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Research on Live-Streaming E-Commerce Regulatory Strategies Considering Dual Herd Mentality

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Abstract

The optimization of regulatory strategies for live-streaming e-commerce is essential for tackling misleading marketing behaviors (MMBs) and protecting stakeholders' rights. This is fundamental to building a healthy and sustainable live-streaming e-commerce ecosystem. To address governance challenges and regulatory inefficiencies, this paper adopts a behavioral perspective and constructs a tripartite evolutionary game model involving platforms, live streamers, and consumers. It unveils the interactive mechanism between dual herd mentality and overconfidence in shaping regulatory strategy evolution, with numerical simulations validating the dynamic regulatory pathway. The findings indicate: (1) The severity of platform penalties is the linchpin of collaborative governance. Under low penalties, herd mentality may spur consumers to report live streamers who choose the MMB strategy, but the absence of deterrence traps the market in a "more reports, more MMBs" vicious circle. Moderate-to-high penalties align herd behavior with non-MMBs by live streamers, but risk unleashing irrational herd conduct among consumers. A dynamic matching mechanism that adapts penalty intensity to prevailing herd levels is therefore essential. Once a critical threshold is crossed, it enables synergistic benefits through joint supervision by consumers and platforms. (2) Overconfidence on the live streamer's side magnifies the illusion of inflated returns. At low levels, the herd mentality from consumers can correct this psychological bias, but once overconfidence becomes pronounced, only large-scale supervising can outweigh the expected gains from MMBs. (3) These two behavioral traits jointly shape the equilibrium of the live-streaming e-commerce system and should therefore be treated as key considerations when designing dynamic regulatory strategies.

Keywords: regulatory strategy; herd mentality; overconfidence; live-streaming e-commerce; evolutionary game theory

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1. Introduction

As an emerging business form born from the deep integration of e-commerce and the live-streaming sector, live-streaming e-commerce is spearheading a disruptive transformation of the digital consumer market. According to a data report released by iResearch in 2024, the scale of China's live-streaming e-commerce market has reached 4.9 trillion yuan, maintaining a year-on-year growth rate of 35.2% [1]. However, beneath the exuberant "buy, buy, buy" spectacle, a string of scandals keeps erupting in China: sugar-water sold as premium bird's-nest, Crazy Xiaoyang's counterfeit luxury mooncakes, and "Northeast Rain Sister" sweet-potato noodles that contained no sweet-potato starch at all. These

misleading marketing behaviors (MMBs), defined as the intentional dissemination of false, exaggerated or misleading product information by business entities to induce irrational consumption decisions [2], throw the glaring contradiction between product quality and promotional truthfulness in live-streaming e-commerce [3]. At the same time, the very anonymity of the internet has spawned an avalanche of manipulation: paid click-farms that churn out fake five-star reviews, professional black-hat reviewers who extort sellers with malicious bad ratings, cash-for-praise rebates that bias feedback, and orchestrated mass-reporting campaigns, all of which erode trust and inflict collateral damage on both sides of the live-streaming e-commerce [4,5].

To standardize the order of the live-streaming e-commerce market, safeguard the legitimate rights and interests of all relevant entities, and promote the healthy development of live-streaming e-commerce, on 10 June 2025, the State Administration for Market Regulation, in conjunction with the Cyberspace Administration of China, organized the release of the Draft Measures for the Supervision and Administration of Live-Streaming E-Commerce (hereinafter referred to as the "Measures"). The introduction of these Measures not only underscores the importance of supervising the live-streaming e-commerce market but also means that the regulatory requirements for multiple entities in the live-streaming e-commerce have become more comprehensive and stringent. This will inevitably trigger a new round of autonomous gaming among stakeholders, including consumers, live streamers, and live-streaming e-commerce platforms. Therefore, mapping how the stakeholders in live-streaming e-commerce interact and working out what rules will keep live streamers choosing the non-MMB strategy have become a top priority for regulators and the platforms themselves.

Scholars have increasingly focused on regulatory strategies within the live-streaming e-commerce. However, previous studies have typically been based on the assumption that decision-makers are fully rational, largely overlooking the heterogeneous behavioral preferences of multiple stakeholders in live-streaming e-commerce. In particular, consumers' herd mentality—a classic behavioral bias where individuals abandon independent judgment and mimic the decisions of the majority due to social influence and informational asymmetry [6] and live streamers' overconfidence—the cognitive bias in which decision-makers overestimate their own capabilities and the expected returns of risky behaviors, while underestimating potential risks [7], have become key forces disrupting market order. Take the first-ever "professional bullet-commenter" fine handed down by the Beijing Municipal Market Supervision Bureau in 2025: merchants or live streamers hired paid trolls to flood live-streaming chats with fake reviews, engineering a "viral bestseller" aura that precisely exploits consumers' herd mentality and drives impulse purchases. Meanwhile, top-tier live streamer "Crazy Xiaoyang" has repeatedly faced public backlash over MMBs, yet he still insists that "a clear conscience fears no shadow." Such overconfidence not only blinds him to product defects but also undermines consumer trust. If the live-streaming e-commerce market fails to adequately address these behavioral tendencies, platform-designed regulatory strategies will struggle to effectively coordinate stakeholders, neither breaking the chain of fake reviews nor curbing live streamers' violations. Existing evolutionary game models applied to live-streaming e-commerce regulation typically maintain the assumption of perfect rationality, and rarely embed behavioral biases into their payoff functions or strategy evolution mechanisms [8,9]. Consequently, these studies fail to systematically capture how herd mentality and overconfidence affect the strategic decisions of consumers, live streamers, and platforms. For example, conventional game-theoretic research cannot adequately explain why consumers engage in irrational collective purchases or biased social responses under the influence of herd mentality. Similarly, it cannot fully account for why streamers persist in misleading marketing behaviors, which are often driven by over-

confidence in expected returns and underestimation of regulatory risks. In contrast, this paper constructs a behavioral evolutionary game framework that incorporates these typical behavioral biases, thereby better reflecting realistic decision-making patterns and advancing the theoretical understanding of platform governance in live-streaming e-commerce. Therefore, incorporating consumers' herd mentality and live streamers' overconfidence into regulatory strategy design requires further research.

Given this context, this paper focuses on the widespread issue of MMBs by live streamers in the live-streaming e-commerce environment. The main innovations of this study are as follows: (1) By constructing a tripartite evolutionary game model [10–12] involving the live-streaming e-commerce platforms, live streamers, and consumers, we analyze the evolutionarily stable strategies of each actor within the system and the conditions for achieving an optimal equilibrium. (2) It specifically investigates how consumers' herd mentality and streamers' overconfidence influence the joint supervision between consumers and platforms, thereby steering the system from inefficient equilibria (more-reports, more-MMBs) toward desirable equilibria (like-and-review, non-MMBs). By answering these questions, the study aims to provide systematic theoretical guidance and empirical support for the sustainable development of live-streaming e-commerce.

This study offers clearer theoretical and practical contributions to broader debates on digital platform governance and consumer protection. Theoretically, we extend the literature on platform supervision by incorporating behavioral biases into evolutionary game analysis of digital platform regulation, complementing existing studies on digital consumer protection that largely overlook the psychological drivers of irrational consumption and regulatory behavior. We also enrich the behavioral regulation literature by providing a context-specific analytical framework tailored to live-streaming e-commerce.

Practically, by moving beyond the conventional full-rationality assumption, this study offers actionable regulatory implications for multi-stakeholder collaboration among platforms, streamers, and authorities. More importantly, the core insights regarding the interactions among herd behavior, overconfidence, and dynamic penalty mechanisms are not limited to the Chinese market but can be generalized to other live-streaming e-commerce markets worldwide facing similar challenges of misleading marketing and behavioral disorders in digital consumption.

The remainder of this paper is organized as follows. Section 2 provides a comprehensive review of the relevant literature. Section 3 defines and estimates the model parameters and develops a tripartite game model. In Section 4, evolutionarily stable strategies are derived, along with their corresponding stability conditions. Section 5 examines the impact of various parameters on the system's equilibrium strategies through simulation analysis. Finally, Section 6 presents the conclusions and management implications.

2. Literature Review

In order to grasp the coverage of the large number of the works done, the literature review below is organized into three main streams: (1) live-streaming e-commerce regulatory strategies; (2) consumers' dual herd mentality; and (3) live streamers' overconfidence.

2.1. Live-Streaming E-Commerce Regulatory Strategies

Theories on the regulation of live-streaming e-commerce have gradually emerged, primarily focusing on two aspects: the design and evolution of regulatory strategies. From the former perspective, Chen et al. [13] proposed enhancing regulatory efficiency through cooperative supervision and examined the strategic choices of key stakeholders using evolutionary game theory. Dong et al. [14] constructed an evolutionary game model involving both live-streaming e-commerce platforms and live streamers. Their findings

indicate that effective regulation can be achieved by imposing stricter penalties on platforms and live streamers choosing MMBs. Zhang et al. [15] examined how celebrity and ordinary live streamers influence quality choices in the live-streaming e-commerce supply chain and evaluated the effectiveness of sector-specific governance policies. They identified two critical barriers that prevent these policies from promptly curbing industry disorder: ambiguous responsibility allocation among stakeholders and low supervision success rates during real-time, dynamic interactions.

In decision-making and evolution research, Liu et al. [16], drawing on evolutionary game theory, argued that live-streaming e-commerce platforms themselves must establish accountability mechanisms to lead value-co-destruction governance across all actors within the commercial system. Chen et al. [17] constructed a Bayesian model revealing that leveraging platform reputation can effectively curb the proliferation of fake reviews. Wang and Ren [18] constructed an evolutionary game model between governments and platforms, finding that tighter government supervision coupled with stronger platform incentives markedly boosts platforms' propensity to adopt an active supervision strategy. Hu et al. [8] analyzed the dynamic evolution of strategy choices among the three parties under different regulatory models and identified the drivers of these shifts, proposing tailored optimization paths for pre-event, during-event, and post-event regulation in live-streaming e-commerce.

Beyond studies on regulatory strategy evolution, another important strand of platform governance research focuses on endogenous detection, penalty mechanisms, and disclosure regimes. Recent work has increasingly emphasized upstream fraud discovery and technical detection tools, such as the LOKI system for scam identification and data-driven methods for uncovering deceptive marketing signals [19]. These technical approaches improve the accuracy and coverage of violation detection and provide critical complements to governance strategies based on strategic interaction [20].

However, most existing studies either focus on technical detection performance or examine behavioral and strategic interactions in isolation [21]. Few studies integrate endogenous detection/penalty schemes, fraud discovery technologies, disclosure regimes, and behavioral biases into a unified analytical framework. For instance, existing research often treats penalty mechanisms as exogenous variables, whereas actual regulatory systems increasingly adopt endogenous penalty designs, where penalty severity dynamically adjusts based on factors such as regulatory intensity and herd mentality. In particular, the literature still widely adopts the perfect rationality assumption and largely ignores behavioral traits, such as herd mentality and overconfidence, that characterize real-world decision-making in live-streaming e-commerce.

