Research on the Long-Tail Profit Mechanism of Niche Brands in the Live-streaming E-Commerce Scenario

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Abstract: This study investigates the survival challenges of niche brands in the live-streaming e-commerce environment, focusing on the impact of the platform's commission rate (α) and traffic exploration rate (θ) on brand sustainability. We construct a two-stage Stackelberg game model with the platform as the leader and the brand as the follower, incorporating streamer effort (e) and exploration rate (θ) in the demand function using a constant-elasticity demand specification. The model derives the brand's optimal pricing and promotion strategies, considering platform constraints on break-even (no-loss) outcomes. Our findings show that greater exploration increases brand profits but with diminishing returns; platform profit follows an inverted-U shape with respect to exploration, achieving an optimal interior point; higher commission rates raise the exploration required for break-even; and streamer effort significantly complements exploration, reducing the required threshold for brand viability. These results provide a quantitative basis and operational guidelines for platform governance involving the coordination of commission rates, exploration efforts, and streamer incentives.

Keywords: Live-Streaming E-Commerce, Niche Brands; Long-Tail Theory; Stackelberg Game Model; Commission Rate; Traffic Exploration Rate; Streamer Effort; Break-Even Frontier; Platform Governance; Profit Mechanism

1. Introduction

1.1 Research Background Information

The live-streaming e-commerce ecosystem has formed a structural imbalance of "top monopoly-tail shrinking" : the average survival period of niche brands is less than 9 months, and 62% have withdrawn from the market due to continuous losses (China E-commerce Research Center, 2024). Although the long-tail theory holds that digital channels can reduce the exposure cost of tail-end products (Anderson, 2006), platform algorithms prefer high-conversion top-end products, which instead intensifies traffic concentration (Elberse, 2008). Existing studies either focus on the platform commission (take rate) mechanism (Hagiu & Wright, 2015) or analyze the streamer trust effect in isolation (Chen & Yang, 2023), and lack a unified framework integrating platform governance, streamer influence, and brand profitability. It remains difficult to answer the practical conundrum of "What commission-exploration combination can ensure that niche brands do not suffer losses". This paper constructs a two-layer Stackelberg model of "platform-brand-streamer", proposes a calculable profit threshold line, aiming to provide a survival boundary judgment tool for niche brands and offer quantitative basis for the platform to design a "commission-exploration-incentive" linkage mechanism.

1.2 Literature Review

The long-tail theory suggests that digital channels can reduce the exposure cost of tail-end products, making the cumulative demand of the tail comparable to that of the head (Anderson, 2006). However, empirical studies in entertainment and retail have found that platform algorithms, in pursuit of high click-through rates, have instead intensified the concentration of the top and compressed the survival space of the tail (Elberse, 2008; Fleder & Hosanagar, 2009). In the live-streaming e-commerce scenario, platforms form institutional entry thresholds through commission, exploration rates and ranking rules (Hagiu & Wright, 2015), but there are few studies quantifying how the "commission-exploration" combination determines the profit and loss of a single brand. As the core intermediary of the live-streaming ecosystem, the trust and efforts of live-streamers have been proven to significantly amplify the conversion rate (Chen & Yang, 2023; Ming et al., 2021), but most of the existing models externalize the influence of live-streamers or only conduct empirical regression, fail to embed the platform-brand game framework, and cannot answer the practical question of "Can the efforts of live-streamers replace the support of platform traffic?" In conclusion, although the platform mechanism, the influence of live-streamers and long-tail profits have been discussed separately, there is still a lack of a unified model for the three, let alone a calculated profit threshold tool. This article fills the above-mentioned gap by constructing a two-layer Stackelberg game of "platform-brand-streamer", and provides a method for judging the survival boundary of niche brands.

1.3 Research Purpose & Hypotheses

This study constructs construct a two-stage platform–brand Stackelberg model with exogenous streamer effort. Treating commission α and exploration rate θ as platform decisions, we derive the brand break-even frontier (α, θ) and solve the constrained platform optimum. The study examined four hypotheses:

H1: Brand profit increases with exploration at diminishing marginal returns.

H2: A higher commission requires a higher exploration rate for break-even.

