer adopts, manufacturer does not). But the manufacturer's stance depends on recommendation cost: when cost is low (Region II), the manufacturer wants to adopt while the retailer does not, leading to no agreement; when cost is high (Region III), the manufacturer agrees with the retailer not to adopt, making (N,N) win-win again.

Region IV
Recommendation strength is at a medium-high level, and recommendation cost is low. Here, the retailer wants to adopt (SN), while the manufacturer wants to adopt alone (NS). With no consensus, a win-win scenario cannot be achieved. However, if recommendation cost further decreases, the manufacturer may be willing to forgo its own system and support retailer adoption, making (N,S) a potential win-win.

Region V
Recommendation strength is sufficiently high. Here, the manufacturer prefers SN, while the retailer prefers SS (both adopt). With conflicting goals, a win-win scenario cannot be achieved.

Analysis of Win-Win Scenarios Under CPC Payment Scheme
Proposition 8.Under the CPC payment scheme, two possible win-win scenarios similarly exist:

- When $(c \in (c_{r1}^{NN}, c_{r2}^{NN}) \cap (c_{m3}^{NN}, c_{m4}^{NN})$, scenario (N,N) is win-win.
- When $(c \in (c_{r1}^{NC}, c_{r2}^{NC}) \cap \{(0, c_{m3}^{NN}) \cup (c_{m4}^{NN}, 1)\}$, scenario (N,S) is win-win.

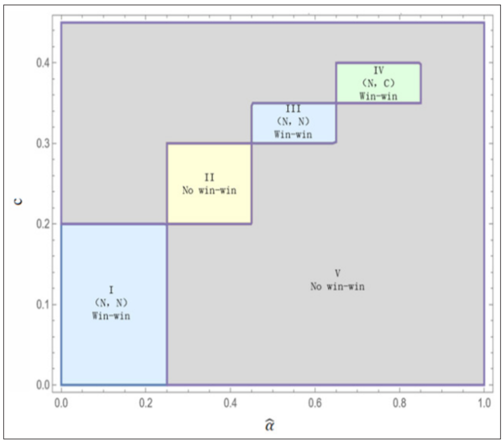

Figure 4: Win-Win Regions Under CPC Payment Scheme

We present win-win regions under CPC through Figure 4 (parameter values same as Figure 3). Analysis shows: The overall pattern of win-win scenarios is similar to CPS, but with important differences. Under CPC, the win-win region for only the manufacturer adopting (NC) is smaller than the corresponding region under CPS (NS). The win-win region where neither adopts (NN) is significantly larger. This is because under CPC, due to uncertainty in click conversion, adopting recommendation systems often fails to bring significant sales uplift.

Compared to CPS, CPC requires lower recommendation costs for the manufacturer and retailer to achieve a win-win. Moreover, recommendation cost plays a more critical role in influencing both parties' decisions: when cost is sufficiently low, both may be willing to adopt; when cost exceeds a certain threshold, win-win scenarios become unattainable.

Extended Model Analysis
In this section, we relax certain assumptions of the baseline model to explore the robustness of the manufacturer's and retailer's recommendation system adoption decisions in more general market environments. Specifically, we consider the following four extension scenarios:

- Simultaneous determination of direct sales and retail prices;
- Introduction of consumers' external options;
- Consideration of consumer channel preference heterogeneity;
- Coexistence of CPS and CPC payment schemes.

These extensions aim to test the robustness of the main conclusions and provide additional perspectives for understanding the role of recommendation systems in different market environments.

Simultaneous Pricing Decision

In the baseline model, we assume the manufacturer, as the Stackelberg leader, sets direct sales and wholesale prices before the retailer decides the retail price. However, in some market environments, manufacturers and retailers may set their retail prices simultaneously. To test the robustness of baseline results, this section considers a model with simultaneous pricing by manufacturer and retailer. Under CPS and CPC, the pricing sequence is: 1.The recommendation system decides its service price p_e. 2.The manufacturer decides the wholesale price w. 3.The retailer and manufacturer simultaneously decide retail price p_r and direct sales price p_m.

