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AI Self-Streaming or KOL Live Streaming with Service Assurance? Pricing and Strategy under Product Returns

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Abstract

Live-streaming commerce has become an important retail format, yet retailers still face substantial uncertainty regarding livestreaming mode choice and service design when product returns are significant. This paper develops an analytical decision model to study a platform retailer's joint decision on livestreaming mode and service assurance. Specifically, the retailer chooses between AI self-streaming and KOL live streaming, while also deciding whether to adopt service assurance in the presence of demand expansion, return risk, platform commission, KOL commission, AI investment, and the salvage value of returned products. The results show that service assurance always increases the retailer's optimal price under a given livestreaming mode, and that the optimal price under KOL live streaming is higher than that under AI self-streaming. However, service assurance does not necessarily improve demand or kept sales; it is beneficial only when its willingness-to-pay effect is sufficiently strong relative to the induced return burden. In addition, both the service-assurance decision and the livestreaming-mode choice follow threshold rules. Most importantly, service assurance is more likely to complement AI self-streaming than KOL live streaming, because AI self-streaming is less sensitive to expectation-induced returns. Numerical analysis further illustrates the underlying mechanisms and strategy regions.

Keywords

Live-Streaming Commerce, Product Returns, Pricing, Channel Strategy, Service Assurance, Game Theory

1. Introduction

Live-streaming commerce has become one of the most visible retail innovations in the digital economy because it combines real-time product display, interactive communication, entertainment, and immediate transaction conversion in a single shopping interface [1]. Recent market reports show that live commerce has already become mainstream in China and continues to expand in the United States and Europe, suggesting that it is no longer a niche format but an increasingly important component of platform-based retailing [1] [2]. Meanwhile, digital retail is being reshaped by the broader convergence of streaming media, social platforms, and AI-enabled interfaces, which further strengthens the practical relevance of studying live-streaming selling mechanisms [3].

Compared with conventional online retailing, live-streaming allows sellers to demonstrate products in real time and respond to consumers' questions instantly, thereby reducing information asymmetry and enriching the shopping experience [4]. Prior consumer-behavior research has shown that live streaming can build customer trust and engagement through utilitarian, hedonic, and symbolic value [5]. Real-time interactivity also affects engagement through communication intensity and social ties [6]. More recent empirical studies further confirm that live-streaming features and anchor-related characteristics significantly shape purchase intention and impulse buying [7] [8].

As this research stream expands, review studies increasingly identify trust formation and impulse buying as two of the most central themes in live-streaming commerce research [9] [10]. However, the commercial attractiveness of live streaming also has a darker side: strong conversion may be followed by substantial post-purchase losses. At the industry level, product returns remain a major burden for retailers, especially in online channels [11] [12]. This concern is particularly salient in live-streaming commerce, where urgency, emotional arousal, and parasocial interaction can stimulate impulsive orders that may later be reversed [10].

These tensions have motivated a growing stream of operations and supply chain research on live-streaming strategy. Existing analytical studies show that introducing a live-stream channel is not always profitable, even when live streaming expands consumer awareness or alleviates valuation uncertainty [13]. Research on selling-format design further indicates that the preferred live-stream format depends on price-discount strategy and channel structure [14]. Related work also shows that resale and agency formats can have different advantages once live-stream selling is taken into account [15]. In platform settings, the choice between merchant live-streaming and influencer live-streaming likewise depends on commissions, demand expansion, and channel competition [16]. Platform governance and operating mode also matter for live-stream performance and coordination [17]. When influencers are involved, the retailer must additionally consider inventory and business-model trade-offs [18].

Recent studies have examined more specific live-streaming choices in supply chains and electronic retailing. For example, retailers may choose between influencer channels and third-party channels when introducing live-stream selling [19].

They may also combine self-run live-streaming with return-related services such as buy-online-and-return-in-store [20]. Research on KOL promotion further shows that stronger influencer effects do not necessarily improve firm profit, because the outcome depends on commission rates, retain rates, and network externalities [21]. At the same time, AI livestreaming has started to attract attention as a new business model because it changes the decision maker, cost structure, and revenue-sharing mechanism relative to KOL livestreaming [22].

A parallel stream of literature focuses on platform service assurance and return-related service design. Guo *et al.* show that platform-based Worry-Free-Shopping can increase consumers' willingness to pay, but it may also induce more returns because consumers form higher expectations before purchase [23]. Similar ambiguity appears in studies of return-freight insurance and related return services, which may benefit or hurt retailers depending on the operating environment [24]. These issues are highly relevant in practice because major platforms have already institutionalized assurance mechanisms such as money-back guarantees, purchase protection, and easy-return programs [25] [26].

Despite this progress, the literature remains fragmented. Recent synthesis work shows that live-streaming commerce research now spans consumer behavior, platform strategy, channel design, and operational optimization [27]. Within this broader literature, newer studies have examined KOL introduction and pricing under network effects [28], live-stream platform promotion strategy [29], and competitive spillover effects across online retailers [30]. Nevertheless, limited attention has been paid to the joint problem of AI-versus-KOL mode choice and platform service assurance when product returns are endogenous.

This paper develops a retailer-centered analytical model in which a platform retailer chooses between AI self-streaming and KOL live streaming while also deciding whether to adopt service assurance. The model explicitly incorporates demand expansion, return risk, platform commission, KOL commission, AI investment, and the salvage value of returned products. Four operational scenarios are then compared: AI self-streaming without service assurance, AI self-streaming with service assurance, KOL live streaming without service assurance, and KOL live streaming with service assurance. The analysis yields four main findings. First, service assurance always raises the retailer's optimal price under a given livestreaming mode. Second, for a given assurance status, the optimal price under KOL live streaming is higher than that under AI self-streaming. Third, service assurance does not necessarily increase demand or kept sales; it does so only when its valuation-enhancing effect is sufficiently strong relative to the induced return burden. Fourth, service assurance is more likely to complement AI self-streaming than KOL live streaming, so introducing service assurance may even shift the retailer's preferred livestreaming mode from KOL live streaming to AI self-streaming.

The remainder of this paper is organized as follows. Section 2 describes the problem setting and model structure. Section 3 develops the analytical model and derives the main results. Section 4 presents numerical analysis to illustrate the key mechanisms and threshold effects. Section 5 discusses possible extensions. Section 6 concludes the paper.

2. Problem Description

We consider an e-retailer selling a product on an e-commerce platform. In the base model, the platform provides the transaction infrastructure, a service-assurance option, and a fixed commission scheme, while the retailer is the focal decision-maker. Before setting the retail price, the retailer needs to determine an appropriate livestreaming strategy. In the base model, the platform commission rate, the KOL commission rate, and the availability of service assurance are treated as exogenous institutional conditions. Therefore, the base model is formally a retailer optimization problem rather than a multi-player strategic game. We retain the scenario-comparison structure because the retailer makes sequential operational decisions over livestreaming mode, service-assurance adoption, and retail pricing. Strategic interaction between the platform and the retailer is introduced only in the platform-subsidy extension in Section 5. Specifically, the retailer faces two operational decisions. The first is the choice of livestreaming mode, namely, AI self-streaming (A) or KOL live streaming (K). The second is whether to adopt the platform's service assurance (S), where $S=1$ indicates adoption and $S=0$ otherwise. Therefore, four mutually exclusive scenarios are considered in the base model: $(A,0)$, $(A,1)$, $(K,0)$, and $(K,1)$.

This setting is motivated by three stylized facts in livestream e-commerce. First, compared with AI self-streaming, KOL live streaming is generally more effective in attracting traffic and stimulating impulsive purchases, but it usually requires revenue sharing and may lead to a higher post-purchase return risk. Second, AI livestreaming provides a more standardized product presentation and avoids KOL commission, but it requires fixed technology investment. Third, platform-provided service assurance, such as worry-free shopping labels or return-related guarantees, can increase consumers' willingness to pay, while it may also induce more returns because consumers form higher expectations before purchase. To keep the base model analytically tractable, we adopt a reduced-form formulation that captures the above trade-offs through demand expansion, return risk, and cost differences across scenarios.

Let $m \in \{A, K\}$ denote the livestreaming mode and $S \in \{0,1\}$ denote the service-assurance decision. Under scenario (m,S), the retailer sets the retail price p_{mS}. Following the standard reduced-form approach in analytical operations models, the realized market demand under scenario (m,S) is specified as

$$Q_{mS} = \mu + \delta_m + \alpha S - b p_{mS}, \tag{1}$$

where $\mu > 0$ is the baseline market size, $b > 0$ is the price sensitivity parameter, δ_m captures the demand expansion effect brought by livestreaming mode m, and $\alpha > 0$ measures the additional willingness-to-pay effect generated by service assurance. We assume

$$\delta_K > \delta_A > 0, \tag{2}$$

which reflects that KOL live streaming generally creates stronger consumer attention, social interaction, and impulse-buying stimulation than AI self-streaming.

