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Optimizing film and television advertising placement strategies in the digital media ecosystem: a study based on a three-party stochastic evolutionary game

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With the acceleration of digitalization, digital media and streaming platforms have driven the rapid development of advertising placement business models in the film and television industry. Producers increasingly depend on advertising revenue, advertisers prioritize return on investment, and viewers' grow more resistant to advertising interruptions, intensifying the tension among stakeholders. Most existing studies focus on bilateral relationships and neglect the strategic behavior of viewers, which limits their ability to explain persistent cooperation failures in real-world advertising ecosystems. To address this, this study develops a three-party stochastic evolutionary game model involving film producers, advertisers, and viewers, incorporating key variables such as advertising dissemination effectiveness, content quality, and advertising costs to simulate strategy evolution under uncertainty. Simulation results indicate that improving content quality from 100 to 200 increases viewers' ad acceptance from 0.32 to 0.84 and raises producer cooperation willingness by more than 70 percent. In contrast, when embedded advertising costs rise from 100,000 to 500,000 RMB, cooperation willingness among both producers and advertisers drops below 0.1. While increased returns from inserted ads may briefly raise producer engagement, they have minimal effect on viewers' acceptance and tend to destabilize the system. This study identifies a structural mismatch in stakeholder incentives and introduces a dynamic modeling approach that captures nonlinear interactions and adaptive behavior using continuous strategies and stochastic disturbances. The findings suggest that technical improvements or revenue redistribution alone are insufficient to ensure sustainable cooperation. Enhancing content quality is the only effective lever for aligning stakeholder interests, breaking low-cooperation equilibria, and promoting long-term system stability, offering both theoretical contributions and practical guidance for platform governance and advertising strategy design.

KEYWORDS

stochastic evolutionary game, film and television advertising, digital media ecosystem, advertising strategy optimization, multi-agent interaction

1 Introduction

With the accelerating global digitalization, the rise of digital media and streaming platforms worldwide has profoundly transformed the revenue model of the film and television industry. Advertising placement—defined in this study as both embedded advertising (e.g., product placements integrated into plots) and inserted advertising (e.g., pre-roll or mid-roll commercials)—has emerged as a crucial commercialization path, serving not only as a stable source of income for film producers and advertisers but also as a key mechanism linking content, users, and brands (Pardo, 2013). Compared to traditional linear broadcasting, digital platforms operate within algorithm-driven ecosystems where advertising strategies are shaped by user engagement, personalization algorithms, and real-time feedback. Technologies such as artificial intelligence and big data have enabled increasingly precise, contextual, and personalized ad placements (Hallur et al., 2021). From conventional inserted ads and plot-integrated product placements to emerging forms such as interactive, shoppable, and virtual reality-based advertising, the growing array of ad formats has expanded monetization opportunities for advertisers and introduced new commercial models for film producers (Nyarko, 2023). Meanwhile, viewers' acceptance of ads and demands for content quality have also been continuously rising, posing greater challenges to the formulation and implementation of advertising strategies (Hashim et al., 2018).

Despite the revenue opportunities created by diverse advertising formats, balancing advertising revenue and experience remains a pressing issue. In practice, film producers often face a dilemma: on one hand, high-intensity ad placements may deteriorate viewers' experience, leading to negative emotions and lower viewership; on the other hand, overly conservative advertising strategies may result in insufficient advertising revenue, limiting the commercial development potential of film producers (Vadakkepatt et al., 2022). Although game-theoretic approaches have been widely used to study advertising strategy, existing research has key limitations. First, most models adopt static or simplified bilateral structures, typically modeling interactions between advertisers and platforms while neglecting the producer–viewers–advertiser triad (An and Kang, 2014). Second, models often assume fixed or one-shot strategies and overlook long-term adaptive behavior, making them ill-suited to capture how strategies evolve in response to feedback. Third, few studies incorporate environmental uncertainty, bounded rationality, or trial-and-error learning, all of which are prevalent in real-world digital advertising contexts. As a result, standard models fall short of capturing the dynamic and stochastic nature of strategic evolution in modern digital ecosystems—where viewers' preferences shift unpredictably, platforms alter algorithmic rules, and producers face uncertain returns on ad decisions. To better reflect these realities, this study develops a stochastic evolutionary game model that explicitly incorporates film producers, advertisers, and viewers as strategic agents. Random perturbations are introduced to simulate behavioral noise and market uncertainty, allowing for a more realistic representation of long-term strategic adjustment.

This model captures how all three stakeholders dynamically balance advertising revenue, content quality, and viewers' satisfaction over time. Furthermore, a series of numerical simulations and sensitivity analyses, based on empirically grounded parameters, are conducted to explore how variables such as dissemination effectiveness, ad format costs, and content quality influence system behavior and strategic outcomes. The findings reveal two key insights. First, improvements in ad effectiveness and content quality significantly boost producer–advertiser cooperation and viewers' tolerance for ads, while rising ad costs suppress strategic engagement. Second, viewers are highly sensitive to content quality but relatively indifferent to ad format innovations—suggesting that improving content is more effective than relying solely on ad format optimization. These insights offer a more nuanced understanding of advertising strategy under uncertainty and inform both content producers and policymakers on how to design sustainable, viewer-centered monetization models.

The structure of this paper is as follows: Section 1 introduces the research background, problem statement, and research framework; Section 2 reviews related literature on advertising strategies in film and television, including ad formats and their strategic implications; Section 3 provides a detailed explanation of the model construction, parameter settings, and methodological choices; Section 4 focuses on sensitivity analysis and results discussion, examining the dynamic evolutionary impacts of various external parameters on the strategies of the three parties and revealing optimal advertising strategies under different market conditions; Section 5 presents the conclusions and policy implications, summarizing the main findings, offering policy recommendations for optimizing advertising strategies, and proposing directions for future research.

2 Literature review

With the rapid development of digital media, advertising placement has become increasingly critical in the film and television industry. Existing literature has provided valuable theoretical foundations in three major areas: advertising effects and viewers' behavior, mathematical models for advertising strategy, and evolutionary game-theoretic approaches for multi-agent interaction. However, few studies integrate these perspectives into a unified framework capable of modeling the dynamic and stochastic nature of advertising decisions. This section systematically reviews relevant work in each area and outlines the research gap addressed by this study.

2.1 Advertising effects and viewers' behavior: behavioral foundations for strategy modeling

A growing body of research has examined how advertising format, content integration, and contextual relevance shape viewers' perception and ad effectiveness. Studies consistently find that embedded advertising—particularly when aligned with narrative structure—is perceived as less intrusive and more persuasive than inserted ads. For instance, Jin and Villegas (2007) demonstrated that product placements integrated with humor and plot consistency significantly enhanced brand attitudes. Similarly, Pompper and Choo (2008) highlighted that subtle product placement strategies are particularly effective among younger demographics. More recent findings by Wu et al. (2020) confirm that narrative congruence enhances both recall and brand favorability.

In strategy modeling, this behavioral agency has led to growing interest in how viewers' tolerance can be treated as an endogenous decision variable. For example, Liu et al. (2021) propose a utility-based framework in which ad exposure is evaluated against personal disruption thresholds. Other studies have modeled behavioral feedback loops, where excessive advertising not only lowers content satisfaction but leads to adaptive resistance behaviors, altering future engagement (Pahari et al., 2024; Pavlou and Stewart, 2000). Some simulation-based approaches, particularly in adaptive systems, attempt to capture the evolution of viewers' tolerance as a function of content relevance, ad load, and delivery context (Cesar and Chorianopoulos, 2009).

This line of research highlights the importance of treating viewers' behavior not as a static parameter but as an adaptive process influenced by content quality, ad delivery, and user context. However, most existing models stop at describing behavioral responses rather than embedding them within formal strategic interactions. As a result, they fall short in guiding actionable advertising strategies that balance economic returns with viewers' experience.

2.2 Mathematical models for advertising strategy optimization: methods and limitations

Mathematical modeling has long played a central role in advertising strategy optimization. Prior studies have developed a variety of tools—such as dynamic programming (Khalilzadeh et al., 2021), integer linear programming (Alipour-Vaezi et al., 2022), and reinforcement learning (Lou et al., 2021) to support decisions around budget allocation, ad timing, and format selection. In recent years, game theory has gained prominence for its ability to model strategic interactions and adaptive behavior. While traditional game-theoretic models often focus on advertiser–platform dynamics (Zhou et al., 2025; Huang and Yu, 2021), newer studies have begun to incorporate content producers as independent agents, highlighting the trade-offs they face among advertising revenue, viewers' satisfaction, and platform constraints (Hödl and Myrach, 2023). In platform-driven media environments, producers must navigate algorithmic exposure, revenue-sharing rules, and viewers' feedback. This creates ongoing tension between monetization through ad integration and maintaining content appeal (Bhargava, 2022). The pressure is especially acute on short-video platforms, where creators frequently restructure narratives to accommodate sponsors—behavior that traditional static models often fail to capture (Tandberg, 2022).