Similar to the baseline, we solve for equilibrium using backward induction.

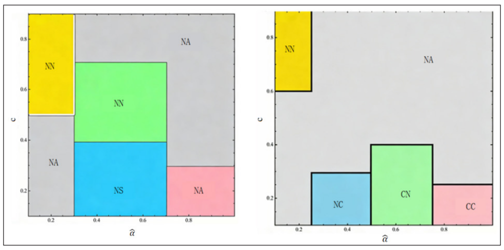

Figure 5: Win-Win Outcomes Under Simultaneous Pricing Decision

Figure 5 shows win-win regions for the manufacturer and retailer under CPS and CPC with simultaneous pricing (parameter values:(α=1,θ=0.8,k=0.2,λ=1.2,ρ=0.1)). NN, NS, and CN denote win-win regions; NA denotes non-win-win.

Main Findings 1

Through model comparison, we find that win-win scenarios under CPS are consistent with the baseline. Under CPS, when recommendation strength is low and cost high, both achieve a win-win by not adopting. However, when recommendation strength is high, both tend not to adopt.2.When both recommendation strength and cost are low, both achieve a win-win under the CN model, contrary to the baseline. This result indicates that power structure influences recommendation system usage strategy under CPC. When the manufacturer holds absolute power advantage, it can afford recommendation fees; when it lacks such advantage, it prefers indirect benefits through retailer adoption.

External Competition

In our baseline model, we assume consumers always purchase from the manufacturer or retailer. In this extension, we relax this assumption, allowing consumers not to purchase from either—i.e., in a competitive market, consumers can buy from other manufacturers or choose not to purchase the product. We use d_o to characterize this external competitive option. The more intense the external competition, the lower the utility consumers derive from purchasing the manufacturer's or retailer's product.

Model Setup and Demand Functions

Considering external option d_o, the consumer utility function can be expressed as:

$$U=\sum_{i=m,r}\left[(\alpha-D_o)D_i-p_iD_i-\frac{1}{2}D_i^2\right]-\theta D_mD_r$$

Maximizing U, we obtain aggregate demand functions for the direct and wholesale channels in the traditional market:

$$D_m=\frac{(1-\theta)(\alpha-d_o)-p_m+\theta p_r}{1-\theta^2},D_r=\frac{(1-\theta)(\alpha-d_o)-p_r+\theta p_m}{1-\theta^2}$$

Similarly, when the manufacturer or retailer adopts a recommendation system, demand in the recommendation market for the corresponding channel is:

$$\widehat{D}_i=\lambda\widehat{\alpha}-d_o-p_i,i=m,r$$

When both adopt, aggregate demand for the two channels in the recommendation market is:

$$\widehat{D}_m=\frac{(1-\theta)(\lambda\widehat{\alpha}-d_o)-p_m+\theta p_r}{1-\theta^2},\widehat{D}_r=\frac{(1-\theta)(\lambda\widehat{\alpha}-d_o)-p_r+\theta p_m}{1-\theta^2}$$

Equilibrium Analysis and Impact of Social E-commerce Variables

Using backward induction, we can derive equilibrium results for all scenarios (SN, SS, CN, CC, NN, NS, NC) considering external competition. Taking scenario CC as an example, we analyze the impact of external competition intensity d_o on profits $(\pi_i^{CC})((i\in\{m,r,e\}))$.

Corollary 1

The manufacturer's profit $(\overline{\pi}_i^{CC})$ decreases with (d_o) when ($d_o<d_{om}$) and increases with (d_o) when ($d_o>d_{om}$). The retailer's profit $\overline{\pi}_r^{CC}$ increases with (d_o) when ($d_o<d_{or}$) and decreases with (d_o) when ($d_o>d_{or}$). The recommendation system's profit $(\overline{\pi}_e^{CC})$ decreases with (d_o) when ($d_o<d_{oe}$) and increases with (d_o) when ($d_o>d_{oe}$).