In addition to sales generation, the retailer also faces product returns after order fulfillment. Let r_{mS} denote the realized return rate under scenario (m,S). We specify it as

$$r_{mS} = r_m + \eta_m S, \tag{3}$$

where r_m is the baseline return rate under livestreaming mode m, and η_m captures the incremental return effect caused by adopting service assurance in mode m. We further assume

$$0 < r_{mS} < 1, \tag{4}$$

and

$$r_K > r_A, \eta_K > \eta_A \geq 0. \tag{5}$$

The first inequality means that KOL live streaming is more likely to induce over-purchase and post-purchase regret, thereby resulting in a higher baseline return rate. The second inequality means that service assurance is more likely to amplify expectation-induced returns in the KOL scenario than in the AI scenario. Accordingly, the quantities of kept products and returned products under scenario (m,S) are given by

$$K_{mS} = (1 - r_{mS}) Q_{mS}, \tag{6}$$

$$R_{mS} = r_{mS} Q_{mS}. \tag{7}$$

The platform charges the retailer an exogenous ad valorem commission rate β, where $0 < \beta < 1$. In addition, if the retailer adopts KOL live streaming, it needs to pay a KOL commission rate ϕ, where $0 < \phi < 1 - \beta$. We assume that both the platform commission and the KOL commission are settled only on kept sales. If an order is returned, the transaction is reversed and the corresponding commission is fully cancelled. Hence, commission payments are calculated based on retained transactions rather than gross orders. This settlement rule is consistent with the profit expressions developed in Section 3. If commissions were charged on gross orders, the profit coefficients would change, but the basic trade-off between demand expansion, commission burden, and return losses would remain. By contrast, AI self-streaming does not involve KOL commission but requires a fixed technology investment $F > 0$. To unify the notation, we define

$$\phi_A = 0, \phi_K = \phi, \tag{8}$$

and

$$F_A = F, F_K = 0. \tag{9}$$

Let c denote the unit operating cost of the product, and let s denote the salvage value of a returned product, where $0 \leq s < c$. The salvage value is interpreted as the net recovery value of a returned product. It already incorporates resale value as well as possible repackaging, inspection, refurbishment, restocking, and return-handling losses. Therefore, we do not introduce an additional per-unit return-processing cost in the base model. Equivalently, such a cost can be absorbed by reducing the salvage value. If the retailer adopts service assurance, it incurs an additional fixed service cost $C > 0$. Therefore, the economic trade-off faced by the retailer can be summarized as follows. KOL live streaming can create stronger demand expansion, but it also involves extra commission payments and a higher return rate. AI self-streaming avoids KOL commission and usually has a lower return risk, but it requires fixed technology investment. Meanwhile, service assurance can stimulate demand, but it may also intensify the return burden.

The sequence of events in the base model is as follows. First, the retailer chooses the livestreaming mode $m \in \{A, K\}$ and decides whether to adopt service assurance $S \in \{0,1\}$. Second, given (m, S), the retailer sets the retail price p_{mS}. Third, consumers observe the retailer's operational strategy and place orders, generating total demand Q_{mS}. Finally, after product fulfillment, a fraction r_{mS} of the orders is returned and the remaining fraction $1 - r_{mS}$ is kept, after which the retailer's profit is realized. To make the feasible parameter region explicit, we impose the following conditions throughout the base analysis. For each livestreaming mode $m \in \{A, K\}$ and service-assurance decision $s \in \{0,1\}$, the total return rate is required to satisfy $0 \le r_m + s\eta_m < 1$. In particular, when service assurance is adopted, we require $r_m + \eta_m < 1$. The effective commission burden must also satisfy $0 \le \rho + \lambda_m < 1$, where $\lambda_A = 0$ for AI self-streaming and $\lambda_K = \lambda$ for KOL live streaming. In addition, we assume $b > 0$, $c \ge v \ge 0$, and that the scenario-specific interior-solution condition holds for all four scenarios. Equivalently, the non-price demand potential must be sufficiently large relative to the effective cost term so that the optimal demand is positive. These restrictions ensure feasible return rates, positive retained-sales revenue, and a unique interior pricing solution before the propositions are stated. Based on the above setting, the next section formulates the retailer's expected profit under each scenario and derives the corresponding optimal pricing decisions and mode-selection conditions. We use the same price-sensitivity parameter across all scenarios. This assumption means that livestreaming mode and service assurance affect the demand intercept through market expansion and willingness-to-pay enhancement, but do not change consumers' marginal price sensitivity. This reduced-form specification allows us to isolate the effects of traffic generation, service assurance, and return risk. Allowing price sensitivity to vary across livestreaming modes is a meaningful extension, but it is beyond the scope of the base model.

At the end of this section, **Figure 1** illustrates the sequence of events in the base model. Specifically, the retailer first chooses the livestreaming mode and the service-assurance decision, then sets the retail price, after which consumers make purchase decisions and product returns are realized. In addition, **Table 1** summarizes the notation and parameter definitions used throughout the paper, including the main demand, return, cost, and decision variables. Based on the timing structure in **Figure 1** and the notation in **Table 1**, the next section develops the analytical model and derives the corresponding equilibrium results under the four scenarios.

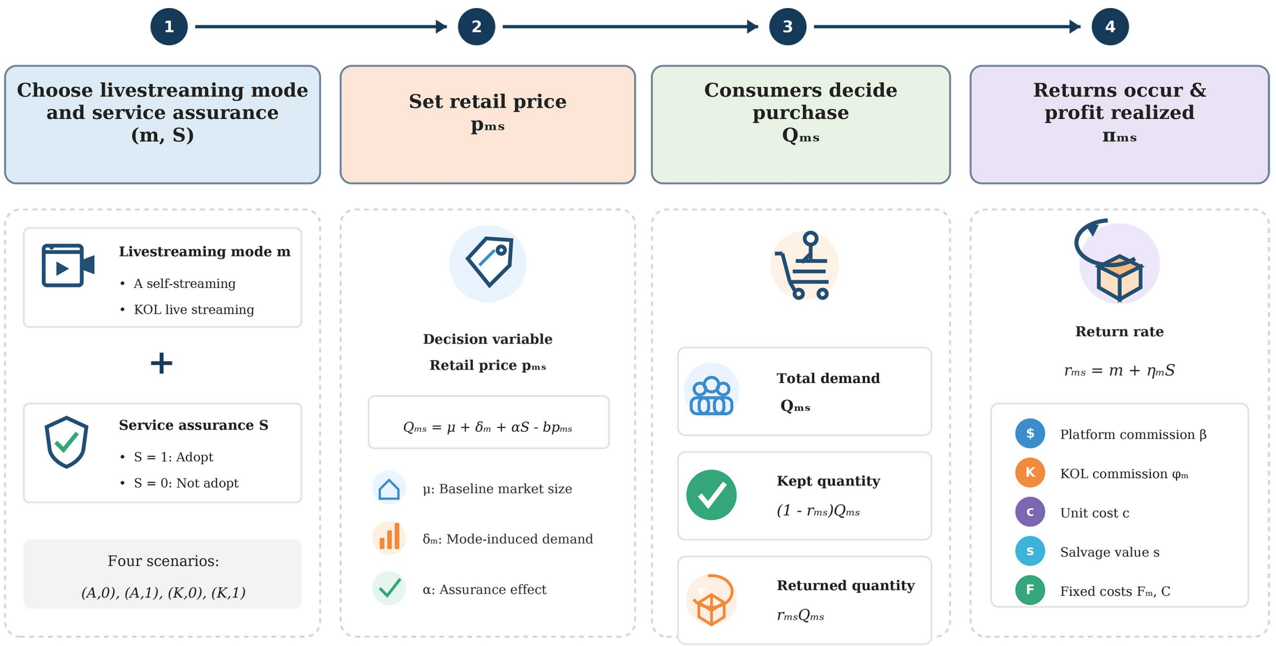

Figure 1. Sequence of events in the base mode.

Table 1. Summary of notation and parameters.

Notation	Definition
$m \in \{A, K\}$	Livestreaming mode, where A denotes AI self-streaming and K denotes KOL live streaming
$S \in \{0,1\}$	Service-assurance decision; $S = 1$ if service assurance is adopted, and $S = 0$ otherwise
p_{mS}	Retail price under scenario (m, S)
Q_{mS}	Total demand under scenario (m, S)
K_{mS}	Quantity of kept products under scenario (m, S)
R_{mS}	Quantity of returned products under scenario (m, S)
r_{mS}	Return rate under scenario (m, S)
μ	Baseline market size
δ_m	Demand expansion effect of livestreaming mode m
α	Demand-enhancing effect of service assurance
b	Price sensitivity parameter
r_m	Baseline return rate under livestreaming mode m
η_m	Incremental return effect of service assurance under mode m
β	Platform commission rate
ϕ	KOL commission rate
F	Fixed investment cost of AI self-streaming
C	Fixed cost of adopting service assurance
c	Unit operating cost
s	Salvage value of a returned product, with $0 \le s < c$

3. Model Development and Analysis

Given the problem setting in Section 2, the retailer first selects an operational scenario (m,S), where $m\in\{A,K\}$ denotes the livestreaming mode and $S\in\{0,1\}$ denotes the service-assurance decision. The retailer then sets the retail price p_{mS}. Under scenario (m,S), total demand is given by

$$Q_{mS}=\mu+\delta_m+\alpha S-bp_{mS}, \tag{10}$$

where $\mu>0$ is the baseline market size, δ_m captures the demand-expansion effect generated by livestreaming mode m, $\alpha>0$ measures the willingness-to-pay effect of service assurance, and $b>0$ is the price sensitivity parameter. We assume $\delta_K>\delta_A>0$, implying that KOL livestreaming creates a stronger market-expansion effect than AI self-streaming.