Despite these advances, existing models share several key limitations. Most are built on bilateral structures, typically modeling advertisers and platforms while excluding content producers or viewers as strategic agents. Viewers' response is usually treated as a fixed input—such as click-through rate or conversion probability—rather than as a behavior shaped by evolving content quality and ad experience (Kim et al., 2021). In addition, the assumption of deterministic and static environments makes these models poorly equipped to handle the uncertainty and volatility inherent in digital media ecosystems (Liu et al., 2021). Finally, the use of discrete or binary strategy spaces often fails to capture the continuous, adaptive nature of real-world advertising decisions, such as partial product integration or variable ad intensity (Alipour-Vaezi et al., 2022).

These limitations constrain the ability of traditional models to explain long-term cooperation breakdowns, shifting user tolerance, or feedback-driven strategy evolution. To address these issues, it is necessary to move beyond static optimization and toward models that integrate multi-agent learning, adaptive decision-making, and system-level dynamics.

2.3 Evolutionary game theory and multi-agent interaction: methodological extensions and gaps

To model strategic interactions in dynamic and uncertain advertising environments, this study adopts a stochastic evolutionary game framework. Unlike classical game theory, which assumes fixed preferences and fully rational agents, evolutionary games simulate how strategy distributions shift over time as agents adapt based on observed outcomes and bounded rationality (Sun et al., 2022). This is especially relevant in digital advertising, where producers, advertisers, and viewers repeatedly adjust decisions based on content performance, user feedback, and algorithmic changes. A key advantage of this approach lies in its ability to incorporate stochastic disturbances—random shocks that reflect real-world uncertainties such as platform policy shifts, viewers' sentiment volatility, and ad performance fluctuations. These factors directly influence each party's decision process and can destabilize cooperation, making deterministic models inadequate.

Stochastic evolutionary game models have been successfully applied in various domains that share key structural features with digital advertising systems. In platform economics, Cao et al. (2024) modeled dynamic pricing competition among algorithm-driven service providers, capturing how strategies evolve under information asymmetry and user feedback loops. In environmental policy, Qi and Han (2023) examined carbon quota strategies among firms, showing how regulatory uncertainty and peer influence shape long-term behavior adaptation. In transportation, Ahmad et al. (2023) used evolutionary games to analyze route choice and congestion under stochastic traffic conditions. In cybersecurity, Hu et al. (2024) simulated multi-agent defense strategies evolving against uncertain threats.

These applications illustrate the framework's capacity to model multi-agent, feedback-driven, and uncertainty-sensitive systems—conditions that mirror the strategic environment of online advertising, where advertisers, producers, and viewers interact repeatedly under evolving content, market, and platform conditions. The flexibility of stochastic evolutionary games in capturing continuous strategy adjustment, cooperation breakdown, and dynamic stabilization makes them particularly well-suited for this research. In our context, the tripartite structure, continuous strategy space (e.g., ad integration level, viewers' tolerance), and mutual influence among agents call for a modeling approach that captures gradual adaptation, feedback sensitivity, and systemic volatility. Stochastic evolutionary games offer a flexible foundation for exploring how cooperative or unstable outcomes emerge—not just from isolated choices, but from ongoing, interdependent strategy evolution.

In summary, existing research on advertising strategy tends to simplify system structure and agent behavior. Most models focus on advertiser–platform dynamics, treating viewers as passive or fixed-response entities, and often assume static, deterministic environments. These limitations make it difficult to capture the evolving, feedback-driven nature of cooperation in digital advertising. To overcome these gaps, this study adopts a stochastic evolutionary game framework that models producers, advertisers, and viewers as adaptive, interacting agents. By incorporating continuous strategies, behavioral feedback, and environmental uncertainty, the model better reflects real-world dynamics. This approach has proven effective in similar multi-agent systems such as platform pricing, carbon trading, and supply chain coordination. It offers the flexibility needed to analyze how advertising strategies evolve—and sometimes collapse—under complex, uncertain conditions.

3 The model

3.1 Model assumptions

Assumption 1: The decision variable of film producers $a \in [0,1]$ is a continuous variable representing the proportion of advertising placement. Specifically, a indicates the proportion of embedded advertising: a value closer to 1 means that film producers are inclined to embed more ads within the plot (e.g., product placements, brand appearances), which tends to be more subtle and has less impact on the viewing experience but requires a high level of content integration. Conversely, $1-a$ represents the proportion of inserted ads: a value closer to 1 indicates a preference for inserted ads (e.g., pre-roll ads, mid-roll ads) to generate advertising revenue. This type of ad is more direct but tends to have a more negative impact on the viewing experience. The strategy implies that film producers must balance between advertising revenue and viewers' experience. If a approaches 1, it suggests that producers prioritize content placement for ad revenue while maintaining content integrity and viewing experience. If a approaches 0, it implies that producers focus more on short-term ad revenue at the expense of viewers' experience.

The decision variable of advertisers $b \in [0,1]$ is also a continuous variable, representing the level of advertising investment. Specifically, b indicates the intensity of ad investment: a value closer to 1 means that advertisers allocate more funds and resources to advertising, including larger-scale ad production and broader distribution channels. This generally leads to higher ad coverage and conversion rates but also involves higher advertising costs. A value closer to 0 suggests a conservative strategy, with lower investment, possibly focusing on targeted small-scale campaigns or low-cost ad formats. Advertisers need to balance advertising effectiveness and investment costs. If b approaches 1, advertisers aim to achieve higher exposure and market conversion through intensive ad placement. If b approaches 0, it suggests that advertisers prioritize cost control to reduce investment risks.

The decision variable of viewers $c \in [0,1]$ represents their level of ad acceptance. Specifically, ccc indicates the degree of ad tolerance: a value closer to 1 implies that viewers have a higher tolerance for ads, are willing to watch more ad content (whether embedded or inserted), and either accept ads well or perceive a strong connection between ads and content. A value closer to 0 suggests strong resistance to ads, with viewers preferring to skip ads or use ad-blocking tools to minimize ad interference with their viewing experience. The level of ad acceptance depends on ad format, content quality, and individual preferences. If c approaches 1, viewers are more willing to accept ads; if c approaches 0, viewers are less tolerant of ads and more sensitive to ad interference.

Assumption 2: In the process of content creation, film producers must weigh multiple competing factors, including advertising revenue, viewers' reputation, and production costs. The model assumes that embedded advertising and inserted advertising differ significantly in terms of their effects on viewers' experience and advertising efficiency. Young viewers tend to skip overt commercial interruptions but are more likely to recall brands when the placement is subtly integrated into the program content, highlighting the advantage of low-disruption integration. However, excessive product placement can lead to viewer's fatigue and reduce overall content appeal, emphasizing the need for producers to strike a balance between advertising integration and viewers' experience (Song et al., 2015). On one hand, producers can generate revenue through embedded advertising, which typically requires seamlessly incorporating brands or products into the storyline to ensure natural alignment with the narrative. The revenue from embedded advertising depends on the advertisers' investment intensity b, the number of embedded ads N_{ad1}, and viewers' acceptance of advertising ccc. Since embedded ads do not interrupt the viewing flow, their immediate negative impact on viewers' retention is relatively minimal. However, if the integration is forced or overly concentrated, it may still diminish viewers' satisfaction and trigger negative feedback, potentially resulting in viewer loss. Moreover, embedded ads are often prepaid through sponsorship arrangements and can generate sustained brand exposure over the long term. Some studies show that well-executed brand placements in high-quality films can continue to yield advertising effects even years after the initial release (Wilbur et al., 2009). On the other hand, producers may choose inserted advertising, which is more direct and typically placed at the beginning or in the middle of episodes. The resulting revenue depends on advertisers' investment intensity b, the total duration of inserted ads T_{ad2}, and the viewers' tolerance for ad interruptions $1-c$. Compared to embedded ads, inserted ads are more disruptive. Empirical evidence shows that for every 10% increase in ad duration, the real-time viewer's retention rate drops by an average of 15% (Wilbur et al., 2009). Inserted ads are usually priced by time slot, with revenue closely tied to actual viewership. Integrating brands into entertainment content can offer significant economic returns to producers, as successful product placements in films have been linked to increased revenue (Karniouchina et al., 2011). However, other studies have reported that overly conspicuous placements can impair viewers' enjoyment and effectively compromise narrative quality for commercial purposes (Cowley and Barron, 2008). Additionally, producers' reputation-related benefits are closely tied to the quality of the content Q_{content}, which may be negatively affected by a high proportion of ad integration that weakens narrative coherence and viewers' perception. Increasing the number of embedded ads also raises production costs, including the base production cost C_0 and additional integration-related costs C_{ad1}. Accordingly, the revenue function for film producers is defined as Equation 1:

$$U_P = abN_{\text{ad1}}c + (1-a)bT_{\text{ad2}}(1-c) + Q_{\text{content}}(1-a)c - (C_0 + aC_{\text{ad1}}) \tag{1}$$