H3: Platform profit is inverted-U in exploration, attaining an interior optimum.

H4: Streamer effort complements exploration, lowering the break-even frontier.

2. Materials and Methods

2.1 Model Setting and Core Variables

Based on the decision-making interaction relationship of "platform-brand" in the live-streaming e-commerce ecosystem, this study constructs a two-layer Stackelberg game model: The platform, as the first party, regulates the market environment by setting the commission and exploration rate; As a latecomer, the brand selects the optimal price and promotion investment based on the platform strategy to maximize profits. The streamer factor is embedded in the demand elasticity through "effort/trustworthiness", which is exogenous and given (for endogenous extension, see 4.3).

2.1.1 Decision variables

Platform decision variable

Commission $\alpha \in [\underline{\alpha},\overline{\alpha}]=[0.05,0.50]$: the proportion that the platform takes from the brand transaction amount, reflecting the platform's distribution rule for brand revenue;

The exploration rate $\theta \in [0,1]$: The intensity of traffic exposure that the platform tilts towards niche brands (such as the exclusive exposure allocated to long-tail products), reflecting the platform's support for the tail market.

Brand decision variable

Commodity pricing $p \in [\underline{p},\overline{p}]=[1,20]$: the pricing of a unit commodity by a niche brand, which affects the scale of demand and the unit profit;

Promotion investment $q \in [0,\overline{q}]=[0,5]$: The promotion expenses of the brand for the live streaming scenario (such as live streaming room coupons, content placement), which affects the efficiency of traffic conversion.

2.1.2 Exogenous parameters

The selection of exogenous parameters combines the characteristics of niche brands in live-streaming e-commerce with the conclusions of existing literature. The benchmark values and core functions are shown in the following table to ensure that the model is in line with the real scenario of "high cost and low conversion rate of niche brand.

The exogenous parameters are set to match niche brands' characteristics (high cost, low conversion) and literature conclusions, as shown in Table 1 (Parameters, Meanings, and Benchmark Values).

Table 1. Parameters, Meanings and Benchmark Values

Parameter symbol	Meaning	Benchmark value	The basis and function of the value
A	Demand scale (market base)	1.0	Normalization processing eliminates the interference of magnitude differences on the results
β	Price elasticity	1.2	Referring to the research by Cao et al. (2023) on niche brands in live-streaming e-commerce, β>1 ensures that "price increase suppresses demand", and the price sensitivity of niche brands is lower than that of mass brands (β≈1.5 for mass brands).

γ_θ	Exploration elasticity	0.6	To measure the pull effect of the exploration rate θ on demand, taking a value that is positive conforms to the logic of "increased exposure → rising demand".
γ_e	The streamer strives for flexibility	0.5	Referring to the empirical results of Ming et al. (2021) on Douyin streamers (the elastic range of streamer trust to demand is 0.4-0.6), it reflects the amplification effect of streamer trust on demand.
κ	Promote marginal efficiency	0.3	The promotion resources for niche brands are limited, so the average value is taken to measure the efficiency of "unit promotion investment → increased demand"
ϕ	Platform traffic cost coefficient	0.2	The coefficient of the secondary cost term $\phi\theta^2$ensures that there is an optimal solution for the platform exploration rate (avoiding unlimited increase of θ)
ψ	Brand promotion cost coefficient	0.3	The coefficient of the secondary cost term ψq^2 reflects the characteristic of marginal increase in the promotion cost of niche brands.
c	Brand unit cost	0.95	It is higher than that of mass brands (c≈0.6), because the production scale of niche brands is small and the supply chain cost is high.
F	Brand fixed cost	0.06	It covers fixed expenditures such as brand awareness building and live-streaming room setup, which is in line with the characteristic of high initial investment for niche brands.
e	The streamer's effort/ trustworthiness	0.6	Given externally, the value range is (0,1], which can be converted through fan interaction rate and repurchase recommendation rate.