The return rate under scenario (m,S) is specified as

$$r_{mS}=r_m+\eta_m S, \tag{11}$$

where r_m is the baseline return rate under livestreaming mode m, and η_m is the incremental return effect induced by service assurance in that mode. We assume $0<r_{mS}<1$, $r_K>r_A$, and $\eta_K>\eta_A\geq 0$. These assumptions reflect that KOL livestreaming is more likely to stimulate impulsive purchases and post-purchase regret, while service assurance is more likely to amplify expectation-induced returns in the KOL setting than in the AI setting.

Accordingly, the quantities of kept products and returned products are

$$K_{mS}=(1-r_{mS})Q_{mS}, \tag{12}$$

$$R_{mS}=r_{mS}Q_{mS}. \tag{13}$$

The platform charges the retailer an ad valorem commission rate β, where $0<\beta<1$. If the retailer adopts KOL livestreaming, it additionally pays a KOL commission rate ϕ, where $0<\phi<1-\beta$. By contrast, AI self-streaming avoids KOL commission but requires a fixed technology investment $F>0$. To unify notation, let

$$\phi_A=0,\phi_K=\phi, \tag{14}$$

and

$$F_A=F,F_K=0. \tag{15}$$

Let c denote the unit operating cost and s denote the salvage value of a returned product, where $0\leq s<c$. If the retailer adopts service assurance, it incurs an additional fixed cost $C>0$. Hence, under scenario (m,S), the retailer's expected profit is

$$\Pi_{mS}(p_{mS})=(1-r_{mS})(1-\beta-\phi_m)p_{mS}Q_{mS}-cQ_{mS}+sr_{mS}Q_{mS}-F_m-CS, \tag{16}$$

For notational convenience, define

$$M_{mS}=\mu+\delta_m+\alpha S, \tag{17}$$

$$\Gamma_{mS}=(1-r_{mS})(1-\beta-\phi_m), \tag{18}$$

$$H_{mS} = c - r_{mS} s, \tag{19}$$

Then the retailer's profit can be rewritten as

$$\Pi_{mS}\left(p_{mS}\right) = \left(\Gamma_{mS} p_{mS} - H_{mS}\right)\left(M_{mS} - bp_{mS}\right) - F_m - CS, \tag{20}$$

Under the regularity condition $\Gamma_{mS} M_{mS} > bH_{mS}$, the retailer's pricing problem admits a unique interior solution. The optimal price, demand, kept quantity, returned quantity, and profit under scenario (m,S) are respectively given by

$$p_{mS}^{*} = \frac{M_{mS}}{2b} + \frac{H_{mS}}{2\Gamma_{mS}}, \tag{21}$$

$$Q_{mS}^{*} = \frac{\Gamma_{mS} M_{mS} - bH_{mS}}{2\Gamma_{mS}}, \tag{22}$$

$$K_{mS}^{*} = \left(1 - r_{mS}\right) Q_{mS}^{*}, \tag{23}$$

$$R_{mS}^{*} = r_{mS} Q_{mS}^{*}, \tag{24}$$

and

$$\Pi_{mS}^{*} = \frac{\left(\Gamma_{mS} M_{mS} bH_{mS}\right)^2}{4b\Gamma_{mS}} - F_m - CS, \tag{25}$$

Since the platform and the KOL do not make endogenous decisions in the base model, these outcomes should be interpreted as optimal retailer decisions under exogenous institutional conditions, rather than as equilibrium outcomes of a multi-player game. These expressions provide a unified benchmark for the four operational scenarios.

Proposition 1.

Under any scenario $(m,S) \in \{(A,0),(A,1),(K,0),(K,1)\}$, the retailer's expected profit admits a unique interior optimum. The optimal price, demand, kept quantity, returned quantity, and profit are given by Equations (21)-(25).

3.1. Scenario $(A,0)$: AI Self-Streaming without Service Assurance

This scenario captures the case in which the retailer adopts AI self-streaming but does not provide service assurance. In practice, this mode is suitable for firms that prefer a relatively standardized livestreaming format and direct control over the selling process. Compared with KOL livestreaming, AI self-streaming avoids external revenue sharing and usually provides more stable product presentation, although the retailer must bear the fixed technology investment. Under scenario $(A,0)$, we have

$$M_{A0} = \mu + \delta_A, \Gamma_{A0} = \left(1 - r_A\right)\left(1 - \beta\right), H_{A0} = c - r_A s. \tag{26}$$

Therefore, the retailer's optimal price and profit are

$$p_{A0}^{*} = \frac{\mu + \delta_A}{2b} + \frac{c - r_A s}{2\left(1 - r_A\right)\left(1 - \beta\right)}, \tag{27}$$

$$\Pi_{A0}^{*} = \frac{\left(\left(1 - r_A\right)\left(1 - \beta\right)\left(\mu + \delta_A\right) - b\left(c - r_A s\right)\right)^2}{4b\left(1 - r_A\right)\left(1 - \beta\right)} - F. \tag{28}$$

This scenario benefits from the lower return burden of AI self-streaming and the absence of KOL commission. However, its profitability is constrained by the relatively weaker market-expansion effect and the fixed AI investment. Thus, $(A,0)$ is more attractive when return control and operational standardization are particularly valuable.

3.2. Scenario $(A,1)$: AI Self-Streaming with Service Assurance

This scenario extends AI self-streaming by allowing the retailer to additionally adopt service assurance. In practice, service-assurance programs such as worry-free shopping labels, guaranteed return support, or confidence-enhancing service badges are increasingly used by major platforms to stimulate purchase intention. At the same time, they may also raise consumers' expectations and thereby increase return risk.

Under scenario $(A,1)$, we have

$$M_{A1} = \mu + \delta_A + \alpha, \Gamma_{A1} = (1 - r_A - \eta_A)(1 - \beta), H_{A1} = c - (r_A + \eta_A)s. \tag{29}$$

Thus, the optimal price and profit are

$$p^*_{A1} = \frac{\mu + \delta_A + \alpha}{2b} + \frac{c - (r_A + \eta_A)s}{2(1 - r_A - \eta_A)(1 - \beta)}, \tag{30}$$

$$\Pi^*_{A1} = \frac{\left((1 - r_A - \eta_A)(1 - \beta)(\mu + \delta_A + \alpha) - b\left[c - (r_A + \eta_A)s\right]\right)^2}{4b(1 - r_A - \eta_A)(1 - \beta)} - F - C. \tag{31}$$

Relative to $(A,0)$, this scenario enjoys stronger demand because service assurance raises consumers' willingness to pay. However, the retailer must bear both the fixed assurance cost and the additional return burden. Since AI self-streaming usually provides more stable and less exaggerated product presentation, service assurance is more likely to work as a complement rather than a distortion mechanism in this setting.

3.3. Scenario $(K,0)$: KOL Live Streaming without Service Assurance

This scenario represents the retailer's cooperation with a KOL without adopting service assurance. It captures the core logic of fan-driven livestream selling. Prior studies have shown that KOLs can significantly stimulate consumer purchase intention through real-time interaction, fan influence, and social contagion, but such benefits usually come with revenue sharing and a stronger tendency toward impulse buying. Under scenario $(K,0)$, we have

$$M_{K0} = \mu + \delta_K, \Gamma_{K0} = (1 - r_K)(1 - \beta - \phi), H_{K0} = c - r_K s. \tag{32}$$

Hence, the corresponding optimal price and profit are

$$p^*_{K0} = \frac{\mu + \delta_K}{2b} + \frac{c - r_K s}{2(1 - r_K)(1 - \beta - \phi)}, \tag{33}$$

$$\Pi_{K0}^* = \frac{\left((1-r_K)(1-\beta-\phi)(\mu+\delta_K)-b(c-r_K s)\right)^2}{4b(1-r_K)(1-\beta-\phi)}. \quad (34)$$

Compared with AI self-streaming, KOL livestreaming has a stronger demand-expansion effect. However, it is also associated with a higher commission burden and a higher baseline return rate. Therefore, $(K,0)$ is more attractive when traffic generation and conversion are particularly important, while post-purchase losses remain manageable.

3.4. Scenario $(K,1)$: KOL Live Streaming with Service Assurance

This scenario combines KOL livestreaming with service assurance and thus represents the most aggressive demand-enhancement strategy in our framework. On the one hand, KOL live streaming can strongly stimulate purchases, and service assurance further increases consumers' willingness to pay. On the other hand, the retailer also faces the heaviest operational burden, since KOL commission, assurance cost, and expectation-induced returns are all present simultaneously. Under scenario $(K,1)$, we have

$$M_{K1} = \mu+\delta_K+\alpha, \Gamma_{K1} = (1-r_K-\eta_K)(1-\beta-\phi), H_{K1} = c-(r_K+\eta_K)s. \quad (35)$$

Thus, the optimal price and profit are

$$p_{K1}^* = \frac{\mu+\delta_K+\alpha}{2b}+\frac{c-(r_K+\eta_K)s}{2(1-r_K-\eta_K)(1-\beta-\phi)}, \quad (36)$$

$$\Pi_{K1}^* = \frac{\left((1-r_K-\eta_K)(1-\beta-\phi)(\mu+\delta_K+\alpha)-b\left[c-(r_K+\eta_K)s\right]\right)^2}{4b(1-r_K-\eta_K)(1-\beta-\phi)}-C. \quad (37)$$

This scenario does not necessarily dominate the other three. Although it offers the strongest demand-side stimulus, it also involves the highest risk of expectation mismatch and post-purchase returns. Therefore, the combination of KOL livestreaming and service assurance may create a high-sales but low-retention outcome.