Assumption 3: When placing advertisements, advertisers primarily focus on maximizing returns by improving conversion effectiveness while controlling placement costs. Empirical studies and industry reports indicate that increasing advertising investment can significantly enhance brand awareness and purchase intention. For instance, effective product placements can increase brand recall by approximately 20% and improve both consumer favorability and purchase likelihood (Hustle, "The Economics of Movie Product Placements"). Specifically, the advertiser's conversion revenue depends on three factors: the advertising investment intensity b, the viewers' ad acceptance level ccc, and the average revenue from a single conversion V_{conv}. While raising the investment intensity b can increase coverage and exposure, it also escalates overall costs. The complexity arises because different advertising formats—embedded versus inserted—entail distinct cost structures and effectiveness profiles. Embedded ads typically involve in-depth collaboration with content creators and require storyline integration. These formats incur high upfront negotiation and integration costs, but provide long-lasting exposure and are inherently "unskippable." In contrast, inserted ads such as pre-roll or mid-roll commercials are priced flexibly based on slot duration and frequency but are more susceptible to being skipped by viewers, potentially undermining their effectiveness. Evidence suggests that well-integrated product placements—particularly those embedded prominently within film narratives—can lead to positive stock market reactions for the advertised brands, reflecting tangible value creation (Karniouchina et al., 2011). Moreover, recent research shows that campaigns combining embedded and traditional ads result in the highest levels of consumer recall and purchase intent, demonstrating both the benefits and the strategic complexity of dual-format investment (Williams et al., 2011). Current industry trends also indicate a notable shift in advertiser preferences. Global spending on embedded advertising surpassed \$23 billion in 2021, growing by 14% year-on-year, while many brands simultaneously reported plans to cut budgets for traditional TV and print ads (From StackExchange). This shift highlights the increasing prioritization of content-integrated advertising strategies that offer greater engagement and long-term return on investment. Advertisers' placement costs are thus divided into two components: (1) the cost of embedded advertising C_{ad1}, and (2) the cost of inserted advertising C_{ad2}. These costs are dynamically adjusted based on the advertiser's allocation strategy across the two formats. Accordingly, advertisers' revenue is influenced not only by the level of viewers' ad acceptance but also by the film producer's choice of advertising format (i.e., the proportion of embedded ads a). The advertiser's revenue function is therefore defined as Equation 2:

$$U_A = bcV_{\text{conv}} - b\left(aC_{\text{ad1}} + (1-a)C_{\text{ad2}}\right) \tag{2}$$

Assumption 4: When watching films or television content, viewers derive utility primarily from the quality of the content and incur disutility from advertising interruptions. As viewers seek an immersive narrative experience, their positive utility is influenced by both the inherent content quality Q_{content} and the proportion of non-disruptive storytelling, which is inversely related to the embedded ad ratio $1-a$. When embedded advertising is used sparingly, the viewing experience remains natural and uninterrupted, enhancing content enjoyment. Viewers' tolerance toward advertising (c) also moderates this effect, as individuals with higher acceptance levels tend to perceive ad-integrated content more positively. However, viewers are simultaneously subject to the negative utility caused by advertising, which includes both embedded and inserted formats. Intrusive advertisements—such as those that are frequent or highly disruptive—can frustrate viewers and diminish their content enjoyment, making ad intrusiveness a critical determinant of viewers' utility. Moreover, ad tolerance is highly heterogeneous across individuals; different viewers display varying thresholds of acceptance toward advertising content (Song et al., 2025). The negative utility of advertising is composed of two parts: (1) the disutility from embedded ads, denoted by D_{ad1}, and (2) the disutility from inserted ads, denoted by D_{ad2}. The impact of these disutilities is modulated by the viewers' ad acceptance level ccc: higher tolerance leads to lower perceived interference, whereas low tolerance amplifies ad-related annoyance. When ad exposure exceeds a viewers' tolerance threshold, they are likely to adopt avoidance strategies—such as skipping, muting, or using ad blockers—which undermines advertisers' intended reach. Conversely, when a viewer has a high level of ad acceptance ($c \to 1$), they may be more willing to tolerate inserted ads, refrain from skipping, or even engage with well-integrated embedded ads if they align with the storyline. In such cases, the viewers' overall utility is more strongly driven by content quality, and the disutility from ads becomes secondary. The model thus captures this behavioral trade-off through the parameter c, which reflects how viewers balance content value against advertising irritation. When content is compelling and ads are minimally disruptive, viewers are more tolerant; when ads overwhelm the content, utility drops sharply, prompting avoidance behavior. Indeed, empirical studies support this avoidance tendency: in environments where ad skipping is enabled, up to 90% of digital video recorder users choose to fast-forward through commercial breaks, underscoring the critical importance of maintaining acceptable ad loads. Accordingly, the viewers' utility function is defined as Equation 3:

$$U_V = Q_{\text{content}}(1-a)c - \left(aD_{\text{ad1}} + (1-a)D_{\text{ad2}}\right)(1-c) \tag{3}$$

3.2 Stochastic evolutionary game model

The evolutionary game model serves as a powerful tool for dynamic game analysis, particularly well-suited for capturing the strategic evolution of multiple agents over time. It is especially applicable to scenarios involving boundedly rational actors who continuously adjust and optimize their strategies through learning and imitation in repeated interactions. Compared with traditional static game models, evolutionary game theory not only focuses on equilibrium outcomes but also emphasizes how strategies evolve and stabilize dynamically, providing strong theoretical support for understanding complex behavioral mechanisms in multi-agent systems.

However, the standard evolutionary game model, typically based on replicator dynamics, assumes a deterministic strategy update process driven solely by payoff differences. This assumption overlooks a wide range of uncertainties in real-world environments, such as market volatility, policy fluctuations, algorithmic changes on platforms, perceptual biases, and behavioral heterogeneity among participants. In the context of film and television advertising, these uncertainties are particularly prominent, as film producers, advertisers, and viewers are all influenced by sudden events, incomplete information, and non-rational behavior. As a result, the standard model may exhibit rigid dynamic structures, lack responsiveness, and fail to reproduce the actual paths of strategic evolution observed in practice.

To address these limitations, it is necessary to adopt a stochastic evolutionary game model, which incorporates stochastic disturbance terms into the traditional replicator dynamics framework. This model captures both external environmental fluctuations and internal behavioral randomness, thereby providing a more realistic depiction of strategic volatility, stage-wise evolution, and nonlinear responses. By constructing stochastic differential equations with drift and diffusion terms, the model enhances realism and analytical power, allowing for further exploration of system stability and policy optimization under uncertainty.

In the context of advertising placement in the film and television industry, the interactions among film producers, advertisers, and viewers are inherently dynamic and uncertain, making them well-suited for analysis using a stochastic evolutionary game model. This model describes how each party updates its strategy over time, while also accounting for the influence of random factors such as changing market conditions, shifting regulations, and fluctuating individual preferences. Specifically, film producers, advertisers, and viewers adopt continuous strategies—advertising embedding ratio, advertising investment intensity, and ad acceptance level, respectively—and continuously adjust their choices in pursuit of higher payoffs.

The model is built upon a set of assumptions: film producers aim to optimize the format and proportion of ads to balance revenue generation and viewers' reputation; advertisers seek to maximize return on investment by weighing ad conversion effectiveness against placement costs; and viewers make trade-offs between viewing experience and advertising disruption. To realistically simulate the uncertainty in strategy adjustment, the model integrates replicator dynamics with stochastic disturbances. This hybrid framework enables the characterization of strategy evolution patterns and the identification of evolutionarily stable strategies and equilibrium characteristics under different conditions. The following sections present detailed modeling of the strategy update mechanisms and dynamic evolution paths of the three stakeholders.

This study assumes that the probability density functions of the decision variables for film producers, advertisers, and viewers are $f(a), f(b), f(c)$, respectively. These functions objectively reflect the gradual changes in the effort levels of the three parties' strategies during the evolutionary process. To model randomness in the evolution process, a stochastic disturbance term B_t is introduced, where: $\forall s,t>0, B_{s+t}-B_t \sim N(0,t)$ This term represents accumulated noise following a Brownian motion process. The stochastic replicator dynamics are further modified by incorporating disturbance terms of the form: $f(a)(1-f(a))dB_t, f(b)(1-f(b))dB_t$ and $f(c)(1-f(c))dB_t$. These expressions reflect the intensity of random fluctuations experienced by each party as a function of their current strategic distribution. The introduction of these stochastic components is crucial for capturing the complex, dynamic, and often unpredictable nature of real-world decision-making in the advertising ecosystem. In practice, the strategies of film producers, advertisers, and viewers are not shaped solely by deterministic payoff-driven logic, but are constantly influenced by a wide range of exogenous uncertainties. For instance, producers' and advertisers' strategies are frequently disrupted by volatile market trends, such as sudden shifts in viewers' sentiment, the viral popularity of competing content, or changes in platform visibility algorithms. These fluctuations may cause abrupt reassessments of advertising effectiveness or content integration strategies. Similarly, external factors such as evolving regulations, content moderation policies, or sudden shifts in platform monetization models introduce discontinuous and often unpredictable impacts on payoff structures. On the consumer side, viewers' preferences and tolerance toward advertising are inherently unstable—subject to emotional states, social influences, and exposure fatigue—resulting in significant behavioral noise and heterogeneity in acceptance levels. Traditional replicator dynamics assume a smooth and deterministic adaptation process, which fails to account for such irregular and non-linear variations. By embedding stochastic disturbance terms into the evolutionary dynamics, the model is able to represent both continuous strategic learning and the irregular shocks introduced by external and behavioral volatility. This enables a more realistic simulation of how strategies evolve over time under the influence of dynamic environments, noise-driven learning, and information asymmetry, making the model more robust and suitable for analyzing real-world multi-agent interactions.