As a result, prior work cannot fully capture how detection accuracy, penalty intensity, and behavioral biases jointly shape the evolutionary dynamics of platform governance. To fill this gap, our study incorporates both behavioral biases and governance–detection interactions into an evolutionary game framework, which enables a more realistic and comprehensive analysis of regulatory strategy evolution.

2.2. Consumers' Dual Herd Mentality

Unlike the lagging and relatively static nature of consumer reviews in traditional e-commerce, the bullet–chat interaction model in live-streaming e-commerce offers the real-time visibility, the immersive sense of presence, and multi-directional interactivity [22–24]. Within the live-streaming context, consumers simultaneously form perceptions of product value through dynamic demonstrations and real-time interactions with live streamers, while also becoming deeply immersed in a constantly flowing network of feedback from other consumers [25,26]. Within live-streaming e-commerce, the high-frequency scrolling of positive bullet comments like "likes" and "praise" coexists with the immediate display

of negative feedback and "report" complaints (e.g., floating screens, pinned posts), creating a dense information flow that readily influences individual consumer perceptions through collective sentiment [27]. For instance, a high volume of positive comments can rapidly trigger copycat likes and orders, while concentrated complaints easily spark collective skepticism, both occurring at speeds and with impacts far exceeding those of delayed reviews in traditional e-commerce. Scholars refer to this phenomenon as the herd effect, also known as herd bias [6,28].

In live-streaming e-commerce, influenced by factors like live streamer–consumer relationship strength and social presence, this herd mentality manifests more prominently [29]. This herd mentality in live-streaming e-commerce is primarily influenced by three factors: emotional contagion amplified by real-time chat interactions and the live streamers' infectious delivery [30]; group norms formed through viewers' identification with their favorite live streamers [31], fostering collective consensus to support them; and the classic herd mentality triggered by incomplete information. In addition, this herd mentality exhibits dual attributes: on one hand, group consensus accelerates the spread of positive word-of-mouth for quality products, boosting consumer purchase intent and thereby weeding out inferior goods [32]; on the other hand, some live streamers exploit consumers' herd mentality by hiring "professional comment trolls" to flood screens with fake positive reviews and maliciously smear competitors, or by using "live lucky draw rewards" to create buying frenzies. These tactics induce users into irrational behaviors such as posting fake positive reviews and malicious negative feedback [33,34], thereby steering irrational herd behavior. The interplay of these dual forms of herd mentality significantly impacts the development of a healthy and orderly live-streaming e-commerce system.

2.3. Live Streamers' Overconfidence

Overconfidence is one of the most common cognitive biases [35], encompassing overestimation, overplacement, and overprecision. When decision-makers face external uncertainty, they invariably exhibit overprecision behavior, overestimating the accuracy of the information they possess [36]. According to recent research, within the regulatory framework of live-streaming e-commerce, live streamers are often influenced by factors such as asymmetric risk perception and learning. Their overconfidence primarily manifests as an overestimation of their own knowledge and capability levels, which in turn leads to an overestimation of excess returns [2].

Consumers often approach product quality in live-streaming e-commerce with a degree of skepticism [37]. From an individual behavior perspective, some live streamers lack familiarity with the products they sell, lacking professional knowledge and expertise, yet engage in exaggerated claims during sales [38]. From an industry system perspective, when entry barriers are low, some live streamers may resort to unfair practices like MMBs to attract consumers and boost sales for higher profits [39]. This phenomenon typically arises when decision-makers significantly underestimate the supervision of platforms and consumers, leading them to adopt aggressive marketing strategy to maximize personal gains.

Existing research has examined the application of overconfidence as a behavioral bias in live-streaming e-commerce, such as how overconfidence among live streamers negatively impacts their self-discipline [2]. This mirrors the quality risks and credibility crises triggered by overconfidence within supply chains [40]. Overconfident live streamers may overestimate their product selection capabilities and promotional effectiveness, making them more inclined to adopt risky strategy involving MMBs. Without effective governance of violations stemming from live streamers' overconfidence, the live-streaming e-commerce could face a severe crisis of industry trust.

This study aims to integrate the aforementioned three research areas, specifically within a tripartite evolutionary game model involving the live-streaming e-commerce platforms, live streamers and consumers, and by explicitly incorporating the dual herd mentality of consumers and the overconfidence of live streamers into the analysis of regulatory strategies. Most closely related to this paper is the study by Yan et al. [41], which focuses on governance mechanisms of the live-streaming e-commerce system. However, unlike that study, ours further explores the impacts of prevalent irrational behaviors in the live-streaming e-commerce on the system's evolutionary strategies. This extension addresses the limitations of the "homo economicus assumption" in traditional evolutionary game models, and specifically renders the analysis of the system's evolutionary strategies more aligned with practical scenarios. Therefore, this paper represents an interdisciplinary study at the confluence of evolutionary game theory and behavioral decision-making within the domain of live-streaming e-commerce, thereby broadening the scope of research on regulatory strategies.

3. Problem Description and Model Assumptions

Traditional game theory fails to investigate the long-term evolutionary stability of these strategies under conditions of bounded rationality. This study delves into long-term strategic decision-making within the live-streaming e-commerce sector, employing evolutionary game theory to identify evolutionarily stable strategies (ESS) among multiple agents during sustained development. With the rapid growth of the live-streaming e-commerce industry, underlying regulatory issues have become increasingly prominent [42]. To better understand the regulatory mechanisms within this complex system, a tripartite evolutionary game model is constructed to model the behavioral decisions of multiple stakeholders (platforms, live streamers, and consumers) and address conflicts of interest and strategic choices among them. The following fundamental assumptions are made:

Assumption 1. *Strategy selection. Live-streaming e-commerce platforms face two strategies: the strategy of active supervision (AS), which involves actively taking measures to safeguard the rights and interests of all parties, with a probability of* x *and the strategy of passive supervision (PS), which passively addresses MMBs by live streamers and irrational consumers behavior through post-event accountability rather than preemptive prevention, with a probability of* $1 - x$*. The pure strategy set of the platforms is represented as (AS, PS). For live streamers, they can opt for the strategy of non-misleading marketing behaviors (non-MMBs), which involves conveying product information truthfully and accurately, with a probability of* y*; they may also opt for the strategy of misleading marketing behaviors (MMBs), which attracts consumers through exaggerated or misleading statements, with a probability of* $1 - y$*. The pure strategy set of the live streamers is represented as (non-MMBs, MMBs). As for consumers, they face two choices after purchasing a product: the strategy of like-and-review (LR), which involves liking the live streamers and posting positive reviews on the public chat to amplify the product's and live streamers' influence, with a probability of* z *or the strategy of report-and-supervise (RS), which involves exposing the product and live streamers' image through complaints or negative reviews in the chat, with a probability of* $1 - z$*. The pure strategy set for consumers can be represented as (LR, RS).*

These consumers' choices may represent rational behaviors such as liking and praising non-MMBs or reporting MMBs, or irrational behavior like reporting non-MMBs to discredit the live streamers or liking MMBs to promote the live streamers and gain benefits like "live-streaming lucky bag rewards" or psychological benefits from supporting their favorite live streamers. To explicitly distinguish the dual attributes of consumers' herd mentality, we decompose rational and irrational herd behaviors based on the baseline level θ *[43]: rational herd behavior is* $a\theta$ *(with intensity coefficient a), and irrational herd behavior is* $b\theta$ *(with intensity coefficient b). For analytical consistency, we use the unified form* $k\theta$*, where* $k \in \{a, b\}$*.*

To clarify how each type of herd behavior applies in the model, rational herd behavior occurs when consumers choose the LR strategy in response to streamers' non-MMB strategies, or the RS strategy in response to streamers' MMB strategies. By contrast, irrational herd behavior occurs when consumers choose the RS strategy in response to streamers' non-MMB strategies, or the LR strategy in response to streamers' MMB strategies.

Assumption 2. *Belief updating. Due to bounded rationality and asymmetric information, participants form subjective beliefs about others' strategies based on historical game data and update them dynamically [44]. Let x_e, y_e and z_e denote beliefs about the platform's AS strategy, the live streamer's non-MMB strategy and the consumer's LR strategy, respectively. The belief updating follows the exponential weighted moving average (EWMA) rule: $x_e(t) = \alpha x(t-1) + (1-\alpha)x_e(t-1)$, $y_e(t) = \alpha y(t-1) + (1-\alpha)y_e(t-1)$, and $z_e(t) = \alpha z(t-1) + (1-\alpha)z_e(t-1)$, where α is the learning coefficient.*

Assumption 3. *Relevant parameter settings for the platforms. Existing research indicates that actors can artificially manufacture surface credibility by purchasing fake followers in bulk and exploit the sensitivity of algorithms to social signals such as follower counts to enhance their visibility, thereby misleading ordinary users [45]. This finding confirms the manipulability of social signals and their potential impact on platform reputation. In scenarios where group behavior converges, the amplification effect of such manipulation becomes more pronounced, thereby providing a realistic basis for incorporating consumers' herd mentality level θ into the platform profit and loss analysis in this paper. The basic profit of live-streaming e-commerce platforms under normal operations is R_1. Under an AS strategy, platforms can generate incremental revenue $(1+k\theta)R_2$, which is positively correlated with consumers' herd mentality levels θ, by rewarding trustworthy live streamers with traffic support and penalizing misleading live streamers through anti-fraud measures [39]. Simultaneously, platforms incur additional regulatory costs C_1 from establishing supervising systems and implementing reward-punishment mechanisms [46]. Under a PS strategy, if live streamers engage in MMBs, the platform faces social reputation losses $(1+k\theta)C_2$ that are positively correlated with consumers' herd mentality levels. When consumers exhibit irrational behaviors such as malicious negative reviews or fake positive reviews, the platform's commercial system suffers disruption [47]. This may trigger live streamer trust crises and lead to live streamer attrition, ultimately resulting in operational risk losses C_3.*

Assumption 4. *Relevant parameter settings for live streamers. The baseline earnings for live streamers conducting normal product promotions are R_3. When live streamers adopt the non-MMB strategy, if the platforms implement active supervision and the consumers respond with positive comments and favorable reviews, the live streamers will receive traffic support [48], generating incremental revenue $R_4(x) = x_e(1+k\theta)R_4$, where R_4 in the formula represents the baseline earnings from traffic support under conditions of fully active supervision $(x_e = 1)$ and the absence of herd behaviors $(\theta = 0)$. This is assumed to be linearly related to the probability of the platforms' supervision x_e and the level of consumers' herd mentality θ. If consumers choose a RS strategy, the live streamers must prove their non-MMBs through product quality inspections, etc. Considering consumers' herd mentality, the self-justification cost is $(1+k\theta)C_4$, reflecting the negative externalities of herd behavior. When the live streamers adopt the strategy of MMBs, they generate additional revenue εR_3 by exaggerating product performance. ε is the yield rate of live streamers' MMBs. Furthermore, drawing from the research of Malmendier and Tate [7] on managerial overconfidence, as well as the classic overconfidence literature highlighting systematic miscalibration of risk and return [35,49], when live streamers exhibit overconfidence, they tend to overestimate the illegal profits σR_3 from MMBs. σ is the live streamers' overconfidence level. Referencing the studies by Song et al. [3] and Xu et al. [9], if the platform implements active supervision, live streamers will be subject to comprehensive penalties $C_5(x)$, which are linearly related to the probability of the platform choosing an AS strategy. When consumers adopt a rational RS strategy, influenced by positive*

consumers' herd mentality and the platform's regulatory intensity, the live streamers face more severe platform penalties $C_5(x) = x_e(1 + k\theta)C_5$. *Conversely, when consumers choose an irrational LR strategy, the live streamers still incur platform penalties* $C_5(x) = x_e C_5$.