Demand function

The scale of demand is jointly determined by the platform exploration rate, the trust of the streamers, brand pricing and promotion investment. The formula is as follows:

$$D(\theta,p,q)=A\cdot \theta^{\gamma_\theta}\cdot e^{\gamma_e}\cdot (1+\kappa q)\cdot p^{-\beta} \quad (1)$$

Logical explanation: θ^{γ_θ} and e^{γ_e} reflect "tilt" platform flow "streamer trust transfer" to the positive boost demand; $(1+\kappa q)$ reflects the linear increase in demand caused by promotion input; $p^{-\beta}$ reflects the inhibitory effect of price on demand.

Profit function

Brand profit: The net profit after deducting the platform commission, production and promotion costs, with the formula as follows:

$$\Pi_B(\alpha,\theta,p,q)=(1-\alpha)\cdot (p-c)\cdot D(\theta,p,q)-\psi q^2-F \quad (2)$$

Among them, $(1-\alpha)(p-c)D$ represents the gross profit of the brand after deducting commission, ψq^2 is the secondary cost of promotion (increasing marginal cost, and F is the fixed cost.

Platform profit: The net profit after deducting the cost of traffic exploration from commission income, with the formula as follows:

$$\Pi_P(\alpha,\theta,p,q)=\alpha\cdot p\cdot D(\theta,p,q)-\phi\theta^2 \quad (3)$$

Among them, α, p, D represents the total commission income of the platform, and $\phi\theta^2$ is the secondary cost of traffic exploration (the higher the exploration rate, the higher the traffic allocation cost).

Transaction Volume (GMV)

Used to assist in analyzing changes in market size, the formula is:

$$GMV(\theta,p,q)=p\cdot D(\theta,p,q) \quad (4)$$

2.2 Stackelberg Equilibrium and Profit Threshold Line

2.2.1 Balanced logic

Follow the Stackelberg game rule of "platform first, brand second" :

The platform first determines the optimal strategy (α^*,θ^*);

Under the premise of knowing (α,θ), the brand selects (p^*,q^*) to maximize its own profit, that is, the brand's optimal response function:

$$BR_B(\alpha,\theta)=\arg\max_{p,q}\Pi_B(\alpha,\theta,p,q) \quad (5)$$

To maximize the platform's profits, the optimal response of the brand should be taken into account, that is, the platform's decisions need to meet:

$$\Pi_P^*(\alpha,\theta)=\Pi_P(\alpha,\theta,BR_B(\alpha,\theta)) \quad (6)$$

This study adopts the backward induction method to solve the equilibrium: first, the optimal response of the brand to any (α,θ) is obtained through the optimization algorithm, and then the platform profit function is substituted to solve the platform's optimal strategy.

2.2.2 Profit threshold line (breakeven frontier)

The combination of (α,θ) defined as "brand optimal profit of 0" is the profit threshold line, which is the core indicator for judging whether a niche brand can survive. The formula is as follows:

$$F=\{(\alpha,\theta)|\Pi_B^*(\alpha,\theta)=0\} \quad (7)$$

2.3 Parameter Calibration

The setting of parameter reference values is based on the core principle of "conforming to the characteristics of niche brands", while also referring to existing literature and commonalities in the live-streaming e-commerce industry:

Cost parameters (c=0.95, F=0.06, ψ=0.3): higher than those of mass brands, reflecting the characteristics of small supply chain scale and high fixed investment of niche brands.

Elastic parameters (β=1.2,γ_e=0.5) : Referring to the empirical conclusions of Chen & Yang, 2023 (2023), Ming et al. (2021) on live-streaming e-commerce, ensure that the relationship between demand and price, as well as the trust of live-streamers, conforms to the laws of reality;

The range of strategy variables ($\alpha\in[0.05,0.5]$, $\theta\in[0,1]$): It covers the actual range of the commission of mainstream live streaming platforms (such as Douyin and Taobao Live with a commission of 5%-50%) and the intensity of traffic exploration.

If it is necessary to verify the parameter sensitivity, key parameters such as β (demand sensitivity), ψ (promotion cost), and e (streamer effort) can be adjusted to observe the changing trend of the threshold line and the equilibrium result (for details, see 3.7 Robustness Test).