By incorporating these terms, the stochastic evolutionary game model not only depicts the gradual changes in strategies but also simulates the dynamic influence of external environments and incidental factors on strategy evolution.

Based on the assumptions in Section 3.1, given the decisions a, b, and c by film producers, advertisers, and viewers, the expected net payoffs for the three parties are represented as Equations 4–6:

$$EA(a)=\int_0^1\int_0^1\begin{bmatrix} abN_{\mathrm{ad1}}c+(1-a)bT_{\mathrm{ad2}}(1-c) \\ +Q_{\mathrm{content}}(1-a)c-(C_0+aC_{\mathrm{ad1}}) \end{bmatrix} f(b)\,f(c)\,\mathrm{d}b\mathrm{d}c \tag{4}$$

$$EB(b)=\int_0^1\int_0^1\left[bcV_{\mathrm{conv}}-b\left(aC_{\mathrm{ad1}}+(1-a)C_{\mathrm{ad2}}\right)\right] f(a)\,f(c)\,\mathrm{d}a\mathrm{d}c \tag{5}$$

$$EC(c)=\int_0^1\int_0^1\begin{bmatrix} Q_{\mathrm{content}}(1-a)c \\ -\left(aD_{\mathrm{ad1}}+(1-a)D_{\mathrm{ad2}}\right)(1-c) \end{bmatrix} f(a)\,f(b)\,\mathrm{d}a\mathrm{d}b \tag{6}$$

Thus, the average expected payoffs for film producers, advertisers, and viewers are represented as Equations 7–9:

$$\overline{EA}=\int_0^1\int_0^1\int_0^1\begin{bmatrix} abN_{\mathrm{ad1}}c+(1-a)bT_{\mathrm{ad2}}(1-c) \\ +Q_{\mathrm{content}}(1-a)c-(C_0+aC_{\mathrm{ad1}}) \end{bmatrix} f(a)\,f(b)\,f(c)\,\mathrm{d}b\mathrm{d}c\mathrm{d}a \tag{7}$$

$$\overline{EB}=\int_0^1\int_0^1\int_0^1\left[bcV_{\mathrm{conv}}-b\left(aC_{\mathrm{ad1}}+(1-a)C_{\mathrm{ad2}}\right)\right] f(a)\,f(b)\,f(c)\,\mathrm{d}a\mathrm{d}c\mathrm{d}b \tag{8}$$

$$\overline{EC}=\int_0^1\int_0^1\int_0^1\begin{bmatrix} Q_{\mathrm{content}}(1-a)c \\ -\left(aD_{\mathrm{ad1}}+(1-a)D_{\mathrm{ad2}}\right)(1-c) \end{bmatrix} f(a)\,f(b)\,f(c)\,\mathrm{d}a\mathrm{d}b\mathrm{d}c \tag{9}$$

In the process of dynamic strategy evolution, we can use differential equations to describe the rate of strategy change. Considering the presence of stochastic disturbance factors, the strategy evolution of film producers, advertisers, and viewers is influenced not only by differences in payoffs but also by random fluctuations. Therefore, it is necessary to define replicator dynamic equations with stochastic disturbance terms for each party.

Next, we present the stochastic replicator dynamic equations for film producers, advertisers, and viewers, which describe the dynamic rates of change in strategy choices for each party and demonstrate the impact of stochastic disturbances on strategy evolution, as Equations 10–12:

$$df(a,t)=f(a)\left[EA(a)-\overline{EA}\right]dt+\left[1-f(a)\right]f(a)\mathrm{d}B_t \tag{10}$$

$$df(b,t) = f(b)\left[EB(b) - \overline{EB}\right]\mathrm{d}t + \left[1 - f(b)\right]f(b)\mathrm{d}B_t \tag{11}$$

$$df(c,t) = f(c)\left[EC(c) - \overline{EC}\right]\mathrm{d}t + \left[1 - f(c)\right]f(c)\mathrm{d}B_t \tag{12}$$

However, the replicator dynamic equation is not a simple partial differential equation but rather a stochastic differential equation with a stochastic disturbance term. This equation belongs to the class of nonlinear stochastic differential equations, making the solution process quite complex. Nonetheless, under certain preconditions, the solution to this stochastic differential equation can be proven to exist and be unique. Additionally, it is essential to further investigate the fundamental properties of the solution, such as the zero stability of the equilibrium state, as this is crucial for analyzing the stability of system evolution.

To analyze the stability of the equilibrium solution in the stochastic evolutionary game model, it is first necessary to ensure that the solution to the stochastic differential equation is both existent and unique under given conditions. For a general form of the stochastic differential equation $dX(t) = b(t, X(t))dB_t + \sigma(t, X(t))$, which includes the drift term $b(t, X(t))$, the diffusion term $\sigma(t, X(t))$, and the effect of the stochastic disturbance term B_t, the sufficient conditions for the existence and uniqueness of the solution are:

(1) Measurability Condition: The drift term $b(t, X(t))$ and the diffusion term $\sigma(t, X(t))$ must be bivariate measurable functions and square-integrable.
(2) Lipschitz Condition: There must exist a constant K such that the drift and diffusion terms satisfy Lipschitz continuity, which is a common condition to ensure the uniqueness of the solution.
(3) Linear Growth Condition: The growth of the drift and diffusion terms should not exceed the bounds of a linear function, ensuring the stability and finiteness of the solution.
(4) Initial Condition: The state variable $X(t)$ must be measurable concerning the initial moment and have a finite expected value.

If the above conditions are satisfied, the solution $X(t)$ to the stochastic differential equation exists, is unique, and has finite expectation within the range of t, i.e.,

$$\forall 0 \le s \le T, E\left[X^2(t)\right] < \infty \tag{13}$$

In this paper, to analyze the replicator dynamic equation for film producers, the drift term and diffusion term are defined as Equations 14, 15:

$$b(t, f(a,t)) \overset{def}{=} f(a,t)\left[EA(a) - \overline{EA}\right] \tag{14}$$

$$\sigma(t, X(t)) \overset{def}{=} \left[1 - f(a)\right]f(a) \tag{15}$$

Based on this setup, the stochastic evolutionary game model satisfies the measurability, Lipschitz condition, linear growth boundedness condition, and initial condition, ensuring the existence of a unique process $\{X(t), t \ge 0\}$ that satisfies the given stochastic differential equation. Similarly, the replicator dynamic equations for advertisers and viewers also meet these conditions, ensuring the existence and uniqueness of their solutions.

After confirming the existence and uniqueness of the solution, the next step is to focus on the stability of the equilibrium solution of the stochastic evolutionary game, i.e., whether the solution converges to the equilibrium at a predetermined rate as $t \to \infty$. General stability can be categorized into various types, including stochastic stability, stochastic asymptotic stability, global stochastic asymptotic stability, almost sure exponential stability, and p-th moment exponential stability, each with subtle differences in definition.

Unless otherwise specified, the stability discussed in this paper refers to p-th moment exponential stability. Specifically, p-th moment exponential stability means that as time approaches infinity, the solution converges to the equilibrium at an exponential rate, with its p-th moment satisfying a strict definition. Consider the following form of the stochastic differential equation:

$$\mathrm{d}X(t) = b(t, X(t))\mathrm{d}t + \sigma(t, X(t))\mathrm{d}B_t, X(t_0) = x_0 \tag{16}$$

If the p-th moment Lyapunov exponent of the solution is negative, i.e.,

$$\lim_{t \to \infty} \frac{1}{t} \ln E\left[X(t)\right]^p > 0 \tag{17}$$

the solution is p-th moment exponentially unstable.