Assumption 5. *Relevant parameter settings for consumers. The fundamental utility consumers derive from purchasing in live-streaming e-commerce is* R_5. *Under the guidance of positive group norms, consumers uphold industry honesty through rational LR and RS behaviors: on one hand, they like live streamers with non-MMBs and post positive comments to express support, gaining emotional satisfaction and live-streaming lucky bag rewards* R_6; *on the other hand, they actively report live streamers with MMBs, receiving platform rewards* R_8 *if the reports are substantiated. However, influenced by the real-time interactivity of live streamers, consumers may be driven by profit motives and pressured by the live streamers' atmosphere to engage in irrational behaviors such as liking and commenting on MMB live streamers or filing malicious complaints against non-MMB streamers to obtain illicit benefits* R_7 *(e.g., participating in fake order rebates, claiming illegal perks, or acting as professional comment spammers) [50]. When platforms choose active supervision, consumers face penalties* C_6 *like fines or credit score deductions. While reporting entails time and labor costs* C_7 *for evidence collection, the potential rewards from an RS strategy encourage herd behavior among consumers, with the cost of providing evidence changing to* $C_7/k\theta$ *based on the mechanism of informational cascades [51].*

Assumption 6. *Linear assumption. For analytical tractability, this study adopts linear specifications for key relationships, including herd mentality intensity, overconfidence effects, penalty mechanisms, and payoff sensitivities. While linear formulations simplify the dynamic interactions among behavioral and regulatory factors, we acknowledge that real-world live-streaming e-commerce may exhibit nonlinear or threshold effects. For instance, herd mentality, overconfidence, and penalty intensity may only exert significant influence once crossing a critical threshold, or their marginal effects may change nonlinearly with strategy evolution. This study retains the linear form to focus on the core evolutionary mechanisms, while supplementary robustness analyses on key parameters are conducted in Appendix B to verify the validity of the linear assumption.*

The parameters and terms involved in this research and their definitions are shown in Table 1.

Table 1. Model parameters and definitions.

Participant	Parameters	Definitions	Range
Platform	R_1	Platform operating revenue	$R_1 > 0$
	R_2	The additional revenue of platforms' active supervision	$0 < R_2 < R_1$
	C_1	Costs of platforms' active supervising	$C_1 > 0$
	C_2	Reputational loss caused by unsupervised MMBs on the platform	$C_2 > 0$
	C_3	Reputational loss from not supervising consumers' irrational behaviors	$0 < C_3 < C_2$
Live streamer	R_3	The revenue from live streamers' regular product promotions	$R_3 > 0$
	R_4	The additional revenue of live streamers after receiving traffic support.	$R_4 > 0$
	C_4	Self-justification costs of live streamers	$C_4 > 0$
	C_5	Penalties for MMBs by live streamers	$C_5 > 0$
	σ	Level of overconfidence among live streamers	$\sigma > 0$
	ε	Yield rate of live streamers' MMBs	$\varepsilon > 0$
Consumer	R_5	The utility that consumers derive from normal purchases	$R_5 > 0$
	R_6	The utility that consumers gain from rational positive likes and reviews	$R_6 > 0$
	R_7	The additional utility of irrational consumer behaviors	$R_7 > R_6$
	R_8	Compensation successfully obtained through consumer complaints	$R_8 > 0$
	C_6	Penalty for consumers' irrational behavior	$C_6 > 0$

Table 1. *Cont.*

Participant	Parameters	Definitions	Range
Proportion of strategy	C_7	Evidence collecting costs for consumers' reporting	$C_7 > 0$
	θ	Level of herd mentality among consumers	$\theta \geq 0$
	a	Intensity coefficient of rational conformity	$a > 0$
	b	Intensity coefficient of irrational conformity	$b > 0$
	x	Probability of platform selection under an AS strategy	$0 \leq x \leq 1$
	y	Probability of live streamers choosing a non-MMB strategy	$0 \leq y \leq 1$
	z	Probability of consumers choosing a LR strategy	$0 \leq z \leq 1$
	x_e	Subjective belief probability of a platform's AS strategy	$0 \leq x_e \leq 1$
	y_e	Subjective belief probability of a streamer's non-MMB strategy	$0 \leq y_e \leq 1$
	z_e	Subjective belief probability of a consumer's LR strategy	$0 \leq z_e \leq 1$
	α	Belief learning coefficient	$0 < \alpha < 1$

Table 2 shows a payoff matrix for platforms, live-streamers and consumers.

Table 2. Payoff matrix of the three game subjects.

Live Streamers	Consumers	Platforms	
		AS(x)	**PS**$(1-x)$
Non-MMBs (y)	LR (z)	$R_1 + (1+a\theta)R_2 - C_1$	R_1
		$R_3 + (1+a\theta)x_eR_4$	R_3
		$R_5 + R_6$	$R_5 + R_6$
	RS $(1-z)$	$R_1 + (1+b\theta)R_2 - C_1$	$R_1 - C_3$
		$R_3 + x_eR_4 - (1+b\theta)C_4$	$R_3 - (1+b\theta)C_4$
		$R_5 + R_7 - C_6 - C_7/b\theta$	$R_5 + R_7 - C_7/b\theta$
MMBs $(1-y)$	LR (z)	$R_1 + (1+b\theta)R_2 - C_1$	$R_1 - (1+b\theta)C_2 - C_3$
		$(1+\sigma+\varepsilon)R_3 - x_eC_5$	$(1+\sigma+\varepsilon)R_3$
		$R_5 + R_7 - C_6$	$R_5 + R_7$
	RS $(1-z)$	$R_1 + (1+a\theta)R_2 - C_1$	$R_1 - (1+a\theta)C_2$
		$(1+\sigma+\varepsilon)R_3 - (1+a\theta)x_eC_5$	$(1+\sigma+\varepsilon)R_3 - (1+a\theta)x_eC_5$
		$R_5 + R_8 - C_7/a\theta$	$R_5 + R_8 - C_7/a\theta$

In the following section, we first calculate the expected returns for each participant under different strategies and then employ replicated dynamic equations to simulate and adjust these strategies. Finally, through stability analysis, we study which strategies are stable and under what conditions the strategy configuration of the population can achieve stability.

4. The Stability Analysis of Evolutionary Game Model

In the field of live-streaming e-commerce, the strategic interactions among three key stakeholders: platforms, live streamers, and consumers, form a complex game-theoretic system. Due to bounded rationality or incomplete market information [52], participants may adjust their strategies based on others' strategies to maximize their own gains. This strategic interaction represents a long-term, dynamic evolutionary process involving multiple players, where stability analysis can identify sustainable strategies for all parties in the long-run game. This section employs stability analysis to explore the conditions under which participants' strategy choices converge toward a stable state and elucidates which strategy combinations can become stable choices for all participants in the persistent dynamic interactions of live-streaming e-commerce.

4.1. The Evolution Path and Stability Analysis of the Platforms

According to the payoff matrix, the expected payoff function E_{11} for the platforms adopting an AS strategy, the expected payoff function E_{12} for adopting a PS strategy, and the average expected payoff function E_1 are respectively:

$$E_{11} = y_e z_e[R_1 + (1+a\theta)R_2 - C_1] + y_e(1-z_e)[R_1 + (1+b\theta)R_2 - C_1] + (1-y_e)z_e[R_1 + (1+b\theta)R_2 - C_1] + (1-y_e)(1-z_e)[R_1 + (1+a\theta)R_2 - C_1] \quad (1)$$

$$E_{12} = y_e z_e R_1 + y_e(1-z_e)(R_1 - C_3) + (1-y_e)z_e(t)[R_1 - (1+b\theta)C_2 - C_3] + (1-y_e)(1-z_e)[R_1 - (1+a\theta)C_2] \quad (2)$$

$$E_1 = xE_{11} + (1-x)E_{12} \quad (3)$$

The dynamic equations for the platforms' replication are:

$$\begin{aligned} F(x) = \frac{dx}{dt} &= x(E_{11} - E_1) = x(1-x)(E_{11} - E_{12}) \\ &= x(1-x)\{y_e[C_3 - (1+a\theta)C_2 + (b-a)\theta R_2] + z_e[C_3 + (b-a)\theta(C_2+R_2)] + \\ &\quad y_e z_e[(a-b)\theta(C_2+2R_2) - 2C_3] + (1+a\theta)(C_2+R_2) - C_1\} \end{aligned} \quad (4)$$

$$\begin{aligned} \frac{\partial F(x)}{\partial x} &= (1-2x)\{y_e[C_3 - (1+a\theta)C_2 + (b-a)\theta R_2] + z_e[C_3 + (b-a)\theta(C_2+R_2)] + \\ &\quad y_e z_e[(a-b)\theta(C_2+2R_2) - 2C_3] + (1+a\theta)(C_2+R_2) - C_1\} \end{aligned} \quad (5)$$

According to the stability theorem of differential equations and the convergence of adaptive expectations (see Appendix A), the steady-state probability for platforms must satisfy $F(x) = 0$ and $F'(x) < 0$. Solving $F(x) = 0$ yields $x = 1$, $x = 0$, and $y = y^* = \frac{(1+a\theta)(C_2+R_2) - C_1 + z[(b-a)\theta(C_2+R_2)+C_3]}{(1+a\theta)C_2 - C_3 + (b-a)\theta R_2 + z[(b-a)\theta(C_2+2R_2)+2C_3]}$. When $y = y^*$, $F(x) = 0$ and $F'(x) = 0$ hold for any x. That is, the x-axis is in a steady state, and any strategy for platforms is a stable strategy (shown in Figure 1a). When $y \neq y^*$, the following cases are discussed.