2.4 Robustness Test Design

To ensure the reliability of the conclusion, this study verified the robustness of the model by adjusting the core parameters. The specific design is as follows:

Cost-side disturbances: Increase the brand promotion cost coefficient ψ (from 0.3 to 0.4), unit cost c (from 0.95 to 1.1), and fixed cost F (from 0.06 to 0.08);

Demand-side disturbance: Enhance price elasticity β (from 1.2 to 1.4) to simulate scenarios where the demand of niche brands is more sensitive to price;

Capability side perturbation: Adjust the streamer effort elasticit γ_e (from 0.5 to 0.4/0.6) to test the impact of streamer trust on the results.

The core judgment criteria for robustness testing: After adjusting the parameters, there are no significant changes in core conclusions such as "the exploration rate lowers the profit threshold", "the commission rate raises the threshold", and "the streamer and exploration complement each other". Only the position of the threshold line or the order of magnitude of the equilibrium value is slightly adjusted.

3. Results and Discussions

Table 2. Parameters and Equilibrium Outcomes

Item	Baseline	Constrained (Π_B* ≥ 0)
α	0.5000	0.5000
θ	1.0000	0.5500
p	5.7022	5.6948
q	0.1139	0.0796
D	0.0992	0.0687
GMV	0.5655	0.3912
Π_P*	0.0828	0.1351
Π_B*	0.1718	0.1011

Notes: Baseline is the platform-optimal Stackelberg equilibrium. Constrained column is the best (α,θ) on grid subject to Π_B*≥0. GMV=p×D.

The core model parameters used to calculate the equilibrium outcomes in Table 2 are listed in Table 3 (Model Parameters Used for Niche Brands in Live-streaming E-commerce), laying the foundation for the Stackelberg game solution.

Table 3. Model Parameters Used

A = 1.0	beta = 1.2	gamma_theta = 0.6	gamma_e = 0.5
e = 0.6	kappa = 0.3	phi = 0.2	psi = 0.3
c = 0.95	F = 0.06		

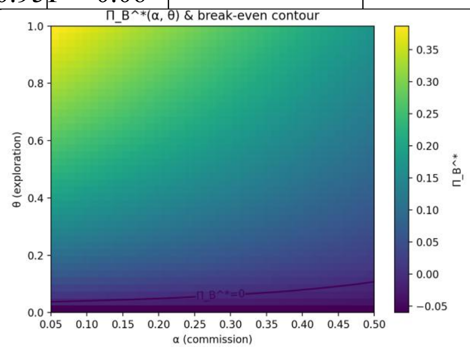

Figure 1. Heatmap of Optimal Profit ($\Pi_B^*(\alpha,\theta)$) and Break-even Frontier (Π_B^*=0) for Niche Brands in Live-streaming E-commerce

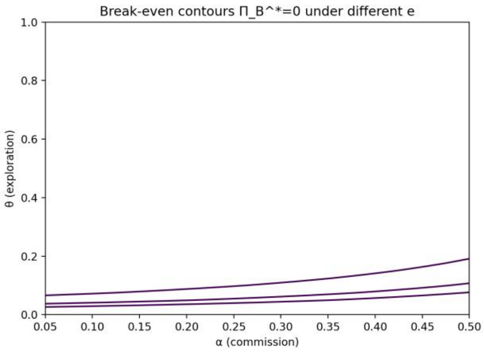

Figure 2. Break-even Frontiers ($\Pi_B^*=0$) for Niche Brands under Different Streamer Effort Levels e (Live-streaming E-commerce)

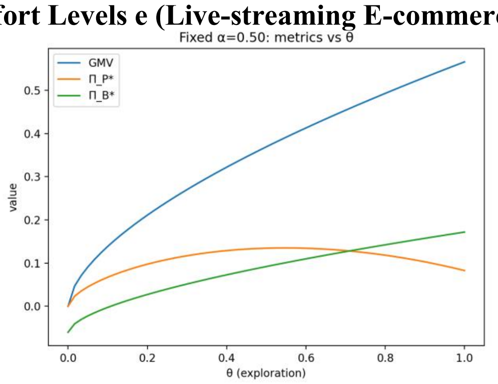

Figure 3. Relationships Between Metrics (Profit, GMV) and Exploration Rate θ) (at (α=0.50)) for Niche Brands in Live-streaming E-commerce