Corollary Indicates: Impact on Manufacturer

In less competitive markets, the manufacturer can achieve higher profits through higher pricing. But as external competition d_o intensifies, the manufacturer may need to lower prices to maintain market share, reducing profit. However, when competition surpasses threshold d_{om}, the market landscape changes. The manufacturer may rely more on the recommendation system to enhance product exposure and attractiveness, thus willing to pay more to maintain or increase market share. The recommendation system then prefers collaborating with the market leader (manufacturer), boosting its profitability.Impact on Retailer:As external competition intensifies, the retailer may attract customers with more competitive prices, increasing sales and profit. But in highly competitive markets, the retailer faces greater pricing pressure, must lower prices to attract customers, reducing profit. Also, if the retailer does not heavily rely on the recommendation system, it may not fully utilize its benefits, affecting profitability. Impact on Recommendation System:

In low competition, the recommendation system's value may be underappreciated; its profit decreases with competition. But in highly competitive markets, manufacturers rely more on it for competitive advantage, willing to pay higher fees, increasing its profit.

Interaction Effects of Social E-commerce Variables

In an external competition environment, the mechanisms of social e-commerce variables ey and ρ change: Defensive Value of Social Interaction Effect Intensity λ: In high competition environments (large d_o), strong social interaction (high λ) becomes a key defensive tool for manufacturers and retailers, helping maintain consumer attention and preference, partially offsetting external competition pressure. Thus, in high d_o regions, the positive impact of λ on profit may strengthen. Budget Constraint Effect of Social Channel Commission Rate ρ:Intensified external competition may compress firms' profit margins, reducing their tolerance for social commission ρ. With large d_o, high ρ may become a key barrier to adoption. Firms may need to renegotiate commission rates with platforms or seek lower-cost alternative channels. Changing Trade-off Between λ and ρ:In low competition, firms may focus more on growth potential from λ; in high competition, they may focus more on cost pressure from ρ. This may influence payment scheme preference.

Consumer Channel Preference Heterogeneity

In previous analyses, the model is deterministic—all consumers derive the same utility from purchasing. However, in reality, different consumers may have different preferences for the same product or purchase channel. To make the model more general and realistic, we consider heterogeneity in consumer preferences across channels. Following Zhou and Zou (2023), we use (t_j) to denote consumer (j)'s preference across channels, assumed uniformly distributed over ([-1,1]) (when (t>0) , (t_j) in ([0,t]); when (t<0) , in ([t,0]), where (t) indicates the level of preference heterogeneity. We assume (t∈[-1,1]); (t∈[0,1]) indicates consumers may prefer the direct sales channel, while (t∈[-1,0)) indicates preference for the wholesale channel.

Model Setup and Demand Functions

Considering heterogeneity, the utility function can be rewritten as:

$$U_j = (\alpha + t_j)D_m + (\alpha - t_j)D_r - p_m D_m - P_r D_r - \frac{1}{2}D_m^2 - \frac{1}{2}D_r^2 - \theta D_m D_r$$

Maximizing (U_j) yields demand functions:

$$D_m = \frac{(1-\theta)\alpha - p_m + \theta p_r}{1-\theta^2} + \frac{t_j}{1-\theta}, D_r = \frac{(1-\theta)\alpha - p_r + \theta p_m}{1-\theta^2} + \frac{t_j}{1-\theta}$$

Correspondingly, expected demand is:

$$E[D_m] = \frac{(1-\theta)\alpha - p_m + \theta p_r}{1-\theta^2} + \frac{t_j}{2(1-\theta)}, E[D_r] = \frac{(1-\theta)\alpha - p_r + \theta p_m}{1-\theta^2} + \frac{t_j}{2(1-\theta)}$$

Using backward induction, we can find equilibrium results for each model. We analyze scenario SS specifically.