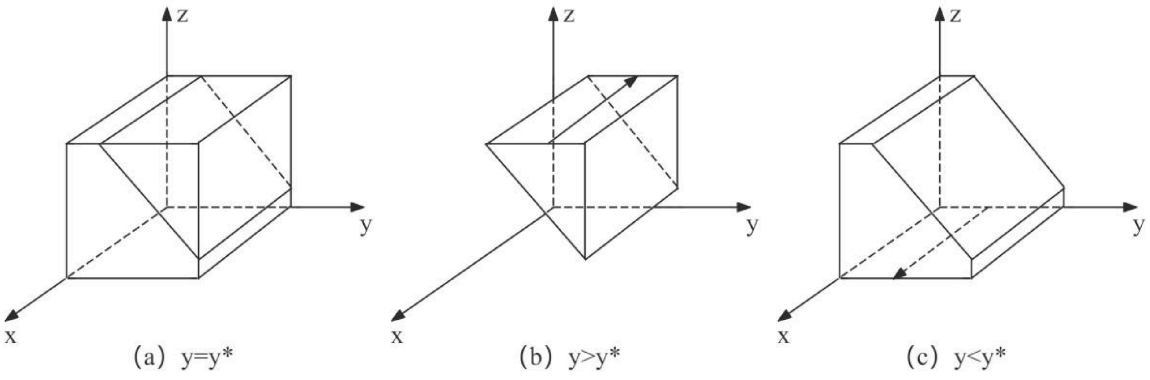


Figure 1. Phase diagram of the evolution of platforms' strategies at high herd-mentality levels. The asterisk (*) marks the critical threshold y^* where platforms' strategies are stable.

Case 1. If $\theta > \frac{(1-2z)C_3 - C_2}{aC_2 + (a-b)R_2 + (b-a)z(C_2+2R_2)}$, we analyze the following two scenarios.

(1) When $y > y^*$, then $F'(x)|_{x=0} < 0$, $F'(x)|_{x=1} > 0$, $x = 0$ is the only ESS.
(2) When $y < y^*$, then $F'(x)|_{x=0} > 0$, $F'(x)|_{x=1} < 0$, $x = 1$ is the only ESS.

Case 1 shows that at high herd-mentality levels, when the live streamers adopt a non-MMB strategy, platforms tend toward a PS strategy to reduce management costs, forming the ESS, as shown in Figure 1b. For instance, when supervising live streamers with good reputations, platforms often adopt passive supervision to reduce management costs. If the live streamers engage in an MMB strategy, and the product receives falsely inflated yet abnormally concentrated positive reviews, it triggers the platforms' anti-fraud mechanisms

and leads to active supervision, forming the ESS, as shown in Figure 1c. This situation is more prevalent in live-streaming e-commerce. For live streamers who engage in an MMB strategy or have previously caused significant social repercussions through MMBs, platforms often implement more active supervision. Some platforms assign dedicated personnel to monitor these live streamers directly.

4.2. The Evolution Path and Stability Analysis of Live Streamers

The expected payoff function E_{21} for the live streamers adopting the non-MMB strategy, the expected payoff function E_{22} for adopting the MMB strategy, and the average expected payoff function E_2 are respectively:

$$\begin{aligned} E_{21} = {} & x_e z_e[R_3 + (1+a\theta)x_e R_4] + x_e(1-z_e)[R_3 + x_e R_4 - (1+b\theta)C_4] \\ & + (1-x_e)z_e R_3 + (1-x_e)(1-z_e)[R_3 - (1+b\theta)C_4] \end{aligned} \tag{6}$$

$$\begin{aligned} E_{22} = {} & x_e z_e[(1+\sigma+\varepsilon)R_3 - x_e C_5] + x_e(1-z_e) \\ & [(1+\sigma+\varepsilon)R_3 - (1+a\theta)x_e C_5] + (1-x_e)z_e[(1+\sigma+\varepsilon)R_3] \\ & + (1-x_e)(1-z_e)[(1+\sigma+\varepsilon)R_3 - (1+a\theta)x_e C_5] \end{aligned} \tag{7}$$

$$E_2 = yE_{21} + (1-y)E_{22} \tag{8}$$

The dynamic equations for live streamers' replication are:

$$\begin{aligned} G(y) = \tfrac{dy}{dt} &= y(E_{21} - E_2) = y(1-y)(E_{21} - E_{22}) \\ &= y(1-y)[(1+b\theta)(z_e - 1)C_4 + (1+a\theta)x_e(1-z)C_5 + x_e^2(R_4 + z_e C_5 + a\theta z_e R_4)] \end{aligned} \tag{9}$$

$$\frac{\partial G(y)}{\partial y} = (1-2y)[(1+b\theta)(z_e - 1)C_4 + (1+a\theta)x_e(1-z_e)C_5 + x_e^2(R_4 + z_e C_5 + a\theta z_e R_4)] \tag{10}$$

According to the stability theorem of differential equations and the convergence of adaptive expectations (see Appendix A), the steady-state probability for platforms must satisfy $G(y) = 0$ and $G'(y) < 0$. Solving $G(y) = 0$ yields $y = 1$, $y = 0$, and $z = z^* = \frac{(1+b\theta)C_4 + (\sigma+\varepsilon)R_3 - (1+a\theta)xC_5 - x^2R_4}{(1+b\theta)C_4 - (1+a\theta)xC_5 + x^2(C_5 + a\theta R_4)}$. When $z = z^*$, $G(y) = 0$ and $G'(y) = 0$ hold for any y. That is, the y-axis is in a steady state, and any strategy for live streamers is a stable strategy (shown in Figure 2a). When $z \neq z^*$, the following cases are discussed.

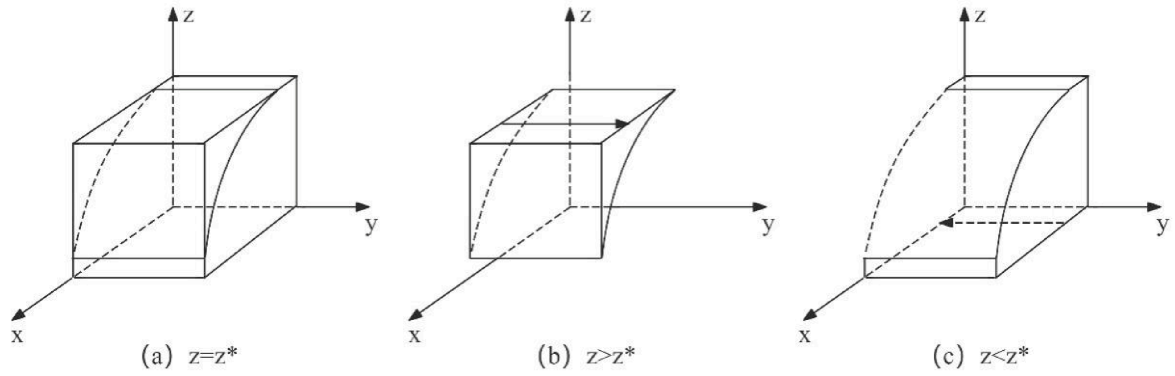


Figure 2. Phase diagram of the evolution of live streamers' strategies at high herd-mentality levels. The asterisk (*) marks the critical threshold z^* where live streamers' strategies are stable.

Case 2. If $\theta \geq [(1-x)xC_5 - C_4]/[bC_4 - axC_5 + ax^2R_4]$, we analyze the following two scenarios.

(1) When $z > z^*$, then $G'(y)\big|_{y=0} > 0$, $G'(y)\big|_{y=1} < 0$, $y = 1$ is the only ESS.
(2) When $z < z^*$, then $G'(y)\big|_{y=0} < 0$, $G'(y)\big|_{y=1} > 0$, $y = 0$ is the only ESS.

Case 2 shows that at high herd-mentality levels, when consumers tend to give positive reviews and likes, live streamers adopt the non-MMB strategy to avoid penalties for MMBs and gain positive reviews and likes for traffic support, resulting in the ESS, as shown in Figure 2b. This also represents a relatively ideal market environment, where many live streamers, after receiving widespread acclaim, become more receptive to consumer feedback. They then use this input to enhance their live-streaming rooms, ultimately earning more likes and positive reviews. When consumers tend to report and supervise, only by adopting MMB strategies that generate additional revenue can live streamers meet their profit targets, resulting in the ESS, as shown in Figure 2c. This is also the situation we least want to see, as live streamers who resort to MMBs often receive more reports and face penalties, ultimately choosing to leave the live-streaming e-commerce industry.

4.3. The Evolution Path and Stability Analysis of Consumers

The expected utility function E_{31} for the LR strategy, the expected utility function E_{32} for the RS strategy, and the average expected utility function E_3 are respectively:

$$\begin{aligned} E_{31} = {} & x_e y_e (R_5 + R_6) + x_e (1 - y_e)(R_5 + R_7 - C_6) + \\ & (1 - x_e) y_e (R_5 + R_6) + (1 - x_e)(1 - y_e)(R_5 + R_7) \end{aligned} \tag{11}$$

$$\begin{aligned} E_{32} = {} & x_e y_e (R_5 + R_7 - C_6 - C_7/b\theta) + x_e (1 - y_e)(R_5 + R_8 - C_7/a\theta) + \\ & (1 - x_e) y_e (R_5 + R_7 - C_7/b\theta) + (1 - x_e)(1 - y_e)(R_5 + R_8 - C_7/a\theta) \end{aligned} \tag{12}$$

$$E_3 = z E_{31} + (1 - z) E_{32} \tag{13}$$

The dynamic equations for consumers' replication are:

$$\begin{aligned} H(z) = \tfrac{dz}{dt} &= z(E_{31} - E_3) = z(1 - z)(E_{31} - E_{32}) \\ &= z(1 - z)[(1 - y_e)C_7/a\theta + y_e C_7/b\theta + (1 - 2y_e)R_7 - (1 - y_e)R_8 + (2y_e - 1)xC_6 + y_e R_6] \end{aligned} \tag{14}$$

$$\begin{aligned} \tfrac{\partial H(z)}{\partial z} = {} & (1 - 2z)[(1 - y_e)C_7/a\theta + y_e C_7/b\theta + (1 - 2y_e)R_7 - \\ & (1 - y_e)R_8 + (2y_e - 1)x_e C_6 + y_e R_6] \end{aligned} \tag{15}$$

According to the stability theorem of differential equations and the convergence of adaptive expectations (see Appendix A), the steady-state probability for platforms must satisfy $H(z) = 0$ and $H'(z) < 0$. Solving $H(z) = 0$ yields $z = 1$, $z = 0$, and $x = x^* = \frac{(1-y)C_7/a\theta + yC_7/b\theta + (1-2y)R_7 - (1-y)R_8 + yR_6}{(1-2y)\theta C_6}$. When $x = x^*$, $H(z) = 0$ and $H'(z) = 0$ hold for any z. That is, the z-axis is in a steady state (shown in Figure 3a). When $x \neq x^*$, the following cases are discussed.