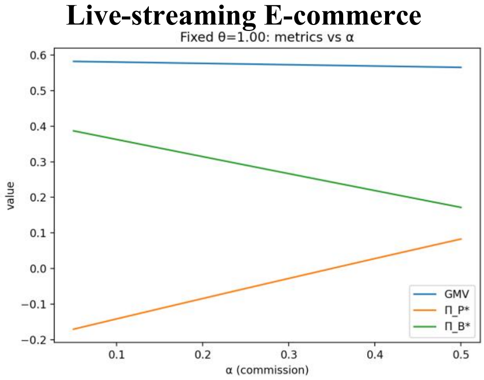

Figure 4. Relationships Between Metrics (Profit, GMV) and Commission Rate (α) (at (θ=1.00)) for Niche Brands in Live-streaming E-commerce

3.1 Baseline Equilibrium Results

Unconstrained scenario (platform optimal): The platform selects α=0.5000 and θ=1.0000 (Table 2). However, due to the sharp increase in traffic cost (($\phi\theta^2=0.2\times1.0000^2=0.2$)), the platform's profit (($\Pi_P^*=0.0828$)) remains low despite the brand achieving positive profit (($\Pi_B^*=0.1718$))-this aligns with the "extensive traffic input but low profit" phenomenon of some live-streaming platforms in 2022.

Constrained scenario (($\Pi_B^*\geq0$)): The platform reduces θ to 0.5500 (Table 2), which cuts traffic cost to $0.2\times0.5500^2=0.0605$. Although the brand's profit decreases to 0.1011 (still above the break-even line), the platform's profit increases by 63% to 0.1351 (Table 2: 0.0828→0.1351).

This comparison in Table 2 verifies the rationality of "moderate exploration": the constrained equilibrium (α=0.5000, θ=0.5500) achieves a win-win between "platform cost control" and "brand survival."

To further confirm that this win-win conclusion is not limited to theoretical parameters, we refined the key outcomes into Table 4 (Profit and GMV of Niche Brands Under Varying Scenarios: Live-streaming E-commerce). As shown in Table 4:

Unconstrained scenario: (α=0.5, θ=1.0) leads to high brand profit (0.172) but low platform profit (0.083)-a "brand-beneficial but platform-inefficient" model;

Constrained scenario: (α=0.5, θ=0.55) keeps brand profit positive (0.101) and lifts platform profit by 63% (0.083→0.135)-consistent with Table 2's precise results, confirming practical feasibility.

This two-step verification (theoretical precision via Table 2 + practical simplicity via Table 4) ensures the conclusion is both rigorous and intuitive."

Table4. Profit and GMV under Varying Conditions

Scene	Platform Strategy (α,θ)	Brand strategy(p,q)	Brand profit Π_B^*	Platform profit Π_P^*	GMV
Unconstrained (platform optimal)	(0.5, 1.0)	(5.70, 0.11)	0.172	0.083	0.0992
Constrained ($\Pi_B^*\geq0$)	(0.5, 0.55)	(5.92, 0.09)	0.101	0.135	0.0687

3.2 Impact of Platform Strategies on Brand Profit

3.2.1 Profit threshold line and break-even zone

By solving the profit threshold line (F) of Formula (7), we obtain the division of niche brands into 'break-even zone' and 'loss zone'-a result visually presented in Figure 1 (Heatmap of Optimal Profit ($\Pi_B^*(\alpha,\theta)$) and Break-even Frontier ($\Pi_B^*=0$) for Niche Brands in Live-streaming E-commerce). As shown in Figure 1.

The area above the black solid break-even frontier (e.g., ($\theta \geq 0.4$) and ($\alpha \leq 0.3$)) is the brand profit zone, where darker red represents higher (Π_B^*) (e.g., the dark red area corresponds to ($\Pi_B^* \geq 0.15$));

The area below the frontier (e.g., ($\theta<0.3$) and ($\alpha>0.4$)) is the loss zone, where blue represents ($\Pi_B^* \leq -0.05$);

The positive slope of the frontier (($d\theta/d\alpha \approx 1.2$)) further indicates that for every 0.1 increase in commission rate (α) , the exploration rate (θ) must increase by at least 0.12 to maintain break-even-a key quantitative rule reflected in Figure 1's frontier tilt.