Beyond the four scenario-specific results, the model also yields several further implications regarding pricing and quantity outcomes. We first compare prices across different service-assurance decisions within a given livestreaming mode.

Proposition 2.

For a given livestreaming mode $m \in \{A,K\}$, the retailer charges a higher optimal price when service assurance is adopted, that is, $p_{m1}^* > p_{m0}^*$.

Proposition 2 indicates that service assurance always pushes the retailer toward a higher optimal price. The intuition is that service assurance strengthens consumers' perceived value and thus enlarges the retailer's pricing room. At the same time, it also increases the retailer's exposure to returns. Therefore, the retailer responds by charging a higher price to both extract the enhanced willingness to pay and partially compensate for the higher post-purchase risk.

We next compare prices across livestreaming modes under a given service-assurance decision.

Proposition 3.

For a given service-assurance decision $S \in \{0,1\}$, the optimal price under KOL live streaming is higher than that under AI self-streaming, namely, $p^*_{KS} > p^*_{AS}$.

Proposition 3 shows that KOL live streaming is associated with a higher optimal price than AI self-streaming. This result is driven by three forces. First, KOL livestreaming generates a stronger market-expansion effect. Second, it is associated with a higher return burden. Third, it requires an additional commission payment to the KOL. These effects jointly make KOL livestreaming a higher-price operational mode in equilibrium.

We then turn to the quantity implications of service assurance. Although service assurance improves consumers' willingness to pay, it also raises the return rate. Therefore, its quantity effect is not always positive.

Proposition 4.

For a given livestreaming mode $m \in \{A,K\}$, there exists a threshold α_m^Q such that service assurance increases the retailer's optimal demand if and only if $\alpha > \alpha_m^Q$.

Proposition 4 shows that service assurance does not necessarily increase market demand. When the willingness-to-pay effect is sufficiently strong, the retailer can benefit from both stronger demand and a favorable pricing response. However, when this effect is weak, the retailer may mainly react by raising the price, so that the final demand level does not increase. Therefore, service assurance can be demand-enhancing only when its positive effect on consumer valuation is strong enough relative to the induced return burden.

Since firms are often more concerned with retained transactions than with gross orders alone, we further examine the effect of service assurance on kept sales.

Proposition 5.

For a given livestreaming mode $m \in \{A,K\}$, there exists a threshold α_m^K such that service assurance increases the retailer's kept sales if and only if $\alpha > \alpha_m^K$.

Proposition 5 further shows that service assurance may fail to improve the retailer's effective sales even when it raises consumer purchase intention. The reason is that a higher service level may also intensify expectation-induced returns. Hence, only when the willingness-to-pay effect is sufficiently strong can service assurance lead to more retained transactions. This result is managerially important because firms are typically more concerned with kept sales than with gross orders alone.

After understanding the pricing and quantity mechanisms, we finally characterize the retailer's strategy choice in terms of profit comparisons. For a given livestreaming mode $m \in \{A,K\}$, service assurance is adopted if and only if $\Pi^*_{m1} > \Pi^*_{m0}$.

Equivalently, there exists a threshold C_m^* such that service assurance is adopted if and only if $C < C_m^*$.

Proposition 6.

For a given livestreaming mode $m \in \{A, K\}$, the retailer adopts service assurance if and only if $C < C_m^*$.

Proposition 6 indicates that service assurance follows a threshold rule. It is more likely to be adopted when the demand-enhancing effect of assurance is sufficiently strong and the induced return effect is relatively mild. Hence, service assurance is more likely to complement a livestreaming mode with lower return sensitivity. In our setting, this observation suggests a stronger natural fit between service assurance and AI self-streaming than between service assurance and KOL live streaming.

Similarly, for a given service-assurance decision $S \in \{0,1\}$, AI self-streaming is preferred to KOL live streaming if and only if $\Pi_{AS}^* > \Pi_{KS}^*$.

Equivalently, there exists a threshold F_S^* such that AI self-streaming is preferred if and only if $F < F_S^*$.

Proposition 7.

For a given service-assurance decision $S \in \{0,1\}$, the retailer prefers AI self-streaming to KOL live streaming if and only if $F < F_S^*$.

Proposition 7 shows that the choice between AI self-streaming and KOL live streaming also follows a threshold rule. KOL livestreaming enjoys a stronger market-expansion effect, whereas AI self-streaming avoids KOL commission and is associated with better return control. Thus, KOL is more attractive when traffic generation dominates, while AI is more attractive when cost efficiency and return mitigation are more critical. In particular, once return-related losses become sufficiently important, the operational advantage of AI self-streaming becomes more pronounced.

Taken together, Propositions 2 - 7 imply that the retailer's optimal strategy can be fully determined by comparing Π_{A0}^*, Π_{A1}^*, Π_{K0}^*, and Π_{K1}^*, while also understanding how service assurance and livestreaming mode jointly affect price, demand, and effective sales. A central implication of the model is that service assurance and AI self-streaming may be mutually reinforcing, whereas service assurance may be less compatible with KOL live streaming when expectation-induced returns become sufficiently severe. These analytical implications will be illustrated more intuitively in the next section through numerical analysis.

The exact threshold expressions and all proofs are provided in **Appendix A**.

4. Numerical Analysis

In this section, we conduct numerical analysis to illustrate the main analytical results developed in Section 3. The objectives are threefold. First, we examine how service assurance and livestreaming mode jointly affect the retailer's optimal price, demand, kept sales, and profit. Second, we investigate the threshold-type operational choices characterized in Propositions 6 and 7. Third, we show more intuitively that service assurance is more likely to complement AI self-streaming than KOL live streaming when expectation-induced returns become sufficiently important. Unless otherwise specified, the baseline parameters are set as follows:

$$\mu = 1, b = 1, \delta_A = 0.25, \delta_K = 0.50, \alpha = 0.20, \beta = 0.10, \phi = 0.20, c = 0.25,$$
$$s = 0.10, r_A = 0.15, \eta_A = 0.02, r_K = 0.30, \eta_K = 0.08, F = 0.06, C = 0.05.$$

These parameters satisfy all the regularity conditions in Section 3 and capture the key economic features of the model. In particular, KOL live streaming has a stronger demand-expansion effect than AI self-streaming $(\delta_K > \delta_A)$, but it is also associated with a higher baseline return rate and a larger service-assurance-induced return increment $(r_K > r_A, \eta_K > \eta_A)$. Moreover, KOL live streaming involves additional commission payment ϕ, whereas AI self-streaming requires a fixed technology investment F. The baseline setting therefore reflects the central trade-off between stronger traffic generation and heavier post-purchase losses.

Under the above baseline parameters, the equilibrium outcomes of the four scenarios are summarized in Table 2.

Table 2. Baseline equilibrium outcomes.

Scenario	p^*	Q^*	K^*	R^*	Π^*
$(A,0)$	0.779	0.471	0.401	0.071	0.110
$(A,1)$	0.881	0.569	0.472	0.097	0.132
$(K,0)$	0.974	0.526	0.368	0.158	0.135
$(K,1)$	1.094	0.606	0.376	0.230	0.109

Table 2 immediately yields several observations. First, adopting service assurance increases the optimal price under both AI and KOL livestreaming, which is consistent with Proposition 2. Second, for a given service decision, KOL live streaming leads to a higher price than AI self-streaming, supporting Proposition 3. Third, service assurance increases demand under both modes in the baseline setting, but the increase in returned quantity is much stronger under KOL live streaming. Most importantly, service assurance improves profit under AI self-streaming but reduces profit under KOL live streaming. This suggests that service assurance is more compatible with AI self-streaming than with KOL live streaming, even though both modes experience demand expansion.

To better visualize these mechanisms, we next vary several key parameters.

We first examine the impact of the fixed AI investment F. Figure 2 plots the retailer's optimal profits under $(A,0)$ and $(K,0)$, as well as under $(A,1)$ and $(K,1)$, with F varying over a feasible range.

Figure 2 shows that the profits under the AI scenarios decrease linearly in F, whereas the profits under the KOL scenarios are unaffected by F. This result is intuitive because F is a pure fixed cost of AI self-streaming. More importantly, Figure 2 illustrates the threshold property stated in Proposition 7. When F is sufficiently low, AI self-streaming dominates KOL live streaming. When F becomes sufficiently high, the retailer switches to KOL live streaming. An interesting observation is that the switching threshold is higher when service assurance is adopted. In other words, service assurance makes AI self-streaming more competitive relative to KOL live streaming. This is because service assurance interacts more favorably with the lower return sensitivity of AI self-streaming.