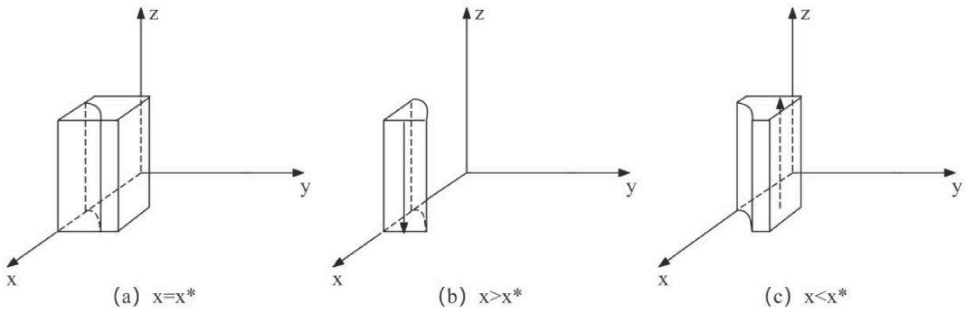


Figure 3. Phase diagram of the evolution of consumers' strategies when live streamers adopt MMBs. The asterisk (*) marks the critical threshold x^* where consumers' strategies are stable.

Case 3. If $y_e(t) < 0.5$, we analyze the following two scenarios.

(1) When $x > x^*$, then $H'(z)|_{z=0} < 0$, $H'(z)|_{z=1} > 0$, $z = 0$ is the only ESS.

(2) When $x < x^*$, then $H'(z)|_{z=0} > 0$, $H'(z)|_{z=1} < 0$, $z = 1$ is the only ESS.

Case 3 shows that when the live streamers' strategies lean toward MMBs, if the platform actively supervises, consumers are more inclined to choose the RS strategy to protect their rights due to the platforms' active supervision. This constitutes the ESS, as shown in Figure 3b; if the platform adopts passive supervision, consumers, influenced by the platform's passive supervision, high supervision costs, incentives from live streamers' rebates, and the time cost of writing reviews, are more inclined to give positive ratings and reviews or default to positive reviews without writing them. This constitutes the ESS, as shown in Figure 3c.

4.4. Stability Analysis of the Tripartite Evolutionary Game System

The trajectories of the dynamic system reveal potential development paths for the e-commerce livestreaming mechanism constructed based on our model. Given the model's parameters, the state space of the dynamical system is defined as a unit cube. The equilibria of the dynamical system can be found by solving the set of equations $F(x) = 0$, $G(y) = 0$, $H(z) = 0$ [53]. Eight equilibrium points correspond to the vertices of the cube: $K_1(0,0,0)$, $K_2(0,0,1)$, $K_3(0,1,0)$, $K_4(0,1,1)$, $K_5(1,0,0)$, $K_6(1,0,1)$, $K_7(1,1,0)$, and $K_8(1,1,1)$. The remaining equilibrium points lie on the faces, edges, or within the interior of the cube. We now focus on the vertices of the cube. To analyze the stability of the equilibrium points of the evolving system, the Jacobian matrix is constructed [54]:

$$J = \begin{pmatrix} \frac{\partial F(x)}{\partial x} & \frac{\partial F(x)}{\partial y} & \frac{\partial F(x)}{\partial z} \\ \frac{\partial G(y)}{\partial x} & \frac{\partial G(y)}{\partial y} & \frac{\partial G(y)}{\partial z} \\ \frac{\partial H(z)}{\partial x} & \frac{\partial H(z)}{\partial y} & \frac{\partial H(z)}{\partial z} \end{pmatrix}$$

Using the first method of Lyapunov [55], the stability of equilibrium points can be determined by analyzing the eigenvalues of the Jacobian matrix. If all eigenvalues of the Jacobian matrix have negative real parts, the equilibrium point is asymptotically stable. If at least one eigenvalue has a positive real part, the equilibrium point is unstable. If the Jacobian matrix has eigenvalues with zero real parts (aside from those with negative real parts), the equilibrium point is in a critical state, and its stability cannot be determined solely by the sign of the eigenvalue. By substituting the eight pure strategy points of the game into the linear transformation matrix, the eigenvalues corresponding to the equilibrium points are obtained, as shown in Table 3 below:

Table 3. Eigenvalues corresponding to the equilibrium points.

Equilibrium Point	λ_1	λ_2	λ_3
$K_1(0,0,0)$	$(1+a\theta)(C_2+R_2)-C_1$	$-(1+b\theta)C_4-(\sigma+\varepsilon)R_3$	$R_7-R_8+C_7/a\theta$
$K_2(0,0,1)$	$(1+b\theta)(C_2+R_2)-C_1+C_3$	$-(\sigma+\varepsilon)R_3$	$R_8-R_7-C_7/a\theta$
$K_3(0,1,0)$	$(1+b\theta)R_2-C_1+C_3$	$(1+b\theta)C_4+(\sigma+\varepsilon)R_3$	$R_6-R_7+C_7/b\theta$
$K_4(0,1,1)$	$(1+a\theta)R_2-C_1$	$(\sigma+\varepsilon)R_3$	$R_7-R_6-C_7/b\theta$
$K_5(1,0,0)$	$C_1-(1+a\theta)(C_2+R_2)$	$(1+a\theta)C_5-(1+b\theta)C_4+R_4-(\sigma+\varepsilon)R_3$	$R_7-R_8-C_6+C_7/a\theta$
$K_6(1,0,1)$	$C_1-(1+b\theta)(C_2+R_2)-C_3$	$C_5+(1+a\theta)R_4-(\sigma+\varepsilon)R_3$	$R_8+C_6-R_7-C_7/a\theta$
$K_7(1,1,0)$	$C_1-C_3-(1+b\theta)R_2$	$(\sigma+\varepsilon)R_3+(1+b\theta)C_4-(1+a\theta)C_5-R_4$	$R_6+C_6-R_7+C_7/b\theta$
$K_8(1,1,1)$	$C_1-(1+a\theta)R_2$	$(\sigma+\varepsilon)R_3-C_5-(1+a\theta)R_4$	$R_7-R_6-C_6-C_7/b\theta$

Based on actual conditions, building a harmonious live-streaming e-commerce system is key to driving sustainable development in live-streaming e-commerce. This entails achieving a scenario where platforms tend to opt for the AS strategy $(x \to 1)$, live streamers tend to choose a non-MMB strategy $(y \to 1)$, and consumers adopt a rational LR strategy

$(z \to 1)$. Consequently, by calculating the eigenvalues at each equilibrium point in Table 3 according to the ESS equilibrium conditions, the following scenarios can be derived:

Proposition 1: *When the net benefit of consumers' "rational positive live-and-review" strategy exceeds that of their "irrational behavior" strategy (i.e., $R_6 - (R_7 - C_6) > 0$), the condition $R_7 - R_6 - C_6 - C_7/b\theta < 0$ is satisfied simultaneously. Furthermore, when $C_1 < (1 + a\theta)R_2$ (meaning the platforms' gains from active supervision exceed its costs) and $(\sigma + \varepsilon)R_3 - C_5 < (1 + a\theta)R_4$ (meaning the excess profits of live streamers' MMBs minus penalties are less than the platform's promotional profits from non-MMBs), the system will converge to the ESS (1,1,1). This represents a virtuous cycle of (AS, non-MMBs, LR).*

Proposition 2: *When the net benefit of consumers adopting the "rational positive live-and-review" strategy is lower than that of their "irrational behavior" strategy (i.e., $R_6 - (R_7 - C_6) < 0$), the stability conditions for platforms and live streamers remain unchanged. The stability of the equilibrium point can be analyzed under two distinct scenarios: (1)When herd mentality level is low and consumers' evidence costs remain high (i.e., $\theta < C_7/b(R_7 - R_6 - C_6)$), the system consistently converges to the stable state (1,1,1), corresponding to the strategy combination (AS, non-MMBs, LR). (2)When herd mentality level is high and consumers' evidence costs are significantly reduced through social sharing (i.e., $\theta > C_7/b(R_7 - R_6 - C_6)$), the system consistently converges to the stable state (1,1,0), corresponding to the strategy combination (AS, non-MMBs, RS). This demonstrates that consumers' strategies are significantly influenced by behavioral factors.*

5. Simulation Analysis

5.1. Background

The model incorporates a relatively large set of parameters to reflect the institutional, economic, and behavioral characteristics of live-streaming e-commerce. All parameters are assigned clear economic interpretations and calibrated consistently with the existing literature on evolutionary game analysis and digital platform regulation. Furthermore, we conduct systematic sensitivity analyses for core parameters including herd mentality, overconfidence, and penalty intensity to verify the robustness of evolutionary trajectories and equilibrium outcomes. These simulations confirm that the main findings remain stable under reasonable parameter variations, thereby strengthening confidence in the reliability and robustness of our results.

In what follows, we present numerical simulations to illustrate the evolutionary results and further examine the effects of key parameters. Simulation analysis is indispensable for confirming equilibrium stability and demonstrating the model's robustness against parameter perturbations. Furthermore, by evaluating the effects of parameter changes on strategic decisions and the system stability, we can identify the key drivers of system evolution. To intuitively examine how key factors, such as herd mentality, overconfidence, and punishment intensity, affect the evolution of the three-party game strategies, we conduct numerical simulations in MATLAB R2024b (24.2.0.2712019) and identify the parameter ranges that steer the system to a stable equilibrium [16,56].

Based on the previously set parameters and the constraints of the stable points, we assign values to each parameter to simulate how the strategic choices of different participants affect the overall stability of the system. For key parameters, drawing on the relevant literature on strategic interactions among platform, live streamer and consumers, we specify the initial parameter values for the model simulation [17,35]. In practice, parameter calibration should be tailored to the specific context and actual data of individual platforms.