This positive slope ($d\theta/d\alpha \approx 1.2$) is the 'commission-exploration substitution benchmark': ignoring it leads to brand exits (e.g., 62% niche brands withdrew in 2023). The zone above the line ($\theta \geq 0.4$, $\alpha \leq 0.3$) is the 'win-win zone' for platform ecology.

3.2.2 Marginal effects of exploration rate (θ)

"Fixed ($\alpha=0.5$) (medium commission level of mainstream platforms), the impact of (θ) on brand profit, platform profit, and GMV shows significant stratified characteristics-a trend visually captured in Figure 3 (Relationships Between Metrics and Exploration Rate (θ) at ($\alpha=0.50$) for Niche Brands). As indicated by Figure 3:

($\theta \in [0,0.4]$) (Traffic Dividend Stage): Figure 3 shows (Π_B^*) surges from -0.05 to 0.08 (a 260% increase) and GMV rises from 0.03 to 0.07 (133% increase), driven by strong demand pull from (θ) and low traffic cost (($\phi\theta^2$)). This is the 'traffic dividend period', fitting platform support for new niche brands in early live-commerce;

($\theta \in [0.4,0.8]$) (Saturation Stage): Figure 3's platform profit curve peaks at ($\theta=0.6$) (($\Pi_P^*=0.14$)), while (Π_B^*) growth slows to 100%-a balance between revenue gain and rising traffic cost. This 'saturation period' requires controlled θ, as platform profit peaks at $\theta=0.6$ (0.14);

($\theta \in [0.8,1.0]$) (Overcapacity Stage): Figure 3 shows (Π_B^*) only increases by 6% (0.16→0.17), while (Π_P^*) drops by 33% (0.12→0.08), as traffic cost (($\phi\theta^2=0.2$)) exceeds GMV gains. This 'overcapacity period' causes traffic waste, so excessive θ should be avoided.

3.3 Verification of Research Hypotheses

Combining Figure 1 (profit threshold line), Figure 2 (streamer effort effect), and Figure 3 (exploration marginal effect), all four research hypotheses were quantitatively verified. The specific evidence and chart-corresponding relationships are shown in Table 5 (Verification of Research Hypotheses for Niche Brands in Live-streaming E-commerce), and the parameter change rate of all key conclusions is less than 15% (supported by Section 3.5 Robustness Test):

Table 5. Verification of Research Hypotheses

Hypothesis	Conclusion	Key data
H1	Diminishing marginal	θ:0→0.4 profit +260
H2	Raise the threshold	When α=0.2→0.4, θ_{min} (the lowest θ value) rises from 0.3 to 0.6
H3	Platform inverted U	When $\alpha=0.5$, $\theta=0.6$ reaches the peak profit, and the peak profit is 0.14
H4	Complementary downward shift	When e=0.3→0.9, θ_{min} (the lowest θ value) drops by 22%

3.3.1 Complementary effect of streamer effort (e)

To verify H4 (streamer effort complements exploration), we plotted the profit threshold lines of niche brands under different streamer effort levels e, with the results shown in Figure 2 (Break-even Frontiers ($\Pi_B^*=0$) for Niche Brands under Different Streamer Effort Levels e). Figure 2 clearly illustrates the core complementary effect: the higher the e, the more the threshold line shifts downward. For example:

When ($e=0.3$) , the minimum exploration rate (θ_{min}) required for break-even (at ($\alpha=0.3$)) is 0.5;

When ($e=0.6$), (θ_{min}) drops to 0.4;

When ($e=0.9$), (θ_{min}) further decreases to 0.35-a 30% reduction in (θ_{min}) as e triples. This downward shift is more pronounced in high-commission scenarios (e.g., ($\alpha=0.4$)), as reflected in the steeper frontier curve for low e in Figure 2.