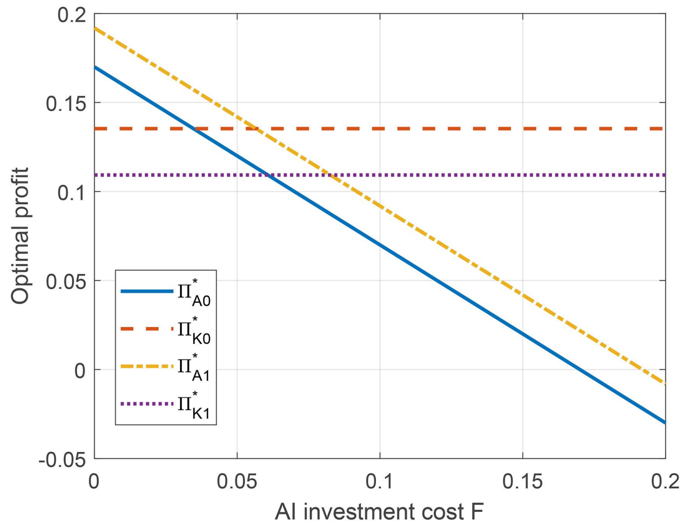

Figure 2. Effect of the AI investment cost F on optimal profits.

Next, we investigate the role of the service-assurance cost C. **Figure 3** plots Π^*_{A1} and Π^*_{A0}, as well as Π^*_{K1} and Π^*_{K0}, against C.

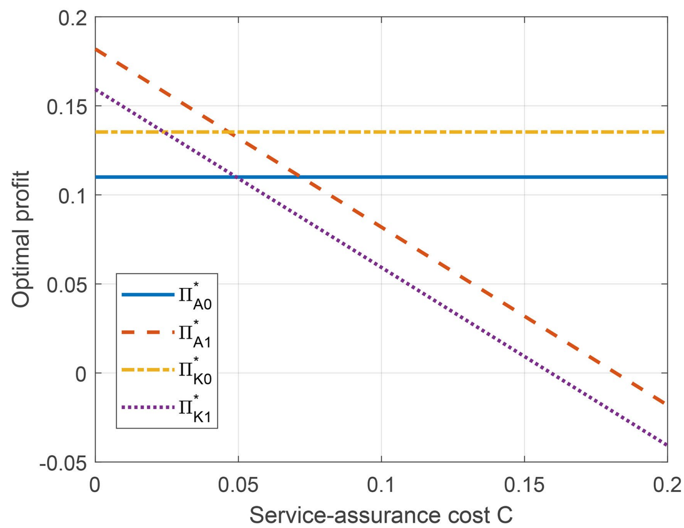

Figure 3. Effect of the service-assurance cost C on optimal profits.

Figure 3 confirms the threshold rule in Proposition 6. As C increases, the profits under $(A,1)$ and $(K,1)$ decrease linearly, while the profits under $(A,0)$ and $(K,0)$ remain unchanged. Therefore, for each livestreaming mode there exists a critical assurance-cost threshold above which service assurance is no longer profitable. More importantly, the threshold under AI self-streaming is higher than that under KOL live streaming. This means that the retailer is willing to tolerate a higher service-assurance cost under AI than under KOL. The reason is that service assurance not only improves willingness to pay, but also induces additional returns. Since KOL live streaming is already more return-sensitive, the marginal value of service assurance is eroded more quickly in the KOL case.

We then analyze the effect of the willingness-to-pay parameter α, which measures the market value of service assurance. Figure 4 plots the optimal demand and kept sales under $(A,1)$ and $(K,1)$ as α increases, together with the corresponding benchmarks $(A,0)$ and $(K,0)$.

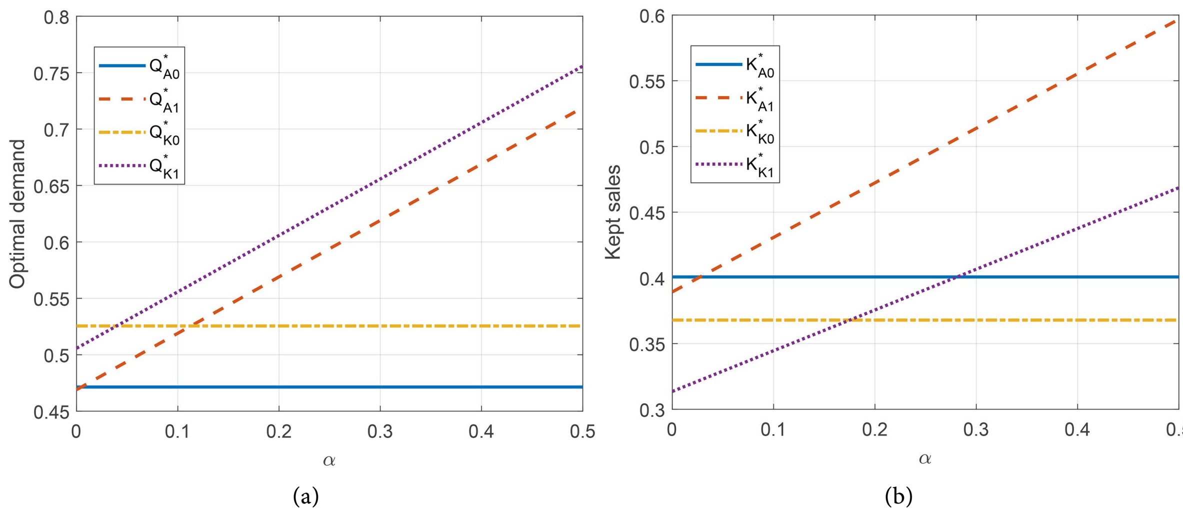

Figure 4. Effect of the willingness-to-pay parameter α on demand and kept sales. (a) Effect of α on optimal demand; (b) Effect of α on kept sales.

Figure 4 illustrates Propositions 4 and 5. When α is small, service assurance may fail to improve effective performance because the retailer mainly responds by charging a higher price, while the induced return effect offsets the demand-side gain. As α increases, both demand and kept sales eventually exceed their no-assurance counterparts. However, the required threshold is lower under AI self-streaming than under KOL live streaming. This means that service assurance begins to create effective operational benefits earlier in the AI case. Put differently, AI self-streaming can convert the valuation-enhancing effect of service assurance into realized retained transactions more efficiently, while KOL live streaming dissipates a larger fraction of this effect through additional returns.

Finally, we examine the importance of expectation-induced returns. Figure 5 varies η_K, while holding η_A fixed, and plots the profits under $(A,1)$ and $(K,1)$.

Figure 5 shows that the profit under $(K,1)$ declines much faster as η_K increases, whereas the profit under $(A,1)$ remains comparatively stable. This result reinforces the central message of the paper. Even when service assurance raises willingness to pay, its interaction with KOL live streaming can become problematic once expectation-induced returns are sufficiently severe. Therefore, the operational value of service assurance is fundamentally mode-dependent. It is not merely the existence of service assurance that matters, but whether the underlying livestreaming mode can absorb the induced expectation risk.

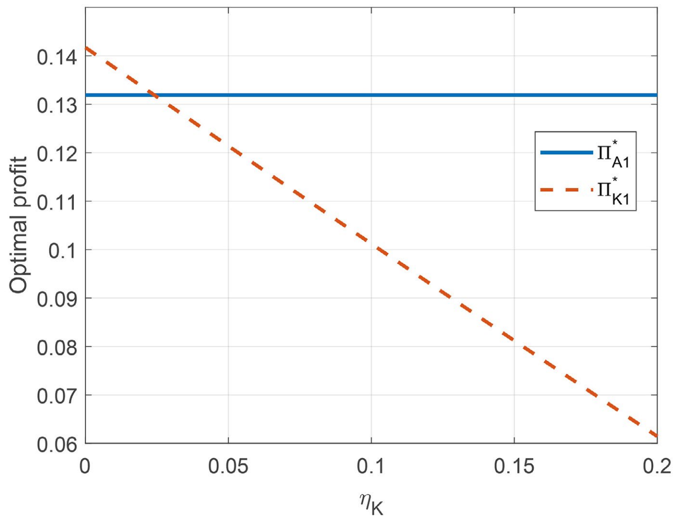

Figure 5. Effect of expectation-induced returns on profits under service assurance.

Figure 6 provides an integrated view of the retailer's optimal operational strategy in the (F, C) plane. The figure partitions the parameter space according to which of the four scenarios yields the highest profit. Two clear patterns emerge. First, a higher AI investment cost shifts the optimal strategy away from AI self-streaming and toward KOL live streaming. Second, a higher service-assurance cost reduces the attractiveness of assurance adoption under both livestreaming modes. More importantly, the $(A,1)$ region is typically larger than the $(K,1)$ region, indicating that service assurance is more likely to complement AI self-streaming than KOL live streaming. Thus, the figure provides an overall summary of how the joint cost structure shapes the retailer's optimal strategy.

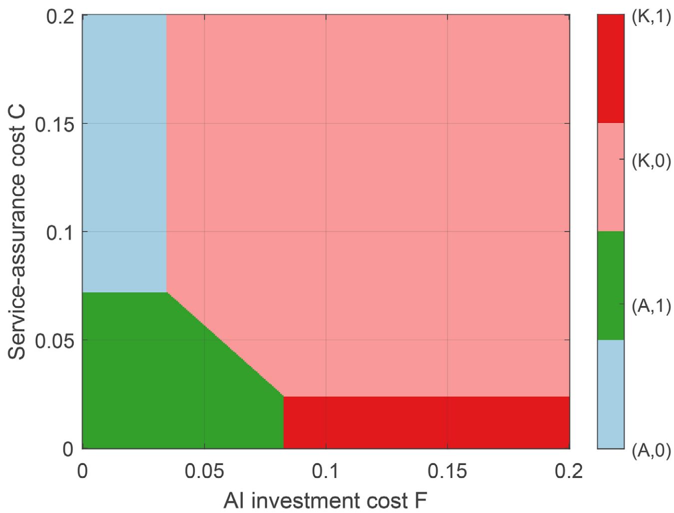

Figure 6. Optimal strategy regions in the (F, C) plane.