Impact of Heterogeneity on Profits: Example of Scenario SS

Considering heterogeneity, profit functions are adjusted to include parameter(t). Analysis yields:

Corollary 2

The manufacturer's profit ($\hat{\pi}_m^{SS}$) decreases with (t) when (t∈ [-1,t_m]) and increases with (t) when (t∈[t_m,1]). The retailer's profit ($\hat{\pi}_r^{SS}$) decreases with (t) when (t∈[-1,t_r)) and increases with (t) when (t∈[t_r,1]). The recommendation system's profit ($\hat{\pi}_e^{SS}$) decreases with (t) when (t∈[-1,t_s)) and increases with (t) when (t∈[t_s,1]).

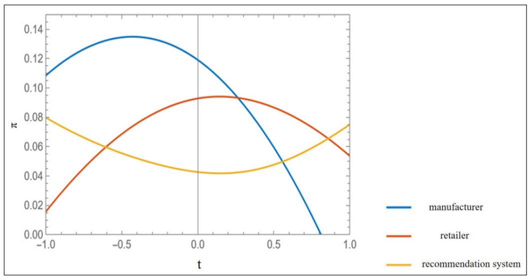

Figure 6: Impact of t on Profits of Manufacturer, Retailer, and Recommendation System

Figure 6 (parameters: (α=1,θ=0.8,c=0.1,$\hat{a}$=0.4,λ=1.2,ρ=0.1)) shows U-shaped trends in profits as t varies from -1 to 1.

Corollary indicates: When heterogeneity is low (near 0), most consumers have similar preferences, leading to homogeneous competition between channels, possibly triggering price wars and profit compression. As heterogeneity increases, consumer demands diversify, allowing firms to serve different segments through different channels, potentially increasing profits. Accordingly, the recommendation system's profitability also improves.

Moderating Role of Social E-commerce Variables

In a heterogeneous preference context, the influence of λ and ρ exhibits new features:

Segmented Market Value of Social Interaction Effect Intensity λ:In high heterogeneity environments (large |t|), consumer preferences are dispersed. Strong social interaction (high λ) can help the recommendation system better match different preferences to channels, improving overall conversion efficiency. The value-added of λ may be amplified in heterogeneous environments, as it not only expands the market but also improves matching quality.

Channel Selection Effect of Social Channel Commission Rate ρ:When consumers clearly prefer a certain channel (large |t|), firms may invest more in that channel's recommendation system. If consumers prefer direct sales (t>0), the manufacturer may be more willing to bear high ρ to build social e-commerce capability; conversely, if they prefer retail (t>0), the manufacturer may prefer the retailer to lead and negotiate lower ρ.

Three-way Interaction of Heterogeneity, λ, and ρ:With high t (clear preference differentiation) and high λ, the recommendation system creates maximum value, and firms may accept higher ρ. With high t but low λ, the system's matching efficiency is limited, and firms' tolerance for ρ may decrease.

Coexistence of CPS and CPC Payment Schemes

In reality, multiple payment schemes may exist, or a system may offer multiple schemes. Here, we consider a recommendation system offering both CPS and CPC, and explore whether the manufacturer and retailer have incentives to switch from one scheme to another when both adopt.

Equilibrium Strategy for Payment Scheme Selection

We consider a system offering both CPS and CPC; the manufacturer and retailer can freely choose one when adopting. Strategic choices now include both adoption and scheme selection.

Corollary 3

- If the retailer adopts CPS, the manufacturer prefers CPS if and only if ($\phi_1<c<\phi_2$); otherwise prefers CPC.
- When $\left(\sqrt{3}-1<\theta\le\frac{\sqrt{2\hat{\alpha}^2+4\hat{\alpha}+3}-1}{\hat{\alpha}+1}\right)$ and $\left(0<k<\frac{-\theta^2-2\theta+2}{\theta^2\hat{\alpha}-2\hat{\alpha}}\right)$, or $\left(\frac{\sqrt{2\hat{\alpha}^2+4\hat{\alpha}+3}-1}{\hat{\alpha}+1}<\theta<1\right)$ if the retailer adopts CPC, the manufacturer prefers CPS if and only if ($c>\phi_3$); otherwise prefers CPC
- If the manufacturer adopts CPS, the retailer prefers CPC if and only if ($c>\phi_4$); otherwise prefers CPS.
- When ($1/2<\theta\le(1+\hat{\alpha})/2$) and ($0<k<(2\theta-1)/\hat{\alpha}$) , or ($\theta>(1+\hat{\alpha})/2$), if the manufacturer adopts CPC, the retailer prefers CPC if and only if ($\phi_5<c<\phi_6$); otherwise prefers CPS.