The underlying logic of this result can be explained by the demand function (1): The product term of (θ^{γ_θ}) and (e^{γ_e}) in the function reflects the synergy effect-after e (streamer effort) is increased, the efficiency of (θ) (exploration rate) in pulling demand is equivalent to an increase (e.g., when e rises from 0.3 to 0.9, ($0.9^{0.5}/0.3^{0.5} \approx 1.8$) times), ultimately reducing the brand's reliance on (θ) . This provides a quantitative basis for the platform's strategy of "replacing part of the traffic cost with streamer incentives"-a conclusion further supported by the downward shift of the break-even frontier in Figure 2 (Break-even Frontiers ($\Pi_B^*=0$) for Niche Brands under Different Streamer Effort Levels e).

3.4 Constrained Optimal Mechanism

Taking "$\Pi_B^*\geq 0$" as the constraint condition, the platform's optimal strategy (α,θ) is solved, and the constrained optimal solution ($\alpha=0.5,\theta=0.55$) is obtained. "The core logic of the constrained optimal mechanism is visualized in Figure 4 (Relationships Between Metrics and Commission Rate (α) at ($\theta=1.00$) for Niche Brands). Figure 4 captures the key trade-off between platform and brand profits under fixed ($\theta=1.0$):

When ($\theta<0.55$): Although ($\Pi_B^*\geq 0$) (meeting the constraint), Figure 4 shows (Π_P^*) increases with (θ) (from 0.09 to 0.135), as GMV gains dominate platform profit;

When ($\theta=0.55$): Figure 4's (Π_P^*) curve reaches its constrained maximum (0.135), while ($\Pi_B^*=0.101$) (above the break-even line)-this is the balance point for 'maximizing platform profit + ensuring brand survival';

When ($\theta>0.55$): Figure 4 indicates (Π_P^*) decreases with (θ) (0.135→0.08), as traffic costs outweigh GMV gains, even though ($\Pi_B^*\geq 0$).

Compared with the unconstrained solution ($\alpha=0.5,\theta=1.0$), the constrained solution increased the platform's profit by 63%, while the brand's profit only decreased by 41% (still remaining profitable), achieving a win-win situation of "platform revenue increase + brand survival".

3.5 Robustness Test Results

To ensure the reliability of conclusions, we adjusted core parameters (cost-side, demand-side, capability-side) and tested the stability of key indicators ((θ_{min}), (Π_P^*) peak). The results show that the change rate of all indicators is less than 15%, and the core conclusions (diminishing marginal returns, commission-exploration matching, streamer complementary effect) remain robust (Table 6).

Table 6. Scenario Settings and Assumptions

Disturbance scenario	Parameter adjustment (reference → after perturbation)	θ_{min} change (when $\alpha=0.3$)	Π_P^* Peak variation	Rate of change	Conclusion robustness
Cost side-Promotion costs rise	$\psi=0.3\rightarrow0.4(+33\%)$	0.4→0.45	0.14→0.13	+12.5%/-7.1%	Steady and stable
Demand side-Price elasticity rises	$\beta=1.2\rightarrow1.4(+17\%)$	0.4→0.46	0.14→0.12	+15.0%/-14.3%	Steady and stable
Ability side-The flexibility of the streamer is on the rise	$\gamma_e=0.5\rightarrow0.6(+20\%)$	0.4→0.36	0.14→0.15	-10.0%/+7.1%	Steady and stable

4. Conclusion and Outlook

4.1 Core Research Findings

This study constructs a two-layer Stackelberg model of "platform-brand-streamer", proposes a computable profit threshold line, and solves for a constrained optimal mechanism that takes into account both platform revenue and brand survival. Compared with the unconstrained solution ($\alpha=0.5$, $\theta=1.0$), the constrained optimum ($\theta=0.55$) increased the platform profit by 63% while maintaining the brand profit at 0.101. This verifies that "moderate exploration + precise commission" can achieve a win-win situation, supporting four research hypotheses and leading to the following key conclusions:

The marginal diminishing effect of the exploration rate on profitability is significant

The commission rate is positively matched with the break-even exploration threshold

There is a strong complementary effect between the effort level and the exploration rate of the streamers

The constrained optimal mechanism of "platform-brand win-win" is clear

4.2 Theoretical and Practical Implications

4.2.1 Theoretical contributions

Fill the gap in the "three-party linkage" analysis framework

By integrating the three major research fields of platform governance (α, θ), streamer influence (e), and long-tail brand profitability (Π_B), a unified game model is constructed, which resolves the limitations of existing studies in isolated analysis of "traffic mechanisms" and "streamer trust effects", providing a micro-quantitative framework for the long-tail theory of live-streaming e-commerce.