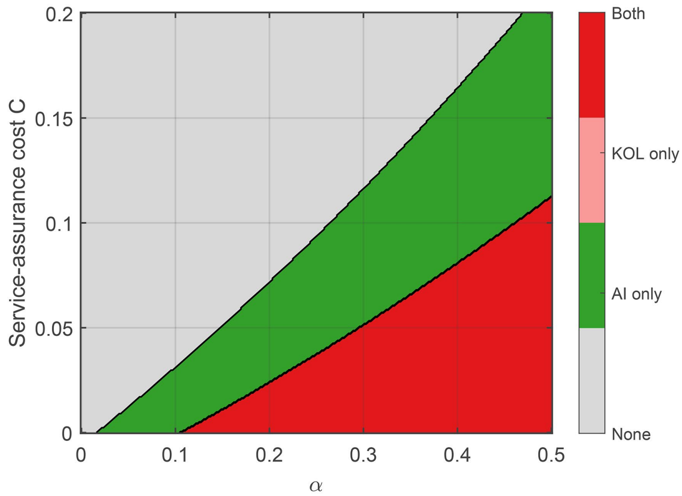

Figure 7. Service-assurance adoption regions in the (α, C) plane.

Figure 7 further illustrates the adoption regions of service assurance in the (α, C) plane. The figure shows how the willingness-to-pay effect of assurance and the assurance cost jointly determine whether assurance is adopted under AI self-streaming and KOL live streaming. As expected, a larger α enlarges the adoption region, whereas a larger C shrinks it. More importantly, the figure exhibits a clear "AI only" region, while the "KOL only" region does not appear under the baseline parameters. This means that, over the plotted parameter range, service assurance becomes profitable under AI self-streaming earlier than under KOL live streaming. The reason is that AI self-streaming is less sensitive to expectation-induced returns, so the valuation-enhancing effect of assurance is more likely to be converted into retained transactions rather than dissipated through post-purchase returns.

Taken together, the numerical results deliver three main insights. First, KOL live streaming is associated with stronger market expansion, but also with a higher price, a larger return burden, and stronger sensitivity to service-assurance-induced returns. Second, service assurance is not always beneficial, and its profitability depends critically on the balance between valuation enhancement and return amplification. Third, service assurance is more likely to complement AI self-streaming than KOL live streaming. In fact, for a reasonable range of parameters, introducing service assurance can even change the retailer's preferred livestreaming mode from KOL to AI. This observation provides strong numerical support for the analytical results in Section 3.

5. Extension: Platform Subsidy for Service Assurance

In the base model, the full cost of service assurance is borne by the retailer. In practice, however, platforms often have incentives to encourage merchants to adopt service-assurance programs through direct subsidies, fee reductions, traffic support, or preferential exposure. This is because service assurance may increase transaction confidence and platform commission revenue, even when the retailer itself is reluctant to adopt it. Motivated by this observation, we extend the base model by allowing the platform to subsidize part of the service-assurance cost.

Specifically, let $\tau \in [0,1]$ denote the subsidy rate chosen by the platform. If the retailer adopts service assurance, the platform bears a fraction τ of the assurance cost, while the retailer bears the remaining fraction $1-\tau$. The sequence of events is modified as follows. First, the platform chooses the subsidy rate τ. The platform anticipates the retailer's response and chooses the subsidy rate to improve its own net payoff. Following the commission settlement rule in the base model, the platform earns commission only from kept sales. Therefore, under mode m and service-assurance decision z, the platform's payoff can be written as commission revenue from retained transactions minus the subsidy payment when service assurance is adopted. The subsidy is profitable for the platform only if the incremental commission revenue generated by service assurance exceeds the subsidy cost. The purpose of this extension is to characterize the mutually acceptable subsidy interval rather than to derive a unique optimal subsidy under all possible tie-breaking rules. Specifically, the lower bound of the interval is determined by the minimum subsidy required to induce the retailer to adopt service assurance, whereas the upper bound is determined by the maximum subsidy that the platform is willing to provide. If a cost-minimizing implementation rule is imposed, the platform may choose the lowest feasible subsidy in this interval. Otherwise, Proposition 10 should be interpreted as a feasibility result rather than as a closed-form characterization of a unique optimal subsidy. Second, after observing τ, the retailer chooses the livestreaming mode $m \in \{A, K\}$ and the service-assurance decision $S \in \{0,1\}$. Third, the retailer sets the retail price. Finally, demand and returns are realized.

Under this extension, the platform subsidy only changes the effective fixed cost of adopting service assurance. Therefore, the optimal price, demand, kept quantity, and returned quantity under a given scenario remain unchanged from the base model. The subsidy affects the retailer's decision only through the profitability of adopting service assurance.

Proposition 8.

For any given scenario (m, S), the platform subsidy rate τ does not affect the retailer's optimal price, demand, kept quantity, or returned quantity. It only affects the retailer's profit through the effective fixed cost of service assurance.

Proposition 8 implies that platform subsidy does not alter the retailer's marginal pricing rule. Instead, it changes the retailer's scenario choice by reducing the net cost of service assurance. In other words, the role of subsidy is not to modify how the retailer operates within a scenario, but to affect whether the retailer is willing to enter that scenario at all.

We next characterize the retailer's service-assurance decision under subsidy. For a given livestreaming mode $m \in \{A, K\}$, there exists a critical subsidy rate, denoted by τ_m^R, such that the retailer adopts service assurance if and only if the platform subsidy is sufficiently high.

Proposition 9.

For a given livestreaming mode $m \in \{A, K\}$, there exists a critical subsidy rate τ_m^R such that the retailer adopts service assurance if and only if $\tau > \tau_m^R$.

Proposition 9 shows that platform subsidy lowers the effective adoption threshold of service assurance. A retailer that would reject service assurance in the base model may be induced to adopt it once the platform covers a sufficiently large share of the assurance cost. This result highlights a simple coordination mechanism: platform subsidy does not change the retailer's pricing rule, but it can change the retailer's willingness to adopt a high-service configuration.

The platform, however, will subsidize service assurance only when doing so is also beneficial to itself. Since service assurance may increase consumers' willingness to pay and stimulate more kept transactions, the platform may collect more commission revenue after subsidy. At the same time, the subsidy is costly. Therefore, for each livestreaming mode m, there exists an upper bound on the subsidy rate, denoted by τ_m^P, above which the subsidy is no longer profitable for the platform.

This gives rise to a coordination region between the retailer and the platform.

Proposition 10.

For a given livestreaming mode $m \in \{A, K\}$, a mutually acceptable subsidy region exists if and only if $\tau_m^R < \tau_m^P$. In this case, any subsidy rate within the interval $\left[\underline{\tau}_m, \overline{\tau}_m\right]$ induces the retailer to adopt service assurance and is also profitable for the platform. This interval characterizes feasible subsidy-based coordination rather than a unique optimal subsidy.

Proposition 10 identifies the condition under which platform subsidy can coordinate the service-assurance decision. The lower bound of the subsidy region is determined by the retailer's willingness to adopt service assurance, while the upper bound is determined by the platform's willingness to finance it. Thus, subsidy-based coordination is feasible only when the incremental commission revenue generated by service assurance is sufficiently large relative to the subsidy cost.

The comparison between AI self-streaming and KOL live streaming is especially revealing. In the base model, we have already shown that service assurance is more likely to complement AI self-streaming than KOL live streaming. The extension provides a further implication: because AI self-streaming is less sensitive to expectation-induced returns, the additional transactions generated by service assurance are more likely to translate into stable kept sales and thus into stable platform commission revenue. By contrast, under KOL live streaming, a larger portion of the additional orders may be dissipated through stronger post-purchase returns, which weakens the platform's incentive to subsidize assurance.

This observation can be summarized as follows.

Corollary 1.

When service assurance generates a larger net commission gain under AI self-streaming than under KOL live streaming, the platform is more likely to subsidize service assurance under AI than under KOL. Consequently, platform subsidy may change the retailer's preferred operational strategy from a no-assurance scenario to $(A,1)$, and in some cases even from $(K,0)$ to $(A,1)$.

Corollary 1 further strengthens the main message of the paper. The value of service assurance is not mode-neutral. Its effectiveness depends not only on its ability to enhance perceived value, but also on whether the underlying livestreaming mode can absorb the induced expectation risk. When return-related losses become sufficiently important, AI self-streaming provides a more favorable environment for both the retailer and the platform to support service assurance. In this sense, platform subsidy does not merely expand the adoption of service assurance; it can also reshape the retailer's equilibrium livestreaming choice.

Overall, this extension shows that platform intervention can partially align incentives between the retailer and the platform. More importantly, it confirms that the complementarity between AI self-streaming and service assurance remains robust even when the platform is allowed to act strategically. The exact threshold expressions and all proofs for this extension are provided in **Appendix B**.

6. Conclusions

This paper studies a platform retailer's joint decision on livestreaming mode and service assurance in the presence of product returns. We develop a retailer-centered analytical model in which the retailer chooses between AI self-streaming and KOL live streaming, while also deciding whether to adopt service assurance. By incorporating demand expansion, return risk, platform commission, KOL commission, AI investment, and the salvage value of returned products, we characterize the retailer's optimal pricing and operational strategy under four scenarios.