To further assess the stability of the solution, a Lyapunov function $V(t, x)$ is introduced, which must satisfy the following conditions: there exist constants e_1 and e_2 such that

$$e_1|x|^p \le V(t,x) \le e_2|x|^p \tag{18}$$

Based on this, the generator of the Lyapunov function is defined as Equation 19:

$$LV(t,x) = V_t(t,x) + V_x(t,x)b(t,x) + \frac{1}{2}\sigma^2(t,x)V_{xx}(t,x) \tag{19}$$

If there exists a constant $\gamma > 0$ such that

$$LV(t,x) \le -\gamma V(t,x) \tag{20}$$

then the solution of the stochastic differential equation can be determined to be p-th moment exponentially stable. Conversely, if

$$LV(t,x) \ge -\gamma V(t,x) \tag{21}$$

the solution is p-th moment exponentially unstable.

In this paper, let $V(t,x) = x^2$. Therefore, the conditions required for the exponential stability of the equilibrium solution in the continuous strategy set of the stochastic evolutionary game are Equations 22–24:

$$2\left[EA(a) - \overline{EA}\right] + (1-a)^2 < 0 \tag{22}$$

$$2\left[EB(b)-\overline{EB}\right]+(1-b)^2<0 \tag{23}$$

$$2\left[EC(c)-\overline{EC}\right]+(1-c)^2<0 \tag{24}$$

Assuming that a, b and c are uniformly distributed over the interval $[0,1]$, the above conditions can be simplified as Equations 25–27:

$$-2C_{ad1}a+C_{ad1}+\frac{N_{ad1}a}{2}-\frac{N_{ad1}}{4}-Q_{content}a+\frac{Q_{content}}{2}-\frac{T_{ad2}a}{2}+\frac{T_{ad2}}{4}+(a-1)^2<0 \tag{25}$$

$$-C_{ad1}b+\frac{C_{ad1}}{2}-C_{ad2}b+\frac{C_{ad2}}{2}+V_{conv}b-\frac{V_{conv}}{2}+(b-1)^2<0 \tag{26}$$

$$D_{ad1}c-\frac{D_{ad1}}{2}+D_{ad2}c-\frac{D_{ad2}}{2}+Q_{content}c-\frac{Q_{content}}{2}+(c-1)^2<0 \tag{27}$$

The above inequalities analyze the stability conditions of film producers, advertisers, and viewers within the stochastic evolutionary game. In this model, the decision variables a, b and c represent the strategies of the three parties: the advertising embedding proportion for film producers, advertising investment intensity for advertisers, and ad acceptance level for viewers. Each inequality reflects the interplay of costs, revenues, and the effects of both advertising and content: For film producers, the inequality indicates that they can achieve a stable payoff over the long term by balancing the benefits of embedded advertising with the impact of content interference. For advertisers, the inequality suggests that they need to find a reasonable balance between costs and revenues to ensure stability in the game, allowing for stable growth in returns over the long term. For viewers, the inequality shows that their tolerance for ads must be balanced with the interference effects of both advertising and content to maintain a stable ad acceptance level over the long term.

These inequalities collectively form the conditions for achieving stable equilibrium in the entire system under the stochastic evolutionary game. Each party's choices regarding its decision variable impact not only its own payoffs and costs but also those of the other parties, thereby influencing the overall game outcome. Only when all three parties satisfy these inequalities can the entire game system achieve stability in the equilibrium solution over the long term. Even under stochastic disturbances, the strategies of the three parties will gradually converge to a stable state.

4 Numerical simulation

4.1 Parameter setting

In the commercialization of film and television works, advertising placement, as one of the main sources of revenue, significantly influences the behavioral choices of film producers, advertisers, and viewers. With the rise of digital media and short video platforms, the diversification of advertising formats has further increased the complexity of the game among these parties.

This study introduces key parameters such as advertising dissemination effects, inserted ad effects, film content quality, production costs, ad conversion effects, and ad interference to construct a model based on real-world data. The aim is to simulate and analyze the dynamic payoffs and behavioral evolution of the three parties under different advertising strategies.

To ensure the model's validity and alignment with real-world scenarios, the parameters are carefully set based on the latest data on advertising performance from video platforms, film production costs, and viewers' behavior feedback. This provides a reliable foundation for the subsequent evolutionary game model and helps deepen the understanding of strategy choices and their effects in film and television advertising placement.

Based on the data, YouTube's click-through rate (CTR) for skippable ads is 0.33%, while non-skippable ads have a CTR of 0.4–0.5%. On Bilibili, embedded ads achieve a 1.2% CTR, whereas TikTok's incentivized video ads have a CTR as high as 4.5%. Therefore, this study sets the ad dissemination effect N_{ad1} at 1.5 to reflect a moderate level of cumulative ad dissemination. For inserted ads, after the broadcast of Singer 2024, 15% of viewers conducted brand searches within 72 h, while about 30% switched channels. To balance the positive and negative effects of inserted ads, this study sets the traditional inserted ad effect T_{ad2} at 1.2. Long video platforms have an average retention rate of 60–75%, while short video platforms have a higher retention rate of 80–85%. To reflect the high retention rates on different platforms, this study sets the film content quality Q_{content} at 80. Based on Joy of Life 2, a high-quality long video production cost reaches \$1.5 million. Thus, the base production cost C_0 is set at 1.5 million RMB to represent a mid-budget film project. Advertising embedding costs can reach \$100,000 (approximately 700,000 RMB), so this study sets the embedded ad production cost C_{ad1} at 500,000 RMB to reflect moderate-depth ad embedding costs. Google Ads has a cost-per-click of \$1–\$2, while traditional TV inserted ad costs range from \$150,000 to \$500,000. This study sets the inserted ad production cost C_{ad2} at 300,000 RMB. TikTok incentivized videos have a 4.5% CTR and a conversion rate of 2–3%. Therefore, this study sets the ad conversion effect V_{conv} at 0.02 to represent the conversion rate after a click. Reasonable ad embedding only causes 15% of viewers to feel annoyed, so the viewers' interference from embedded ads D_{ad1} is set at 20. In contrast, the channel-switching rate for inserted ads is as high as 30%, directly reflecting their interference level. Therefore, the viewers' interference from inserted ads D_{ad2} is set at 30.

4.2 Baseline model simulation analysis

To validate the dynamic characteristics of the tripartite stochastic evolutionary game model under random disturbances, we first conduct a numerical simulation of the baseline scenario using default parameter settings. The simulation focuses on the long-term strategic evolution of the three key stakeholders—film producers, advertisers, and viewers—and examines whether the system exhibits convergence under stochastic conditions.

Figure 1 illustrates the evolutionary trajectories of the three strategic variables. Early stage (time steps 0–200): The strategy levels of the three parties fluctuate significantly, the system displays evident volatility and trial-and-error behaviors. Viewers (green curve) exhibit the most pronounced fluctuations, with strategy values peaking above 8, suggesting high sensitivity to advertising interference and content quality. Advertisers (orange curve) demonstrate a rapid initial surge followed by quick adjustments, reflecting their responsiveness to marginal payoffs. Film producers (blue curve), by contrast, maintain relatively conservative strategies with low amplitude, indicating risk-averse behavior.

Middle stage (time steps 200–400): The strategies of all three parties tend to stabilize. Advertisers and film producers maintain their strategies at relatively low levels, while viewers' strategies continue to fluctuate, but the amplitude decreases significantly. The stabilization in the middle stage indicates that as market transparency improves and participants adapt, strategies become more fixed. Advertisers and film producers should focus on enhancing ad quality and viewers' experience to maintain stable market performance.

Long-term stage (after 600 time steps): As the game progresses, the strategies of all three players gradually decline and converge. By around the 600th time step, all strategies approach zero, marking a transition to a stable but low-activity equilibrium. This result carries two important implications. First, it demonstrates the system's inherent dynamic stability under stochastic disturbances, as the strategies do not exhibit unbounded oscillation or divergence. Second, and more critically, the convergence toward near-zero values may imply a breakdown of sustained cooperation: after a period of exploration, all players reduce their engagement levels, potentially due to unsatisfactory payoff structures or coordination failures.

This outcome—a dynamically stable yet inefficient equilibrium—highlights a latent risk in digital advertising ecosystems: in the absence of external incentives or regulatory mechanisms, stakeholders may disengage from cooperation, resulting in minimal advertising activity, limited investment, and low viewers' acceptance. Consequently, the subsequent sensitivity analysis is built upon this baseline scenario to investigate which key parameters—such as content quality, advertising returns, and placement costs—can effectively break the low-cooperation trap and restore a more robust and sustainable strategic equilibrium among the three parties.

4.3 Sensitivity analysis

4.3.1 Sensitivity analysis of advertising dissemination effect

To examine how advertising dissemination effectiveness influences the strategic dynamics of the system, we vary the parameter N_{ad1}, which represents the efficiency of ad dissemination across channels. Figure 2 shows three subplots illustrating the impact of changes in the advertising dissemination effect. N_{ad1} on the final average values of film producers' willingness to cooperate, advertisers' willingness to cooperate, and viewers' ad acceptance level.