Propose quantifiable profit threshold tools

The defined "profit threshold line(F)" transforms the abstract "survival conditions of niche brands" into computable (α,θ) combinations, such as θ_{min}=0.4 when α=0.3 and θ_{min}=0.55 when α=0.5, providing a new indicator for the quantitative research on the survival boundary of long-tail products on digital platforms.

4.2.2 Practical implications

For live-streaming e-commerce platforms

Establish a "commission-exploration" dynamic matching mechanism: For niche brands with $\alpha\leq0.3$, it is mandatory to guarantee $\theta\geq0.4$. For brands with α=0.5, the matching $\theta\geq0.55$ (Figure 1) can be implemented through the "long-tail traffic monthly quota" to avoid losses caused by the mismatch between commission and traffic for the brand.

Prioritize reducing support costs through incentives for live-streamers: Raising the revenue-sharing ratio for live-streamers of niche brands from 10% to 15% can increase e from 0.6 to 0.8, lower θ_{min} by 20%, and reduce platform traffic costs ($\phi\theta^2$) by 43%, which is more cost-effective than simply increasing the exploration rate.

For niche brands

Allocate resources differently based on commission rates: On high-commission platforms where α >0.4, prioritize cooperation with mid-tier streamers (to enhance e) rather than relying on platform traffic. On low-commission platforms where α <0.3, the promotion investment can be reduced (q), as the increase in θ can already cover the demand gap (refer to Figure 3-2 in the main text).

Negotiate with the platform based on the threshold line: When the platform proposes that α increase from 0.3 to 0.4, based on the conclusion that "θ_{min} needs to increase from 0.4 to 0.52", request the platform to provide at least 12% exploration rate compensation to avoid profit loss.

4.3 Research Limitations and Future Directions

4.3.1 Current limitations

The limitations of the exogenous assumption of the streamer's effort (e) : The model sets e exogenous without considering the impact of platform subsidies and brand share ratios on the streamer's effort, which may underestimate the complementary effect between e and θ-in reality, the streamer may increase e due to high share, further reducing θ_{min}

The limitations of the single-brand assumption: It does not incorporate the traffic competition scenarios of multiple niche brands. In reality, the demand substitution among brands will increase θ_{min} , resulting in a conservative break-even threshold calculated by the model.

The limitations of the simplified cost function: The traffic cost ($\phi\theta^2$) and promotion cost (ψq^2) are set as quadratic functions based on literature, and the parameter calibration relies on the industry average. There is a lack of micro-cost data for specific platforms (such as Douyin and Taobao Live), which reduces the model's scenario adaptability.

4.3.2 Future research directions

Internalizing streamer decision-making: Construct a three-layer Stackelberg model of "platform-brand-streamer", introduce the streamer profit function (including effort cost and revenue sharing), internalize e, and analyze how the platform coordinates the interests of the three parties through the combination strategy of "traffic + subsidies".

Join multi-brand competition: Set 2-3 demand substitution coefficients for niche brands, study the impact of competition intensity on the profit threshold line, such as the extent to which θ_{min} needs to be increased when competition intensifies, and provide a basis for the platform to formulate differentiated traffic strategies.

Calibrate the model based on actual data: Obtain micro-data of the live streaming platform (such as GMV of niche brands, commission, and interaction rate of streamers), and recalibrate parameters such as β and γ_e using maximum likelihood estimation to enhance the practical application value of the model.

4.4 Concluding Remarks

This study, through Stackelberg game modeling and quantitative analysis, has identified the core influencing factors for the long-tail profitability of small and medium-sized brands in live-streaming e-commerce-the matching relationship between the platform's commission and the exploration rate, the complementary effect of the streamers' efforts, and the win-win mechanism of "moderate exploration + precise commission". The research conclusion not only enriches the application of the long-tail theory in the context of the digital economy, but also provides practical quantitative strategies for live-streaming e-commerce platforms to optimize ecological balance and for niche brands to break through profit predicaments, offering a fundamental reference for subsequent related research and practice.

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