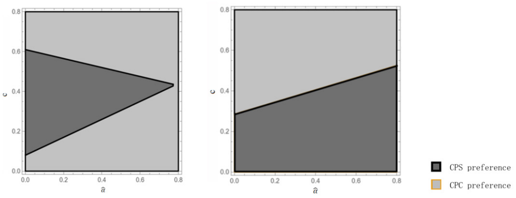

Figure 7: Payment Scheme Preference when CPS is Chosen

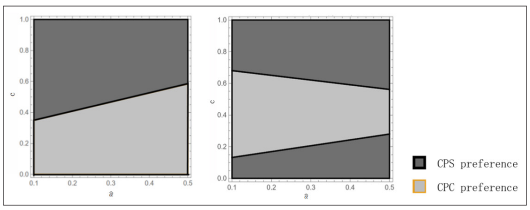

Figure 8: Payment Scheme Preference when CPC is Chosen

Figures 7 and 8 (parameters: ($a=1,\theta=0.8,k=0.2,\lambda=1.5,\rho=0.1$)) visually show manufacturer and retailer preferences under different c.

Observations

When the competitor chooses CPS (Figure 7), both prefer CPC when recommendation cost is high. CPC incentivizes attracting more traffic despite high cost, enhancing product exposure and potential sales opportunities. When the competitor chooses CPC (Figure 8), the situation is more complex: For the manufacturer, switching from CPC to CPS is preferred only when recommendation strength is low and cost is high. With low strength and high cost, clicks under CPC convert inefficiently into sales; switching to CPS reduces inefficiency as payment occurs only upon sale. For retailers disadvantaged by high costs in the game, adopting CPS ensures costs are incurred only upon actual sales, effectively reducing expenditure.

Impact Analysis of Social E-commerce Variables

In a coexisting schemes context, λ and ρ significantly influence preferences: Impact of Social Interaction Effect Intensity λ: Strengthening Effect on CPS: When λ is high, the system effectively drives actual sales, making CPS more attractive. Firms prefer payment directly tied to sales outcomes. Moderating Effect on CPC: In high λ environments, CPC risk is relatively lower because clicks are more likely to convert. This may make CPC a viable choice under specific conditions (e.g., moderate c). Impact of Social Channel Commission Rate ρ:Strengthening Effect on CPS Preference: When ρ is high, the manufacturer already pays commissions for social channel sales. Choosing CPS aligns recommendation costs (pay-per-sale) with social commission costs, simplifying cost structure and improving controllability.Cost Pressure on CPC:High ρ may make CPC less favorable, as the manufacturer bears both per-click recommendation costs and per-sale social commissions, increasing financial risk due to mismatched cost structure. Interaction of λ and ρ:High λ, low ρ: Both CPS and CPC may be attractive, choice depends on c and k. High λ, high ρ: CPS is generally preferred for better cost-revenue matching.Low λ: Regardless of ρ, CPC may lack attractiveness due to difficulty converting clicks into sufficient sales to cover costs.

Conclusion

This paper studies a dual-channel competitive supply chain consisting of a manufacturer and retailer, systematically analyzing the impact of third-party recommendation systems on the manufacturer's strategic choices in a social e-commerce environment. Building upon traditional dual-channel models, we innovatively introduce two core features of social e-commerce—social interaction effect intensity and social channel commission rate—constructing a game model encompassing seven recommendation scenarios. We focus on whether the manufacturer should adopt recommendation services under two situations: when the retailer adopts a recommendation system, and when it does not. For recommendation systems using CPS or CPC payment schemes, we deeply investigate the manufacturer's adoption motivations, payment scheme preferences, and conditions for win-win cooperation among supply chain members.