5.2. Evolutionary Stability Analysis of the Live Streaming E-Commerce System

Scenario 1: *When* $R_6 - (R_7 - C_6) > 0$, $C_1 < (1 + a\theta)R_2$, *and* $(\sigma + \varepsilon)R_3 - C_5 < (1 + a\theta)R_4$ *are satisfied, it is consistent with Proposition 1. We set the values of the parameters:* $R_1 = 6$, $R_2 = 3.1$, $R_3 = 2.5$, $R_4 = 0.9$, $R_5 = 2$, $R_6 = 1$, $R_7 = 5$, $R_8 = 4$, $C_1 = 4$, $C_2 = 3$, $C_3 = 1$, $C_4 = 0.5$, $C_5 = 2$, $C_6 = 5$, $C_7 = 2$, $\sigma = 1$, $\theta = 1$, $\varepsilon = 0.2$, $\alpha = 0.7$, $a = 1$, *and* $b = 1.2$, *and the results are shown in Figure 4.*

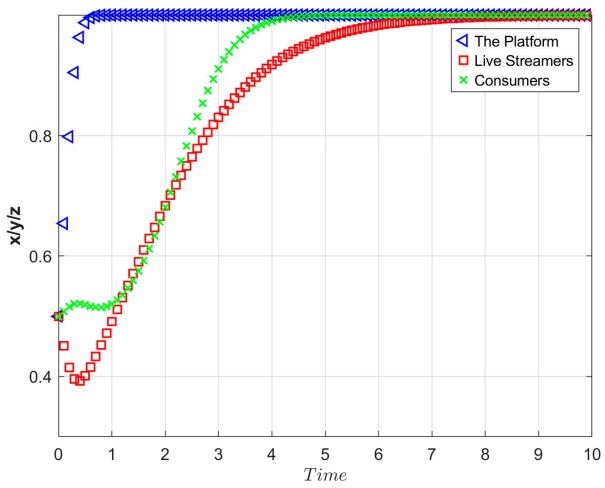


Figure 4. Evolutionary stability analysis of live-streaming e-commerce system under Scenario 1.

Under Scenario 1, since consumers' net gains from "rational positive live-and-review" exceed those from "irrational behavior", the benefits of platforms' active supervision outweigh its costs. The excess profits from live streamers' MMBs are less than the difference between the fines incurred and profits gained from non-MMBs. Although live streamers tend to evolve toward MMB strategies before the evolutionary equilibrium is reached, as the strategies of platforms and consumers evolve, the evolutionary game strategy of the three parties ultimately converges to (AS, non-MMBs, LR), as shown in Figure 4. This validates Proposition 1.

Scenario 2: *When* $R_6 - (R_7 - C_6) < 0$, $\theta < C_7/b(R_7 - R_6 - C_6)$, $C_1 < (1 + a\theta)R_2$, *and* $(\sigma + \varepsilon)R_3 - C_5 < (1 + a\theta)R_4$ *are satisfied, it is consistent with one of the scenarios of Proposition 2. We set the values of the parameters:* $R_1 = 6$, $R_2 = 3.1$, $R_3 = 2.5$, $R_4 = 0.9$, $R_5 = 2$, $R_6 = 1$, $R_7 = 5$, $R_8 = 4$, $C_1 = 4$, $C_2 = 3$, $C_3 = 1$, $C_4 = 0.5$, $C_5 = 2$, $C_6 = 3$, $C_7 = 2$, $\sigma = 1$, $\theta = 1$, $\varepsilon = 0.2$, $\alpha = 0.7$, $a = 1$, *and* $b = 1.2$, *and the results are shown in Figure 5.*

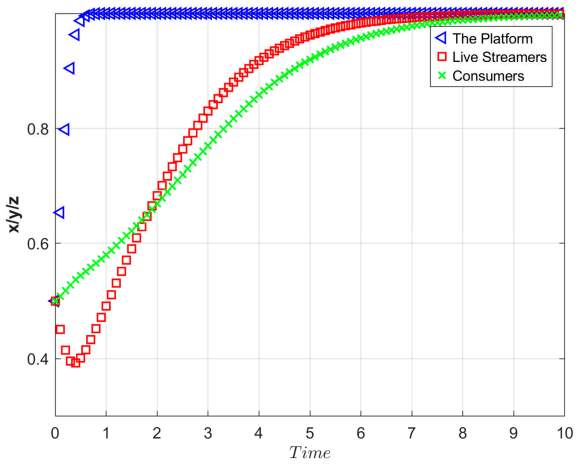


Figure 5. Evolutionary stability analysis of live-streaming e-commerce system under Scenario 2.

Under Scenario 2, although the net benefit of consumers' "rational positive live-and-review" is lower than that of their "irrational behavior", the high cost of consumers 'evidence collecting means the net benefit of consumer reporting and supervising remains lower than the net benefit of positive reviews. The benefits of platforms' active supervision outweigh its costs. The excess profits from live streamers' MMBs, minus the associated fines, are less than platforms' promotional profits from non-MMBs. The evolutionary game strategy for the three parties ultimately converges to (AS, non-MMBs, LR), as shown in Figure 5. This validates the first scenario of Proposition 2.

Scenario 3: *When* $R_6 - (R_7 - C_6) < 0$, $\theta > C_7/b(R_7 - R_6 - C_6)$, $C_1 < (1 + a\theta)R_2$, *and* $(\sigma + \varepsilon)R_3 - C_5 < (1 + a\theta)R_4$ *are satisfied, it is consistent with the other scenario of Proposition 2. We set the values of the parameters:* $R_1 = 6$, $R_2 = 3.1$, $R_3 = 2.5$, $R_4 = 0.9$, $R_5 = 2$, $R_6 = 1$, $R_7 = 5$, $R_8 = 4$, $C_1 = 4$, $C_2 = 3$, $C_3 = 1$, $C_4 = 0.5$, $C_5 = 2$, $C_6 = 3$, $C_7 = 2$, $\sigma = 1$, $\theta = 3$, $\varepsilon = 0.2$, $\alpha = 0.7$, $a = 1$, *and* $b = 1.2$, *and the results are shown in Figure 6.*

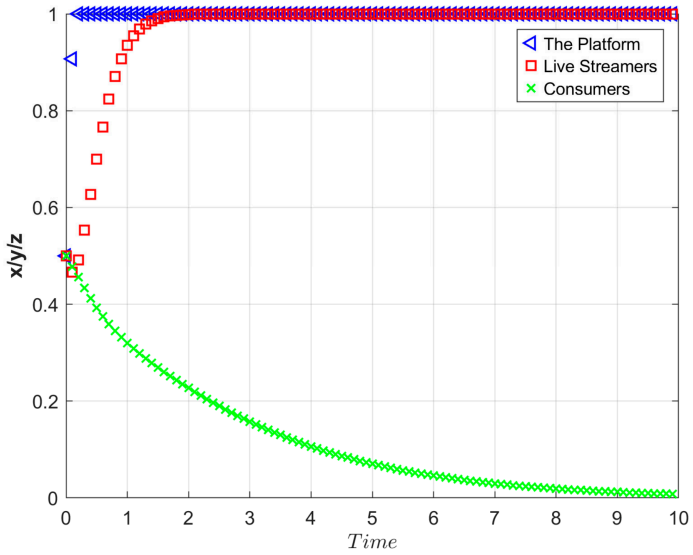


Figure 6. Evolutionary stability analysis of live-streaming e-commerce system under Scenario 3.

Under Scenario 3, the net benefit of consumers engaging in "rational positive live-and-review" is lower than that of their "irrational behavior." Moreover, due to the high level of herd mentality significantly spreading the evidence collecting costs among consumers, the net benefit of consumer reporting and supervising exceeds that of positive like-and-review. Furthermore, the benefits of the platforms' active supervision outweigh its costs. The difference between the excess profits generated by live streamers' MMBs and the resulting fines is less than the platforms' promotional profits from non-MMBs. The evolutionary game strategy of the three parties ultimately converges to (AS, non-MMBs, RS), as shown in Figure 6. This validates the second scenario of Proposition 2.

Comparing Figures 4–6, platforms' stringent regulatory mechanisms for live streamers effectively promote non-MMBs practices. However, gaps exist in managing consumer behavior. If the platforms fail to impose sufficient penalties for consumers' "irrational behavior", or if the costs of evidence collection remains low amid high levels of herd mentality, it may trigger "irrational report-and-supervise behavior." This could lead to chaotic situations where live streamers with non-MMBs face malicious negative reviews and complaints. Therefore, platforms should adopt a dual-pronged management strategy. On one hand, they must strengthen supervision of both live streamers and consumers, increasing the penalty costs for violations to establish effective deterrence. On the other hand, they should actively guide positive herd behavior through educational campaigns

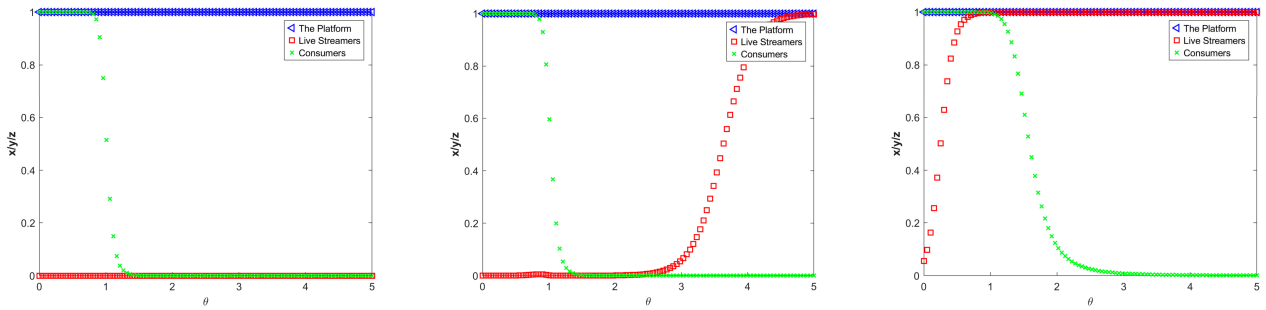
and mechanism design, encouraging rational consumer evaluations. Simultaneously, robust mechanisms for identifying and addressing malicious behavior must be established to curb malicious herd behavior and maintain a healthy, orderly platform system. This strategy directly responds to the call for measures to foster a fair, transparent, and trustworthy environment.

5.3. The Impact of Herd Mentality, Overconfidence, and Punishment on Evolutionary Stability

A reasonable level of herd mentality can effectively mobilize consumers' enthusiasm for participation in supervision, but it may also increase the self-justification costs for live streamers. Therefore, platforms need to employ herd mentality mechanisms more flexibly [57]. For instance, they can guide consumers to report and supervise live streamers engaging in MMBs and to give likes and positive reviews to those with non-MMBs by implementing measures such as visualizing the number of consumer reports in live streamers and adding visual labels like "Quality Preferred" to the live streamers with non-MMBs. Building upon existing research on punishment mechanisms and overconfidence, this study further integrates these key factors to explore the impact of herd mentality levels on the evolutionary stability of live-streaming e-commerce systems.