The analysis yields several main findings. First, service assurance always raises the retailer's optimal price under a given livestreaming mode. Second, for a given assurance status, the optimal price under KOL live streaming is higher than that under AI self-streaming. Third, service assurance does not necessarily improve demand or kept sales; it is beneficial only when its willingness-to-pay effect is sufficiently strong relative to the induced return burden. Fourth, both the assurance decision and the livestreaming-mode choice follow threshold rules. Most importantly, service assurance is more likely to complement AI self-streaming than KOL live streaming, because AI self-streaming is less sensitive to expectation-induced returns. As a result, the adoption of service assurance may even change the retailer's preferred livestreaming mode from KOL live streaming to AI self-streaming.

This study contributes to the literature by integrating livestreaming mode choice, service assurance, and endogenous return risk into a unified analytical framework. It also contributes to the emerging research on AI-enabled livestreaming by clarifying when AI self-streaming can outperform KOL live streaming from an operations perspective. In addition, it extends the literature on platform service assurance by showing that its value depends on the underlying selling mode rather than being universally beneficial.

The findings also offer managerial implications. Retailers should not evaluate livestreaming tools only by their traffic-generation ability, because stronger conversion may be offset by higher commissions and return losses. Platforms should not promote service assurance uniformly across all livestreaming settings, since its effectiveness depends on whether the selling mode can convert additional orders into retained transactions. More broadly, the results suggest that the fit between livestreaming mode and assurance mechanism is critical in platform-based live commerce.

Several directions remain for future research. Future studies may incorporate richer consumer heterogeneity, endogenous platform commission or KOL bargaining power, and competition across retailers or platforms. Empirical validation using transaction-level data would also be valuable for testing the mechanisms identified in this paper.

In summary, this paper shows that the value of livestreaming and service assurance is highly configuration-dependent. The retailer's optimal strategy depends on how demand expansion, commission burden, and return risk interact. By highlighting these mechanisms, the paper provides a more nuanced understanding of operational decision-making in platform-based live-streaming commerce.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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Appendix

For convenience, recall that under scenario (m, S), the retailer's profit is

$$\Pi_{mS}(p_{mS}) = (\Gamma_{mS} p_{mS} - H_{mS})(M_{mS} - bp_{mS}) - F_m - CS, \tag{A.1}$$

where

$$M_{mS} = \mu + \delta_m + \alpha S, \tag{A.2}$$

$$\Gamma_{mS} = (1 - r_{mS})(1 - \beta - \phi_m), \tag{A.3}$$

$$H_{mS} = c - r_{mS} s. \tag{A.4}$$

We impose the regularity condition $\Gamma_{mS} M_{mS} > bH_{mS}$, which guarantees a positive interior solution.

Appendix A. Proofs for Section 3

A.1. Proof of Proposition 1

Expanding Equation (A.1), we obtain

$$\Pi_{mS}(p_{mS}) = -b\Gamma_{mS} p_{mS}^2 + (\Gamma_{mS} M_{mS} + bH_{mS}) p_{mS} - H_{mS} M_{mS} - F_m - CS. \tag{A.5}$$

The second derivative with respect to p_{mS} is

$$\frac{\partial^2 \Pi_{mS}}{\partial p_{mS}^2} = -2b\Gamma_{mS} < 0, \tag{A.6}$$

because $b > 0$ and $\Gamma_{mS} > 0$. Hence, the profit function is strictly concave in p_{mS}, and the optimal price is uniquely determined by the first-order condition

$$\frac{\partial \Pi_{mS}}{\partial p_{mS}} = -2b\Gamma_{mS} p_{mS} + \Gamma_{mS} M_{mS} + bH_{mS} = 0. \tag{A.7}$$

Solving Equation (A.7) yields

$$p_{mS}^* = \frac{M_{mS}}{2b} + \frac{H_{mS}}{2\Gamma_{mS}}. \tag{A.8}$$

Substituting Equation (A.8) into the demand function gives

$$Q_{mS}^* = M_{mS} - bp_{mS}^* = \frac{\Gamma_{mS} M_{mS} - bH_{mS}}{2\Gamma_{mS}}. \tag{A.9}$$

Accordingly,

$$K_{mS}^* = (1 - r_{mS}) Q_{mS}^*, R_{mS}^* = r_{mS} Q_{mS}^*. \tag{A.10}$$

Finally, substituting p_{mS}^* into Equation (A.1) yields

$$\Pi_{mS}^* = \frac{(\Gamma_{mS} M_{mS} bH_{mS})^2}{4b\Gamma_{mS}} - F_m - CS. \tag{A.11}$$

This proves Proposition 1.

A.2. Proof of Proposition 2

For a given livestreaming mode m, let

$$L_m = 1 - \beta - \phi_m. \tag{A.12}$$

Then the optimal price in Equation (A.8) can be written as

$$p_{mS}^{*}=\frac{\mu+\delta_m+\alpha S}{2b}+\frac{c-r_{mS}s}{2\left(1-r_{mS}\right)L_m}. \tag{A.13}$$

For fixed m, we compare p_{m1}^{*} and p_{m0}^{*}. Since $r_{m1}=r_m+\eta_m$ and $r_{m0}=r_m$,

$$p_{m1}^{*}-p_{m0}^{*}=\frac{\alpha}{2b}+\frac{1}{2L_m}\left[\frac{c-\left(r_m+\eta_m\right)s}{1-r_m-\eta_m}\frac{c-r_m s}{1-r_m}\right]. \tag{A.14}$$

Define

$$f\left(r\right)=\frac{c-rs}{1-r}. \tag{A.15}$$

Then

$$f'\left(r\right)=\frac{c-s}{\left(1r\right)^2}>0, \tag{A.16}$$

because $c>s$. Hence $f\left(r\right)$ is strictly increasing in r, and therefore

$$f\left(r_m+\eta_m\right)>f\left(r_m\right). \tag{A.17}$$

Combining Equations (A.14)-(A.17), we have $p_{m1}^{*}>p_{m0}^{*}$. This proves Proposition 2.

A.3. Proof of Proposition 3

For a given assurance decision S, the optimal price is

$$p_{mS}^{*}=\frac{\mu+\delta_m+\alpha S}{2b}+\frac{c-r_{mS}s}{2\left(1-r_{mS}\right)\left(1-\beta-\phi_m\right)}. \tag{A.18}$$

We compare p_{KS}^{*} and p_{AS}^{*}. Since $\delta_K>\delta_A$, the first term of Equation (A.18) is larger under KOL live streaming. For the second term, define

$$g\left(r,\phi\right)=\frac{c-rs}{\left(1-r\right)\left(1-\beta-\phi\right)}. \tag{A.19}$$

Then

$$\frac{\partial g}{\partial r}=\frac{c-s}{\left(1-r\right)^2\left(1-\beta-\phi\right)}>0, \tag{A.20}$$

and

$$\frac{\partial g}{\partial \phi}=\frac{c-rs}{\left(1-r\right)\left(1-\beta-\phi\right)^2}>0. \tag{A.21}$$

Thus $g\left(r,\phi\right)$ is increasing in both r and ϕ. Because $r_{KS}>r_{AS}$ and $\phi_K>\phi_A=0$, the second term of Equation (A.18) is also larger under KOL live streaming. Therefore,

$$p_{KS}^{*}>p_{AS}^{*}. \tag{A.22}$$

This proves Proposition 3.

A.4. Proof of Proposition 4

Using Equation (A.9), the optimal demand can be rewritten as

$$Q_{mS}^{*}=\frac{M_{mS}}{2}-\frac{bH_{mS}}{2\Gamma_{mS}}=\frac{\mu+\delta_m+\alpha S}{2}-\frac{b\left(c-r_{mS}s\right)}{2\left(1-r_{mS}\right)\left(1-\beta-\phi_m\right)}. \tag{A.23}$$

For fixed m, the change in demand caused by service assurance is

$$Q_{m1}^{*}-Q_{m0}^{*}=\frac{\alpha}{2}-\frac{b}{2\left(1-\beta-\phi_m\right)}\left[\frac{c-\left(r_m+\eta_m\right)s}{1-r_m-\eta_m}\frac{c-r_m s}{1-r_m}\right]. \tag{A.24}$$

Using Equation (A.15), the bracketed term becomes

$$f\left(r_m+\eta_m\right)-f\left(r_m\right)=\frac{\eta_m\left(c-s\right)}{\left(1-r_m\right)\left(1-r_m-\eta_m\right)}. \tag{A.25}$$

Substituting Equation (A.25) into Equation (A.24), we obtain

$$Q_{m1}^{*}-Q_{m0}^{*}=\frac{1}{2}\left[\alpha\frac{b\eta_m\left(c-s\right)}{\left(1-\beta-\phi_m\right)\left(1-r_m\right)\left(1-r_m-\eta_m\right)}\right]. \tag{A.26}$$

Hence, $Q_{m1}^{*}>Q_{m0}^{*}$ if and only if

$$\alpha>\alpha_m^{Q}, \tag{A.27}$$

where

$$\alpha_m^{Q}=\frac{b\eta_m\left(c-s\right)}{\left(1-\beta-\phi_m\right)\left(1-r_m\right)\left(1-r_m-\eta_m\right)}. \tag{A.28}$$

This proves Proposition 4.