The results show a generally increasing trend in the cooperation level of film producers, despite some fluctuations. When N_{ad1} reaches a range of 45–55, their willingness significantly rises, with an average value exceeding 0.7. As dissemination becomes more effective, producers perceive greater potential returns from advertising collaboration, which encourages higher levels of strategic engagement. This reflects their sensitivity to marginal gains in ad performance, especially when ads are more likely to reach and influence viewers.

However, advertisers demonstrate a persistently low level of cooperation throughout most of the parameter space, with only occasional minor increases. Advertisers' willingness to cooperate remains generally low across different values of N_{ad1}, with only a brief increase around 30, after which it returns to nearly 0. This suggests that improvements in dissemination alone are insufficient to drive advertiser engagement. A possible explanation lies in

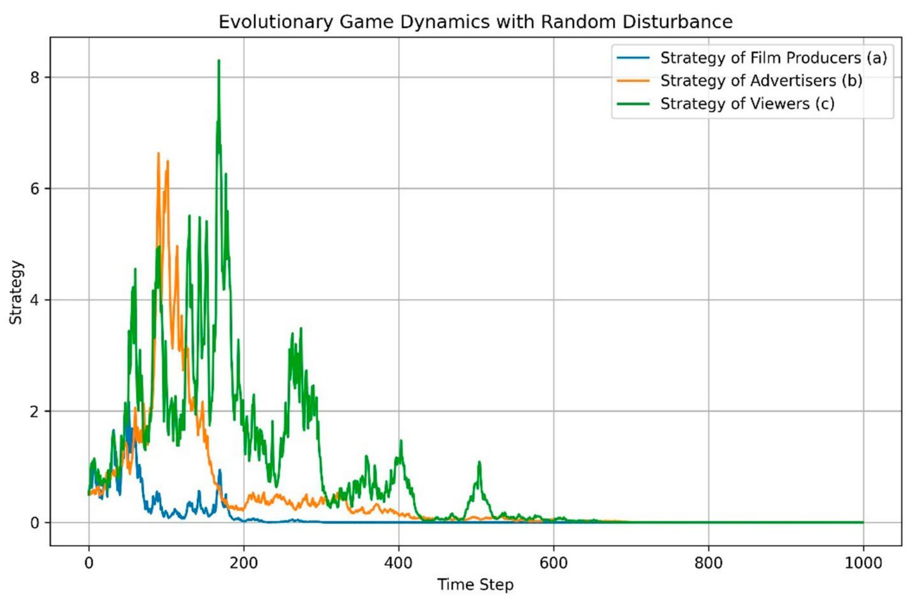

FIGURE 1
Baseline model simulation analysis.

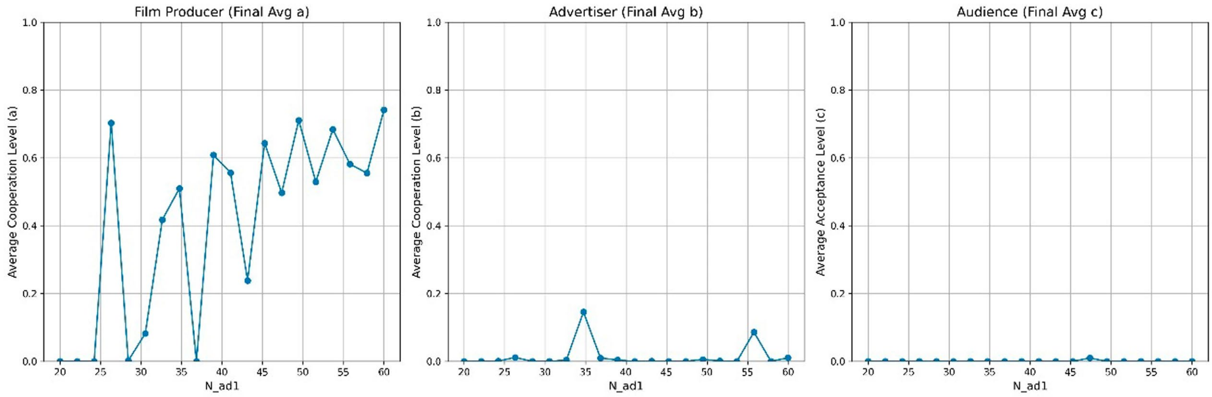

FIGURE 2
Sensitivity analysis of advertising dissemination effect.

structural constraints within the payoff-sharing mechanism or asymmetries in control over content and exposure, which may discourage active investment by advertisers despite improved technical efficiency.

More notably, the viewers' acceptance level remains extremely low and largely unresponsive to changes in N_{ad1}. This indicates that enhanced dissemination does not translate into better user experience or higher tolerance for advertising. On the contrary, more pervasive ads may aggravate viewers' fatigue or resistance, especially if not accompanied by improvements in content quality or delivery format.

The results in Figure 2 highlight the need for strategy adjustments at different stages of market development: Early-stage fluctuations reflect the impact of market uncertainty on strategy choices, emphasizing the need for managers to remain flexible to adapt to rapidly changing market conditions. Mid-stage stability indicates that as market transparency improves and participants adapt, strategies gradually stabilize. Advertisers and film producers should focus on improving ad quality and viewers' experience to maintain stable market performance. Long-term strategy stabilization suggests that low-interference ad strategies are more sustainable in long-term games, underscoring the importance of natural ad integration and protection of viewers' experience. These findings reveal a critical asymmetry: supply-side incentives (e.g., better dissemination) can boost producer behavior but fail to overcome viewers' resistance. In other words, technical improvements in ad reach are not sufficient to resolve the cooperation imbalance in the tripartite system. Effective advertising strategies must therefore be complemented by incentive design and content-centered approaches to ensure alignment across all stakeholders.

4.3.2 Sensitivity analysis of traditional inserted ad effect

To explore the influence of inserted advertising revenue on stakeholder strategies, we adjust the parameter T_{ad2}, which captures the expected income from traditional inserted ad formats. Figure 3 shows the impact of the traditional inserted ad effect T_{ad2} on the final average values of film producers' willingness to cooperate, advertisers' willingness to cooperate, and viewers' ad acceptance level.

From the Figure 3, the film producers' cooperation level increases markedly as T_{ad2} rises, confirming their profit-driven behavior. There are significant jumps in cooperation levels when T_{ad2} ranges between 20–40 and 50–90, reaching a peak in the 80–100 range, with average cooperation exceeding 0.8. This indicates that when inserted ads offer high revenue potential, producers become more inclined to engage in advertising cooperation, even at the cost of possible viewers' dissatisfaction. This demonstrates that financial incentives from advertisers can effectively shift producer strategy, especially in the absence of direct viewer constraints within the producer's payoff structure.

However, advertisers remain largely unresponsive, with their cooperation level hovering near zero across all revenue levels, with only a slight increase between 60–70, showing a conservative approach when adjusting strategies in response to changes in inserted ad effects. This indicates that increased producer enthusiasm does not translate into mutual strategic alignment. Advertisers may be deterred by concerns over return on investment, viewers' pushback, or ineffective allocation of exposure within the inserted format, which is often perceived as intrusive and poorly targeted.

Viewers' acceptance remains negligible throughout, unaffected by revenue incentives. This highlights a critical disconnection: formats that maximize monetary returns for producers do not inherently create value for viewers, and may even degrade the viewing experience.

The results in Figure 3 highlight the potential of inserted ads to enhance the revenue of film producers. Increased inserted ad effects can motivate film producers to opt for more inserted ads in content to gain higher ad revenue, which can boost short-term income. However, for advertisers, inserted ads may involve high placement costs and the risk of viewers' annoyance, leading to more cautious strategies and reluctance to significantly increase investment. This response reflects the advertisers' trade-off between viewers' reactions and placement costs in an inserted ad environment. The low level of viewers' acceptance indicates that although inserted ad effects can increase ad revenue, their negative impact on viewers' experience is evident, as viewers generally dislike frequent interruptions. This suggests that ad strategy formulation requires a balance between short-term revenue and long-term viewer relationships. Film producers should consider

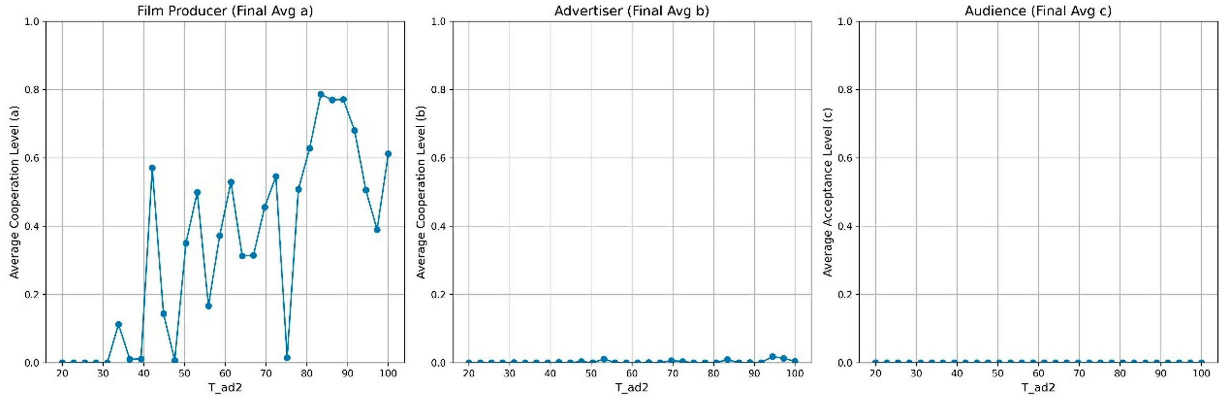

FIGURE 3
Sensitivity analysis of traditional inserted ad effect.