As demonstrated by the stability analysis above, in the supervision of live-streaming e-commerce activities, if $(\sigma + \varepsilon)R_3 - C_5 < (1 + a\theta)R_4$ and $(\sigma + \varepsilon)R_3 - (1 + a\theta)C_5 < R_4 - (1 + b\theta)C_4$ are satisfied, the evolutionary strategy of the three parties is (1,1,1) or (1,1,0). Conversely, if these conditions are not met, the evolutionary strategy becomes (1,0,1) or (1,0,0). This indicates that under the platforms' active supervision strategy, either an increase in consumer herd mentality levels or a strengthening of penalties for MMBs by live streamers will shift the stable strategies from (1, 0, 1) and (1, 0, 0) to (1, 1, 1) and (1, 1, 0). In other words, live streamers will transition from the MMB strategy to the non-MMB strategy.

By altering parameters θ and C_5, we investigate how herd behavior and punishment mechanisms influence the strategic choices of three parties in regulating live-streaming e-commerce. The parameter values are set as follows: $C_5 = \{0, 1, 2\}$, $R_1 = 6$, $R_2 = 3.1$, $R_3 = 2.5$, $R_4 = 0.9$, $R_5 = 2$, $R_6 = 1$, $R_7 = 5$, $R_8 = 4$, $C_1 = 4$, $C_2 = 3$, $C_3 = 1$, $C_4 = 0.5$, $R_3 = 2.5$, $C_7 = 2$, $\sigma = 1$, $\varepsilon = 0.2$, $\alpha = 0.7$, $a = 1$, and $b = 1.2$. The evolutionary results are shown in Figure 7.



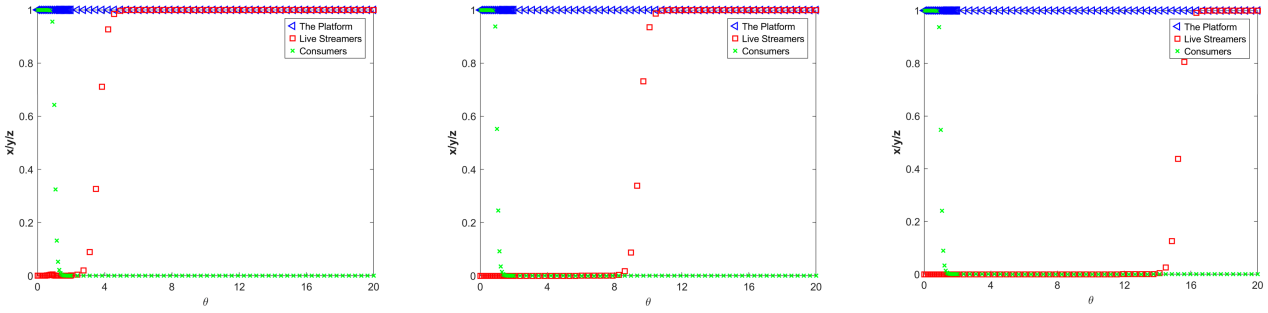
(**a**) $C_5 = 0$ (**b**) $C_5 = 1$ (**c**) $C_5 = 2$

Figure 7. The impact of values C_5 and θ on the strategies of the three parties.

As shown in Figure 7, since the net profit of active supervision exceeds zero, the platform consistently adopts the AS strategy. When the level of herd mentality is low, if it satisfies the condition $\theta < C_7/b(R_7 - R_6 - C_6)$, consumers will choose the LR strategy; when $\theta > C_7/b(R_7 - R_6 - C_6)$ is satisfied, consumers switch to the RS strategy. For live streamers, both herd mentality level and penalty severity influence strategy selection. When the severity of penalties C_5 is sufficiently low (e.g., $C_5 = 0$, shown in Figure 7a),

live streamers consistently choose the MMB strategy as θ increases. When the severity of penalties C_5 is medium (e.g., $C_5 = 1$, shown in Figure 7b), live streamers switch from an MMB strategy to a non-MMB strategy when $\theta > [(\sigma + \varepsilon)R_3 - R_4 + C_4 - C_5]/(aC_5 - bC_4)$ or $\sigma < [(1 + a\theta)C_5 - (1 + b\theta)C_4 + R_4 - \varepsilon R_3]/R_3$, as θ increases. When the severity of penalties C_5 is sufficiently high (e.g., $C_5 = 2$, shown in Figure 7c), live streamers adopt a non-MMB strategy even when consumers choose the LR strategy due to excessively high penalties.

Similarly, by altering the values of θ and σ, one can explore the impact of herd mentality and overconfidence on the strategic choices of the three parties involved in the regulation of live-streaming e-commerce. The parameter values are set as follows: $\sigma = \{1, 2, 3\}$, $R_1 = 6$, $R_2 = 3.1$, $R_3 = 2.5$, $R_4 = 0.9$, $R_5 = 2$, $R_6 = 1$, $R_6 = 1$, $R_8 = 4$, $C_1 = 4$, $C_2 = 3$, $C_3 = 1$, $C_4 = 0.5$, $C_5 = 1$, $C_6 = 3$, $C_7 = 2$, $\varepsilon = 0.2$, $\alpha = 0.7$, $a = 1$, and $b = 1.2$. With the herd mentality level as the continuous variable coordinate axis, the evolutionary results are shown in Figure 8.



(a) σ=1 (b) σ=2 (c) σ=3

Figure 8. The impact of values σ and θ on the strategies of the three parties.

As shown in Figure 8, With the gradual increase in live streamers' overconfidence levels, the threshold for consumers' herd mentality required for the live streamers to adopt the non-MMB strategy also rises accordingly. At this point, stronger external constraints must be formed through heightened consumers' herd mentality pressure. Consumers' herd mentality levels partially offset the impact of live streamers' overconfidence.

An analysis of the evolutionary stability of the live-streaming e-commerce system by focusing on key factors such as herd mentality, overconfidence, and punishment mechanisms reveals the following: when consumers generate moderate herd-supervision pressure through the platforms' evaluation system, herd behavior partially offsets the impact of live streamers' overconfidence, significantly increasing their likelihood of non-MMB strategy. However, irrational herd behavior forces live streamers into a self-justification cycle trap. For instance, when consumers make unsubstantiated accusations of MMB strategy in live-streaming e-commerce, live streamers are compelled to repeatedly provide quality inspection reports, supply chain documentation, and other evidence. Yet each piece of evidence risks being questioned as "fabricated," creating a cycle of "evidence-new questioning-further evidence." Thus, an appropriate level of herd mentality effectively boosts participation enthusiasm among all three parties and accelerates the development of a healthy system for live-streaming e-commerce.

6. Conclusions

6.1. Summary of Findings

This paper focuses on regulatory challenges in the live-streaming e-commerce environment. Considering the herd mentality and overconfidence behaviors exhibited by individuals within the live-streaming e-commerce system, we construct a tripartite evolu-

tionary game model involving "platforms–live streamers–consumers." Through this model, we delve into the mechanisms by which these behavioral traits influence the evolutionary stability of the live-streaming e-commerce system, providing theoretical and practical support for regulatory strategies. The following conclusions are obtained based on the above research.

(1) Synergistic effects of herd mentality and punishment mechanisms. When numerous consumers collectively participate in reporting and supervising, information sharing and coordinated actions can be achieved, thereby effectively reducing costs of evidence collection and enhancing reporting efficiency. However, the effectiveness of such governance is subject to nonlinear regulation by the severity of platforms' penalties. In low-penalty scenarios, rising herd mentality levels may encourage consumers to shift toward reporting and supervising. Yet, due to the absence of platform deterrence, the net benefits of MMBs for live streamers remain higher than the benefits of non-MMBs, creating a vicious cycle of "more reports to more MMBs". In medium-to-high penalty scenarios, herd behavior and platforms' penalties dynamically complement each other. When herd mentality levels surpass a critical threshold, collective consumer supervision significantly raises live streamers' self-justification costs. Combined with platforms' penalties, this forces live streamers to shift strategies.

(2) The moderating effect of herd mentality on overconfidence. Live streamers' overconfidence distorts decision-making logic by inflating false expectations of revenue; however, this impact can be dynamically offset by consumers' herd behaviors. Under low overconfidence, consumer herd behavior activates the supervision of platforms through a "signal-response" mechanism, prompting live streamers to correct cognitive biases and enabling the system to rapidly converge toward a positive equilibrium. Under high overconfidence, static penalties prove ineffective as they cannot offset live streamers' illusory profit expectations, necessitating large-scale supervision driven by herd behavior.

6.2. Managerial Implications

The claim of this paper regarding the dynamic matching between penalty intensity and herd level is supported by relevant studies on Gen-AI disclosure governance. Focusing on heterogeneous creators, these studies explore mandatory disclosure systems that rely on imperfect detection technologies and include penalties for violations as well as trust penalties. They find that the optimal law enforcement strategy of platforms undergoes phased adjustments with the development of AI technology [58], which is highly consistent with the logic emphasized in this paper that penalty intensity needs to be dynamically adapted to scenarios rather than monotonically strengthened. When the herd level is high, a large number of consumers exhibit convergent behaviors, blurring the boundary between real feedback and false interactions in terms of data characteristics and leading to a decline in detection accuracy. At this time, if the traditional approach of linearly increasing penalties is still adopted, it will not only be difficult to accurately identify violations but may also inhibit the real flow of market information by mistakenly harming normal consumers.

Based on the above conclusions, the following management recommendations are proposed.

(1) Guide live streamers and consumers to correct cognitive biases and embed fairness safeguards into the feedback system. Establish a live streamers' credit rating system that incorporates metrics such as non-MMB records and consumer complaint rates into the rating framework, with regular updates and public disclosure. Quantitative metrics should help live streamers objectively assess their capabilities and market performance, reducing overconfidence. A multidimensional product evaluation system should be developed, supplementing traditional star ratings with objective indicators like professional reviews and

third-party inspection reports to lessen consumers' reliance on single-source evaluations. In designing consumer feedback systems, mechanisms such as dynamic thresholds based on historical data distribution and manual review processes should be implemented to mitigate the risk of misjudgment. Meanwhile, a transparent appeal and error-correction mechanism should be established—for instance, by exploring the introduction of a third-party arbitration body composed of platform representatives, consumer delegates, and industry experts—to provide affected individuals with effective recourse channels, thereby forming a closed-loop safeguard encompassing ex-ante calibration and ex-post remedy.

(2) Design a dynamic penalty system with built-in anti-manipulation mechanisms. Establish a live streamers' behavior supervising system to track promotional activities, consumer feedback, and other data in real time, dynamically adjusting penalty severity. Implement a tiered penalty system with measures scaled according to the severity and impact of violations, linking penalties to live streamers' credit ratings to create long-term accountability. To address the strategic manipulation risk wherein live streamers may artificially inflate perceived herd levels through fake interactions to induce policy regimes favorable to their violations, the dynamic adjustment algorithm should, on the one hand, construct a robust indicator system resistant to manipulation—for example, identifying abnormal interactions based on long-cycle statistical indicators and introducing cross-validation of multi-dimensional behavioral features—while periodically calibrating thresholds based on operational data. On the other hand, it is necessary to guard against the risk that excessive penalties under high herd mentality levels may misjudge normal feedback. By introducing a gradient buffer design—such as setting a warning period or observation period before reaching the penalty trigger threshold to provide borderline cases with opportunities for clarification—the system can, to some extent, avoid suppressing normal market feedback through one-time excessive penalties, thereby seeking dynamic equilibrium between punishing violations and maintaining market vitality.