The manufacturer's adoption strategy exhibits a "free-riding" tendency, moderated by social variables. When the retailer adopts, regardless of payment scheme, it is always optimal for the manufacturer to forgo adopting in the direct sales channel. This stems from dual cost pressures (recommendation fee + social commission) and avoidance of channel competition. When the retailer does not adopt, the manufacturer's decision depends on recommendation strength, cost, and social variables. The social interaction effect amplifies recommendation effectiveness, potentially lowering the cost threshold for adoption; whereas the social commission rate increases cost burden, suppressing adoption willingness. The manufacturer chooses to adopt when recommendation costs are low and strength is moderate [23-31].

Payment scheme preference changes dynamically with scenario and cost. When only one party adopts, the manufacturer always prefers CPS due to its tie to actual sales, offering higher certainty and avoiding CPC click fraud risk. When both adopt, preference shifts: CPS is preferred when recommendation costs are low; beyond a threshold, CPC is preferred. In high commission rate environments, CPC is more attractive for its ability to transfer some traffic risk.

Social e-commerce variables are key moderators influencing profit distribution and win-win cooperation. Social interaction effect intensity amplifies recommendation market demand, enhancing the recommendation system's value. Higher intensity expands the manufacturer's profit space and win-win region when adopting alone. Social channel commission rate adds extra cost for the manufacturer, altering profit structure. Higher rates may suppress adoption willingness and expand the win-win region where neither adopts, as commissions erode net benefits from recommendations.

Win-win cooperation is achieved only under specific conditions, and the social environment alters cooperation boundaries. Two typical win-win scenarios:

- When recommendation strength is sufficiently low, neither adopts;
- When strength is medium-high and costs are low, only the manufacturer adopts.

Only the retailer adopting cannot achieve win-win, indicating the retailer's unwillingness to allow "free-riding." Compared to CPS, achieving win-win under CPC requires a lower recommendation cost threshold, and the NN region is larger, due to click conversion uncertainty.

Main conclusions remain robust across multiple extended scenarios. Testing in extensions such as simultaneous pricing, external competition, consumer preference heterogeneity, and payment scheme coexistence confirms that core conclusions remain stable, demonstrating the important moderating role of social e-commerce variables across different market environments.

This study is the first to systematically integrate social e-commerce characteristics into a dual-channel recommendation system adoption analysis framework, revealing how social amplification effects and benefit distribution mechanisms jointly influence equilibrium decisions, addressing a gap in existing research. Implications for Manufacturers: In social e-commerce decision-making, weigh the market gains from social interaction effect intensity against the cost pressure from social channel commission rates. When the retailer has adopted, prioritize "free-riding" over self-building; in high commission rate environments, strategically consider CPC for better risk transfer. Implications for Retailers: In social e-commerce, retailers can gain additional revenue or pass on costs through commission rates; leverage this advantage in negotiations to protect investments and avoid excessive "free-riding. “Implications for Service Providers/Platforms: Design differentiated, dynamic payment schemes based on social interaction effect intensity and commission rate levels in different markets to better meet firms' dual needs for cost certainty and risk control.

This study assumes deterministic demand and focuses on a single supply chain structure. Future research could introduce stochastic demand, multi-agent competitive platforms, or examine how new technologies like generative AI change recommendation costs and the social interaction effect itself, further extending the depth and breadth of this work.

Competing Interests Statement

The authors declare that they have no competing interests to disclose. All authors have no financial or non-financial interests that are directly or indirectly related to the work submitted for publication. No funding, employment, financial holdings, patents, professional relationships, or personal beliefs could reasonably be perceived as influencing the submitted work.

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