the potential negative impact of inserted ads on viewers' experience by controlling ad frequency, optimizing ad content, and timing placements to reduce viewers' annoyance. Advertisers could explore more innovative ad formats, such as dynamically adjusting the duration and content relevance of inserted ads, to improve cost-effectiveness and viewers' acceptance. Ultimately, a balanced advertising strategy can not only boost short-term revenue for film producers but also maintain positive viewer relationships in the long term, creating conditions for sustainable market development. The findings suggest that while inserted advertising can serve as a strong motivator for producers, its benefits are not equitably distributed across stakeholders. A revenue-maximization approach, if pursued in isolation, may worsen systemic imbalance and erode long-term viewers' engagement. Sustainable strategies should therefore account for not only financial viability but also viewer-centric design.

4.3.3 Sensitivity analysis of embedded ad cost

In this experiment, we examine how variations in embedded advertising cost C_{ad1} influence the system's cooperative dynamics. Figure 4 presents the impact of embedded ad cost C_{ad1} on the final average values of film producers' willingness to cooperate, advertisers' willingness to cooperate, and viewers' ad acceptance level.

The results reveal a clear threshold effect: when C_{ad1} remains low, both film producers and advertisers maintain high levels of cooperation, with values near 1. When C_{ad1} is below 20, the cooperation willingness remains above 0.9, indicating that lower embedded ad costs help boost cooperation willingness. However, when the cost exceeds 20, there is a steep drop, with cooperation willingness falling to nearly 0 between 40–50. This indicates that excessive cost burdens rapidly undermine the willingness of both parties to participate in the game, which reflects the significant constraint that embedded ad costs impose on film producers' strategic choices.

Advertisers' willingness to cooperate shows a similar downward trend, especially when C_{ad1} exceeds 30, where cooperation willingness plummets to nearly 0. This result confirms the high cost sensitivity of advertising cooperation: when embedded ad placements become financially unsustainable, even previously motivated stakeholders will disengage. Such a breakdown suggests that ad format viability is not merely a function of expected revenue, but also of manageable implementation costs.

Once again, viewers' acceptance remains static at low levels, implying that producer–advertiser withdrawal occurs independently of viewers' behavior. This decoupling reflects the fact that, under the current model structure, viewers' responses do not feed back into producer or advertiser utilities unless quality or format variables are also affected. The results show that rising embedded ad costs significantly affect the cooperation willingness of film producers and advertisers, indicating that the feasibility of embedded ad strategies heavily depends on cost control. When embedded ad costs are low, both film producers and advertisers are more inclined to cooperate, as lower costs can generate higher returns. However, when costs exceed a certain threshold, ad strategy revenues become insufficient to cover the expenditures, leading to a sharp decline in cooperation willingness for both parties. This phenomenon reveals a balance point between economic benefits and cost investment for embedded ad strategies, requiring managers to be cautious in planning ad investments. This implies that strict cost control is essential when formulating embedded ad strategies to ensure their feasibility and profitability in the market. Companies can lower costs by optimizing embedded ad technologies, enhancing the compatibility between ads and content, and using data analytics to refine placement strategies. Additionally, advertisers should consider the relationship between the marginal cost and revenue of embedded ads when selecting cooperation strategies, avoiding failures due to excessively high costs. Since viewers' acceptance remains largely unaffected by cost changes, managers should focus more on creativity and natural integration of ad content rather than cost adjustments alone when optimizing ad strategies. These strategy adjustments can help improve ad cost-effectiveness and achieve long-term economic benefits in a highly competitive market. From a policy and platform design perspective, this result underscores the importance of lowering the marginal cost of embedded ad production or placement—through technological innovation, standardized formats, or cost-sharing models—to preserve cooperation and avoid systemic collapse.

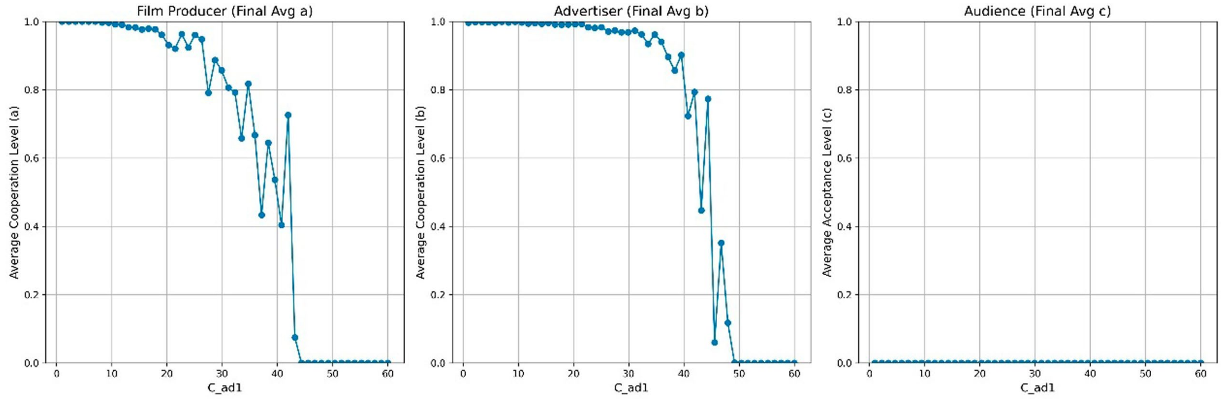

FIGURE 4
Sensitivity analysis of embedded ad cost..

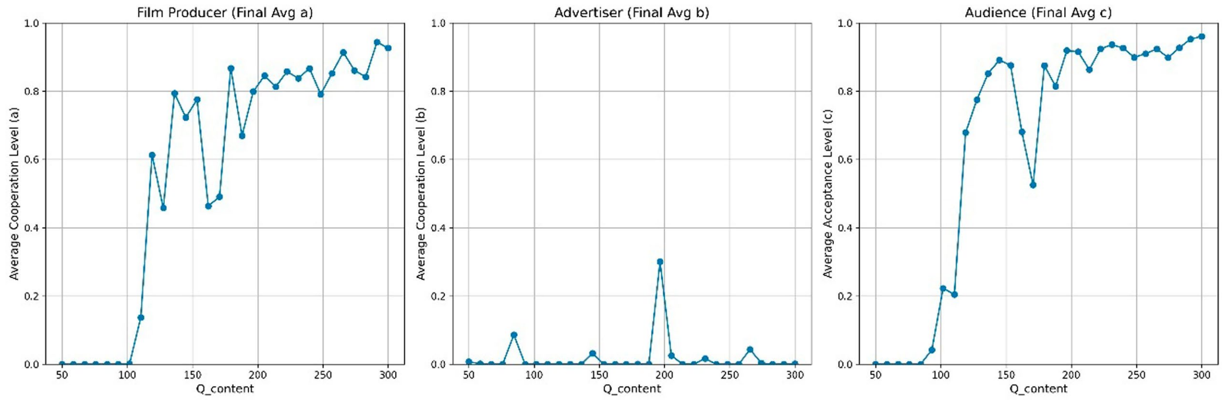

FIGURE 5
Sensitivity analysis of film content quality.

4.3.4 Sensitivity analysis of film content quality

Finally, we analyze the impact of content quality Q_{content} on the final average values of film producers' willingness to cooperate, advertisers' willingness to cooperate, and viewers' ad acceptance level (see Figure 5).

The film producers' willingness to cooperate shows a significant upward trend as content quality improves. When Q_{content} is below 100, cooperation willingness remains low, but it rapidly increases between 100–150 and gradually approaches 1 within the range of 150–300. This suggests that higher-quality content not only enhances producers' brand and reputational value but also improves the effectiveness of advertising integration, thereby justifying increased engagement.

More importantly, viewers' acceptance exhibits a strong, monotonic rise, crossing 0.8 when content quality reaches sufficiently high thresholds. This confirms that viewers are significantly more receptive to advertising when it is embedded within engaging and high-quality content, which reduces perceived intrusiveness and increases ad relevance.