(3) Strengthen national-level regulatory intervention and information sharing mechanisms to systematically prevent institutional loopholes that undermine governance effectiveness. The state regulatory authorities should build a unified national database for recording the credit and violation behaviors of live streamers, platforms and other market participants in the live-streaming e-commerce industry and realize the interconnection and public disclosure of the database across platforms and regions. This national-level information disclosure mechanism can eliminate the regulatory blind spots caused by live streamers switching platforms or unethical platforms rebranding to evade punishment. Meanwhile, the state should formulate unified national-level penalty standards for misleading marketing behaviors and irregular platform operations and impose cross-platform and long-term disciplinary sanctions on illegal subjects, so as to make the benefit-penalty mechanism of the live-streaming e-commerce industry have national binding force and form a normalized and institutionalized regulatory pattern. It is worth noting that imperfect detection methods may weaken consumers' willingness to participate, distort herd levels, and consequently create room for manipulation by live streamers, while the suppression of feedback caused by excessive penalties further exacerbates information asymmetry. Therefore, beyond establishing unified information sharing and penalty standards, national-level institutional design should pay further attention to the transmission mechanisms between these risks to achieve systematic policy implementation.

This research is initially constructed based on the institutional characteristics of China's live-streaming e-commerce system. Thus, the applicability of its conclusions is subject to certain limitations when extended to heterogeneous market environments. For instance, in live-streaming markets where consumers have low willingness to participate in supervision, where scenarios exhibit weak social interaction attributes, or where there is a single

regulatory body and platforms lack strong independent governance capacity, the model and conclusions of this study cannot be directly generalized and would need to be adjusted according to local conditions. Overall, however, the core logic and regulatory insights of this study remain generalizable to other global live-streaming e-commerce markets troubled by misleading marketing behaviors and disordered digital consumption practices, thereby providing a theoretical reference for the design of their regulatory systems.

6.3. Future Research

This study constructs a tripartite evolutionary game model of platforms, live streamers and consumers to explore the regulatory strategies of live-streaming e-commerce considering dual herd mentality and overconfidence, and the research conclusions provide certain theoretical and practical references for the healthy development of the industry. However, there are still some limitations in this study, which can be further expanded and deepened in future research. First, this study focuses on the strategic interaction among three stakeholders, and future research can introduce government regulatory departments as the fourth game subject to construct a quadripartite evolutionary game model, exploring the dynamic interaction mechanism and evolutionary stability strategies among the government, platforms, live streamers and consumers, so as to make the research framework more in line with the actual regulatory practice of the live-streaming e-commerce industry. Second, the research assumptions and parameter settings in this paper are relatively generalized, and future research can combine the characteristics of different types of live-streaming e-commerce (such as commodity live streaming, service live streaming, agricultural product live streaming) to carry out targeted research and design differentiated regulatory strategies. In addition, future research can also use empirical research methods such as questionnaire survey and case analysis to verify the effectiveness of the proposed regulatory strategies, so as to further improve the practical applicability of the research conclusions.

Despite the theoretical and practical contributions of the proposed tripartite evolutionary game model, this study explicitly acknowledges an important limitation: the characterization of overconfidence and dual herd behavior remains relatively simplified and stylized. Although the belief updating mechanism has improved the behavioral realism of bounded rationality, we maintained parsimonious structural assumptions for behavioral biases to ensure model stability and analytical tractability. Consequently, the model still abstracts from the full complexity of heterogeneous psychological traits and dynamic behavioral interactions in practice. This limitation suggests that future research can enrich the behavioral foundations by incorporating more flexible and empirically grounded specifications of herd mentality and overconfidence.

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Appendix A. Convergence of Adaptive Expectations

Assume that the true strategy proportions $x(t)$, $y(t)$, $z(t)$ converge to the steady-state values x^*, y^*, and z^* as $t \to \infty$, i.e.,

$$\lim_{t\to\infty} x(t) = x^*, \lim_{t\to\infty} y(t) = y^*, \lim_{t\to\infty} z(t) = z^*.$$

Then, under the adaptive expectation mechanism, the beliefs $x_e(t)$, $y_e(t)$, and $z_e(t)$ will also converge to the same steady-state values:

$$\lim_{t\to\infty} x_e(t) = x^*, \lim_{t\to\infty} y_e(t) = y^*, \lim_{t\to\infty} z_e(t) = z^*.$$

Proof. Taking the limit of the adaptive expectation formula for $x_e(t)$:

$$\begin{aligned}\lim_{t\to\infty} x_e(t) &= \lim_{t\to\infty} [\alpha x(t-1) + (1-\alpha)x_e(t-1)] \\ &= \alpha \lim_{t\to\infty} x(t-1) + (1-\alpha) \lim_{t\to\infty} x_e(t-1).\end{aligned}$$

□

Let $\lim_{t\to\infty} x_e(t) = x_e^*$. Since $\lim_{t\to\infty} x(t-1) = x^*$, we have:

$$x_e^* = \alpha x^* + (1-\alpha) xe^*.$$

Rearranging gives $\alpha x_e^* = \alpha x^*$. Since $\alpha \in (0,1)$, we obtain $x_e^* = x^*$. The proofs for $y_e^* = y^*$ and $z_e^* = z^*$ are identical.

In the steady state, the beliefs x_e, y_e, and z_e are equivalent to the true strategy proportions x, y, and z. Therefore, when analyzing the stable points of the system, only the true strategy proportions x, y, and z are necessary to characterize the equilibrium, as the beliefs have converged to them. This justifies the use of x, y, and z (instead of x_e, y_e, and z_e) in the stability analysis of the main text.

Appendix B. Robustness Analysis

Here, to verify the robustness of the proposed tripartite evolutionary game model and the reliability of simulation results, a robustness check is conducted by modifying the functional form of the consumer herd mentality coefficient θ. Specifically, the original linear form of θ is replaced with its quadratic nonlinear form θ^2, while all other parameter definitions, value settings, and simulation conditions remain consistent with the main text to ensure the comparability of experimental results.

The parameter values are set as follows:

$C_5 = \{0,1,2\}$, $R_1 = 6$, $R_2 = 3.1$, $R_3 = 2.5$, $R_4 = 0.9$, $R_5 = 2$, $R_6 = 1$, $R_7 = 5$, $R_8 = 4$, $C_1 = 4$, $C_2 = 3$, $C_3 = 1$, $C_4 = 0.5$, $C_6 = 3$, $C_7 = 2$, $\theta = 1$, $\varepsilon = 0.2$, $\alpha = 0.7$, $a = 1$, and $b = 1.2$.

$\sigma = \{1,2,3\}$, $R_1 = 6$, $R_2 = 3.1$, $R_3 = 2.5$, $R_4 = 0.9$, $R_5 = 2$, $R_6 = 1$, $R_7 = 5$, $R_8 = 4$, $C_1 = 4$, $C_2 = 3$, $C_3 = 1$, $C_4 = 0.5$, $C_5 = 1$ $C_6 = 3$, $C_7 = 2$, $\varepsilon = 0.2$, $\alpha = 0.7$, $a = 1$, and $b = 1.2$.

The evolutionary results are shown in Figure A1.

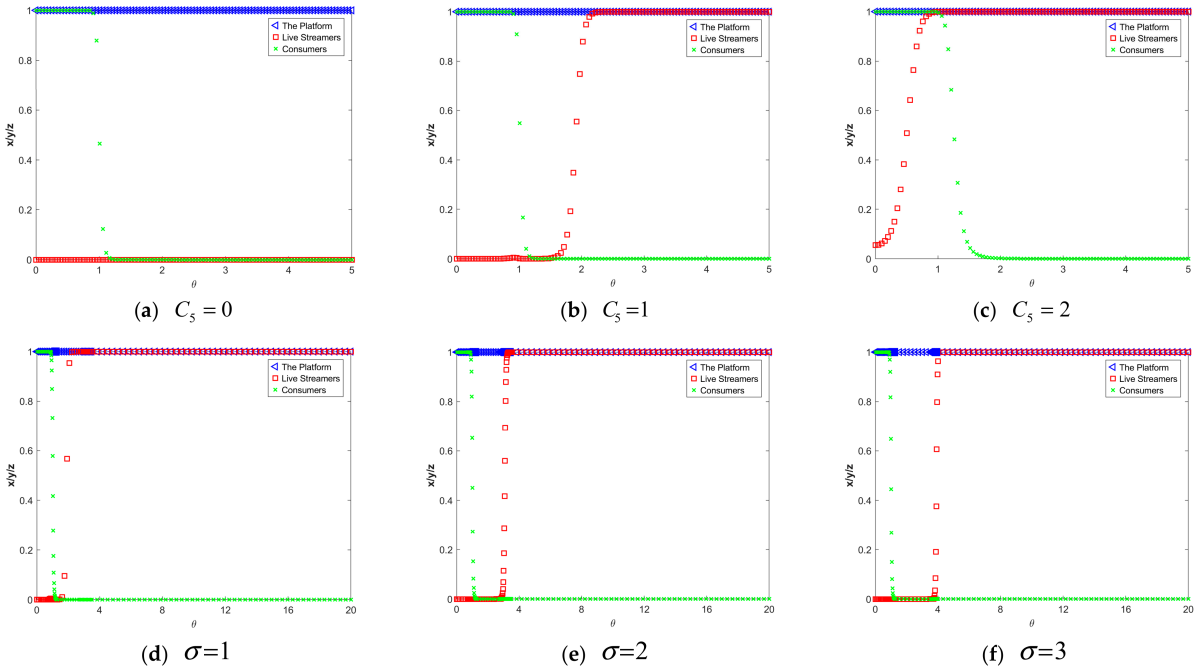

Figure A1. System evolution under secondary nonlinear θ scenarios.

The robustness check results show that after replacing the linear θ with the nonlinear θ^2, the evolutionary trend and stable equilibrium state of the tripartite game strategies remain unchanged. Only the convergence speed of the evolutionary strategies has a slight non-substantive adjustment, which is caused by the nonlinear amplification of the herd mentality effect. This result fully verifies the robustness of the model: the evolutionary mechanism of the live-streaming e-commerce regulatory system revealed by the model has general validity.

Appendix C. Data Availability Statement

The complete MATLAB code (including benchmark simulations, robustness check with nonlinear θ^2 specification, and additional parameter sensitivity analyses) is not included in the manuscript due to the length. The authors will gladly provide the full, runnable code to researchers interested in replicating the results upon request via email.

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