A.5. Proof of Proposition 5

From Equation (A.10), the kept sales under scenario (m,S) are

$$K_{mS}^{*}=\left(1-r_{mS}\right)Q_{mS}^{*}. \tag{A.29}$$

Substituting Equation (A.23) into Equation (A.29), we obtain

$$K_{mS}^{*}=\frac{\left(1-r_{mS}\right)M_{mS}}{2}-\frac{b\left(c-r_{mS}s\right)}{2\left(1-\beta-\phi_m\right)}. \tag{A.30}$$

For fixed m, compare $(m,1)$ and $(m,0)$. Let $L_m=1-\beta-\phi_m$. Then

$$\begin{aligned}K_{m1}^{*}-K_{m0}^{*}=&\frac{\left(1-r_m-\eta_m\right)\left(\mu+\delta_m+\alpha\right)}{2}-\frac{b\left[c-\left(r_m+\eta_m\right)s\right]}{2L_m}\\&-\frac{\left(1-r_m\right)\left(\mu+\delta_m\right)}{2}+\frac{b\left(c-r_m s\right)}{2L_m}.\end{aligned} \tag{A.31}$$

After simplification,

$$K_{m1}^{*}-K_{m0}^{*}=\frac{1}{2}\left[\left(1-r_m-\eta_m\right)\alpha-\eta_m\left(\mu+\delta_m\right)+\frac{b\eta_m s}{L_m}\right]. \tag{A.32}$$

Thus $K_{m1}^{*}>K_{m0}^{*}$ if and only if

$$\alpha>\alpha_m^{K},$$

where

$$\alpha_m^{K}=\frac{\eta_m\left[L_m\left(\mu+\delta_m\right)-bs\right]}{L_m\left(1-r_m-\eta_m\right)}=\frac{\eta_m\left[\left(1-\beta-\phi_m\right)\left(\mu+\delta_m\right)-bs\right]}{\left(1-\beta-\phi_m\right)\left(1-r_m-\eta_m\right)}. \tag{A.33}$$

This proves Proposition 5.

A.6. Proof of Proposition 6

For a given livestreaming mode m, the retailer adopts service assurance if and only if

$$\Pi_{m1}^{*} > \Pi_{m0}^{*}. \tag{A.34}$$

Using Equation (A.11), we have

$$\Pi_{m1}^{*} - \Pi_{m0}^{*} = \frac{\left(\Gamma_{m1} M_{m1} b H_{m1}\right)^{2}}{4b\Gamma_{m1}} - \frac{\left(\Gamma_{m0} M_{m0} b H_{m0}\right)^{2}}{4b\Gamma_{m0}} - C. \tag{A.35}$$

Therefore, the retailer adopts service assurance if and only if

$$C < C_{m}^{*}, \tag{A.36}$$

where

$$C_{m}^{*} = \frac{\left(\Gamma_{m1} M_{m1} b H_{m1}\right)^{2}}{4b\Gamma_{m1}} - \frac{\left(\Gamma_{m0} M_{m0} b H_{m0}\right)^{2}}{4b\Gamma_{m0}}. \tag{A.37}$$

This proves Proposition 6.

A.7. Proof of Proposition 7

For a given assurance decision S, AI self-streaming is preferred to KOL live streaming if and only if

$$\Pi_{AS}^{*} > \Pi_{KS}^{*}. \tag{A.38}$$

Using Equation (A.11),

$$\Pi_{AS}^{*} - \Pi_{KS}^{*} = \frac{\left(\Gamma_{AS} M_{AS} b H_{AS}\right)^{2}}{4b\Gamma_{AS}} - \frac{\left(\Gamma_{KS} M_{KS} b H_{KS}\right)^{2}}{4b\Gamma_{KS}} - F. \tag{A.39}$$

Hence, AI self-streaming is preferred if and only if

$$F < F_{S}^{*}, \tag{A.40}$$

where

$$F_{S}^{*} = \frac{\left(\Gamma_{AS} M_{AS} b H_{AS}\right)^{2}}{4b\Gamma_{AS}} - \frac{\left(\Gamma_{KS} M_{KS} b H_{KS}\right)^{2}}{4b\Gamma_{KS}}. \tag{A.41}$$

This proves Proposition 7.

Appendix B. Proofs for Section 5

In the extension, the platform subsidizes a fraction $\tau \in [0,1]$ of the service-assurance cost. Therefore, when service assurance is adopted, the retailer bears only $(1-\tau)C$, while the platform bears τC.

B.1. Proof of Proposition 8

Under platform subsidy, the retailer's profit becomes

$$\Pi_{mS}^{R}(\tau) = \frac{\left(\Gamma_{mS} M_{mS} b H_{mS}\right)^{2}}{4b\Gamma_{mS}} - F_{m} - (1-\tau) CS. \tag{B.1}$$

Observe that τ enters Equation (B.1) only through the fixed-cost term $(1-\tau)CS$. It does not enter M_{mS}, Γ_{mS}, or H_{mS}. Hence, the optimal price, demand, kept quantity, and returned quantity under a given scenario remain identical to those in the base model. Only the retailer's profit is shifted by the effective fixed cost of service assurance. This proves Proposition 8.

B.2. Proof of Proposition 9

For a given mode m, the retailer adopts service assurance under subsidy if and only if

$$\Pi_{m1}^{R}(\tau) > \Pi_{m0}^{R}. \tag{B.2}$$

Using Equation (B.1),

$$\Pi_{m1}^{R}(\tau) - \Pi_{m0}^{R} = \frac{(\Gamma_{m1}M_{m1}bH_{m1})^2}{4b\Gamma_{m1}} - \frac{(\Gamma_{m0}M_{m0}bH_{m0})^2}{4b\Gamma_{m0}} - (1-\tau)C. \tag{B.3}$$

By Equation (A.38), the first two terms equal C_m^*. Hence

$$\Pi_{m1}^{R}(\tau) - \Pi_{m0}^{R} = C_m^* - (1-\tau)C. \tag{B.4}$$

Therefore, service assurance is adopted if and only if

$$(1-\tau)C < C_m^*. \tag{B.5}$$

Equivalently,

$$\tau > \tau_m^R, \tag{B.6}$$

where

$$\tau_m^R = 1 - \frac{C_m^*}{C}. \tag{B.7}$$

If $C \le C_m^*$, then $\tau_m^R \le 0$, which means that no subsidy is required: the retailer already adopts service assurance in the base model. If $C > C_m^*$, then $\tau_m^R \in (0,1)$, and a sufficiently high subsidy is necessary to induce adoption. This proves Proposition 9.

B.3. Proof of Proposition 10

Under scenario (m,S), the platform's profit is

$$\Pi_{mS}^{P}(\tau) = \beta(1-r_{mS})p_{mS}^{*}Q_{mS}^{*} - \tau CS. \tag{B.8}$$

For a given mode m, the platform's net gain from inducing service assurance is

$$\Delta\Pi_{m}^{P}(\tau) = \Pi_{m1}^{P}(\tau) - \Pi_{m0}^{P} = \beta\left[(1-r_{m1})p_{m1}^{*}Q_{m1}^{*} - (1-r_{m0})p_{m0}^{*}Q_{m0}^{*}\right] - \tau C. \tag{B.9}$$

Define

$$\Delta_m^P = \beta\left[(1-r_{m1})p_{m1}^{*}Q_{m1}^{*} - (1-r_{m0})p_{m0}^{*}Q_{m0}^{*}\right]. \tag{B.10}$$

Then the platform is willing to subsidize service assurance if and only if

$$\Delta\Pi_m^P(\tau) > 0, \tag{B.11}$$

that is,

$$\tau < \tau_m^P, \tag{B.12}$$

where

$$\tau_m^P = \frac{\Delta_m^P}{C}. \tag{B.13}$$

Thus, the retailer requires $\tau > \tau_m^R$, while the platform requires $\tau < \tau_m^P$. A mutually acceptable subsidy rate exists if and only if

$$\tau_m^R < \tau_m^P. \tag{B.14}$$

In that case, any subsidy rate in the interval

$$\tau \in \left(\tau_m^R, \tau_m^P\right) \tag{B.15}$$

induces the retailer to adopt service assurance and is also profitable for the platform. This proves Proposition 10.

B.4. Proof of Corollary 1

Suppose service assurance generates a larger net commission gain under AI self-streaming than under KOL live streaming, so that

$$\Delta_A^P > \Delta_K^P. \tag{B.16}$$

Then, by Equation (B.13),

$$\tau_A^P > \tau_K^P. \tag{B.17}$$

If, in addition, service assurance is more easily adopted under AI self-streaming than under KOL live streaming, so that

$$C_A^* > C_K^*, \tag{B.18}$$

then by Equation (B.7),

$$\tau_A^R < \tau_K^R. \tag{B.19}$$

Hence, the feasible subsidy interval for AI,

$$\left(\tau_A^R, \tau_A^P\right), \tag{B.20}$$

is wider than that for KOL,

$$\left(\tau_K^R, \tau_K^P\right). \tag{B.21}$$

Therefore, the platform is more likely to subsidize service assurance under AI self-streaming than under KOL live streaming. Once such subsidy is introduced, the retailer's payoff under $(A,1)$ may exceed that under the no-assurance scenarios, and in some cases even exceed that under $(K,0)$. This proves Corollary 1.