Advertisers' willingness to cooperate fluctuates with changes in content quality. Although there is a brief peak around 200, the overall level remains low, suggesting that advertisers are less sensitive to changes in content quality. Although advertiser behavior remains somewhat sporadic, with cooperation spikes in select regions, the overall trend indicates growing strategic space for alignment when content quality is high. Viewers' ad acceptance level increases significantly with improved content quality, especially between 100–200, and remains high, approaching 1, within the range of 200–300. This suggests that higher-quality content can substantially boost viewers' ad acceptance. The results demonstrate the critical role of film content quality in enhancing ad effectiveness. High-quality content not only attracts more ad embedding opportunities but also increases viewers' acceptance of ads, boosting short-term ad revenue while laying a foundation for long-term market sustainability. The mutual responsiveness of producers and viewers create a favorable foundation for advertisers to re-engage, especially if supported by better targeting or performance metrics.

For film producers, improving content quality is a key strategy for increasing ad cooperation willingness and market competitiveness, especially in highly competitive markets. High-quality content can generate ad revenue while also enhancing brand image and viewers' loyalty. Advertisers should pay more attention to changes in content quality and design ad strategies that align with high-quality content to improve ad conversion rates and placement efficiency. These findings clearly identify content quality as the most effective lever for aligning interests across all three stakeholders. Unlike revenue or cost-based adjustments, which tend to benefit only one or two parties, investments in content improvement generate shared value, stabilize cooperation, and improve system resilience. This means that content quality should be considered a core variable in ad strategy formulation. Film producers should invest more in content production to enhance quality and attract more ad cooperation, while advertisers need to achieve higher ad conversion rates through precise targeting and deep integration with high-quality content. Additionally, improved content quality positively impacts viewers' experience, reducing the negative effects of ads while increasing ad acceptance and viewers' satisfaction. This win-win outcome not only boosts short-term earnings for market participants but also helps maintain a healthy market environment and user relationships, supporting long-term market growth and sustainable development.

5 Conclusion

In recent years, with the rapid growth of digital media and video platforms, advertising placement has become a critical monetization strategy for streaming platforms and content producers. However, the inherent tension between revenue maximization and user experience—coupled with the divergent objectives of advertisers, producers, and viewers—poses major challenges for optimizing advertising strategies.

This study constructs a three-party stochastic evolutionary game model involving film producers, advertisers, and viewers as strategic agents. By introducing random disturbances and continuous strategy spaces, we simulate the evolution of stakeholder behavior in response to changes in key variables, including dissemination effectiveness, revenue expectations, placement costs, and content quality. Simulation results reveal a structurally unbalanced system: supply-side actors (producers and advertisers) exhibit strong sensitivity to cost–benefit variations, while demand-side actors (viewers) respond almost exclusively to content quality. Without external coordination or institutional design, the system tends to stabilize at a low-cooperation equilibrium, reflecting limited strategic alignment across stakeholders. The simulation results reveal several critical dynamics:

(1) Advertising dissemination improvements primarily incentivize producer cooperation, but have little effect on advertisers or viewers.
(2) Increases in inserted advertising revenue significantly benefit producers, yet fail to promote advertiser engagement or viewers' acceptance.
(3) Rising embedded advertising costs quickly erode supply-side cooperation, triggering system-wide disengagement.
(4) Most importantly, improvements in content quality generate mutual gains for producers and viewers, and offer a potential re-entry point for advertisers.

These findings underscore the asymmetric sensitivities of different stakeholders and identify content quality as the most effective lever for restoring strategic alignment in advertising ecosystems.

From a theoretical perspective, this research advances the fields of media economics and advertising optimization in several key ways. First, by modeling viewers as endogenous, strategic agents, it challenges the traditional advertiser–platform duopoly and provides a formal mechanism to examine how viewers' preferences shape market outcomes. This shift not only enhances the realism of advertising models but also offers a new lens for understanding viewers' influence in revenue-driven content systems. Second, the introduction of stochastic evolutionary dynamics enables the modeling of strategy shifts under uncertainty—capturing real-world behaviors such as noise-driven cooperation breakdowns and boundedly rational adaptation. This contributes a dynamic systems perspective to media economics, where much of the existing literature remains static or deterministic. Third, the adoption of continuous strategy spaces allows for more nuanced modeling of ad intensity, placement strategies, and viewers' tolerance, offering a flexible framework that can accommodate emerging advertising formats and hybrid monetization models.

Together, these contributions offer a more behaviorally grounded and systemically sensitive understanding of how advertising cooperation forms, unravels, and reconfigures in platform-mediated media markets. They lay conceptual groundwork for future models that integrate user agency, feedback loops, and environmental volatility into advertising and media value chain analysis.

On the practical side, the findings support three policy directions. (1) Prioritize content quality investment through public funding, tax incentives, or platform subsidies, to enhance viewers' tolerance and long-term engagement. (2) Redesign revenue-sharing mechanisms to create more transparent and equitable incentive structures between advertisers and producers, fostering sustained cooperation. (3) Implement platform-level viewers' safeguards, such as adaptive ad frequency caps, viewer-controlled ad filters, and algorithmic limits tied to engagement quality, to balance short-term monetization with long-term viewers' satisfaction.

This research develops a theoretical framework that captures the dynamic evolution of advertising strategies in uncertain environments and responds directly to structural tensions in digital advertising ecosystems. It offers actionable guidance for shifting from short-term monetization models toward value co-creation paradigms that align stakeholder interests. However, this study still has several limitations that warrant further exploration. First, the model simplifies complex real-world behaviors into continuous strategy variables and assumes homogeneous responses within each agent group, which may overlook individual-level heterogeneity and contextual differences. Second, the stochastic elements introduced in the model are based on standard Brownian motion, which may not fully capture extreme or rare events such as policy shocks or viral content explosions. Additionally, empirical validation of the model's predictions remains limited due to data constraints, and further integration with real behavioral or market data could enhance its practical applicability.

Future research can incorporate variables of diverse ad formats and new technologies (e.g., AI-driven ad placement) to study their specific impacts on the evolution of strategies among the three parties. This can provide more comprehensive and in-depth theoretical support for optimizing film and television advertising strategies, offering practical guidance for the industry's sustained growth in a dynamic market environment.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

LZ: Writing – original draft, Writing – review & editing.

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The author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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References

Ahmad, F., Shah, Z., and Al-Fagih, L. (2023). Applications of evolutionary game theory in urban road transport network: a state of the art review. *Sustain. Cities Soc.* 98:104791. doi: 10.1016/j.scs.2023.104791

Alipour-Vaezi, M., Tavakkoli-Moghaddam, R., and Mohammadnazari, Z. (2022). Optimization of a television advertisement scheduling problem by multi-criteria decision making and dispatching rules. *Multimed. Tools Appl.* 81, 11755–11772. doi: 10.1007/s11042-022-12027-7

An, S., and Kang, H. (2014). Advertising or games?: Advergames on the internet gaming sites targeting children. *Int. J. Advert.* 33, 509–532. doi: 10.2501/IJA-33-3-509-532

Bhargava, H. K. (2022). The creator economy: managing ecosystem supply, revenue sharing, and platform design. *Manag. Sci.* 68, 5233–5251. doi: 10.1287/mnsc.2021.4126

Cao, H. H., Ma, L., Ning, Z. E., and Sun, B. (2024). How does competition affect exploration vs. exploitation? A tale of two recommendation algorithms. *Manag. Sci.* 70, 1029–1051. doi: 10.1287/mnsc.2023.4722

Cesar, P., and Chorianopoulos, K. (2009). The evolution of TV systems, content, and users toward interactivity. *Found Trends Hum. Comput. Interact* 2, 373–395. doi: 10.1561/1100000008

Cowley, E., and Barron, C. (2008). When product placement goes wrong: the effects of program liking and placement prominence. *J. Advert.* 37, 89–98. doi: 10.2753/JOA0091-3367370107

Hallur, G. G., Prabhu, S., and Aslekar, A. (2021). "Entertainment in era of AI, big data & IoT" in Digital entertainment: The next evolution in service sector. eds. S. Das and S. Gochhait (Singapore: Springer Nature), 87–109.

Hashim, N. H., Normalini, and Sajali, N. (2018). The influence factors towards mobile advertising message content on consumer purchase intention. *Glob. Bus. Rev.* 19, 1187–1206. doi: 10.1177/0972150918788746

Hödl, T., and Myrach, T. (2023). Content creators between platform control and user autonomy. *Bus. Inf. Syst. Eng.* 65, 497–519. doi: 10.1007/s12599-023-00808-9

Hu, S., Ru, L., Lu, B., Wang, Z., Wang, W., and Xi, H. (2024). Stochastic evolutionary analysis of an aerial attack–defense game in uncertain environments. *Mathematics* 12:3050. doi: 10.3390/math12193050

Huang, X., and Yu, L. (2021). Advertising cooperation and green technology R&D strategy in a platform-led stackelberg game. *Math. Probl. Eng.* 2021, 1–17. doi: 10.1155/2021/4873032

Jin, C., and Villegas, J. (2007). The effect of the placement of the product in film: consumers' emotional responses to humorous stimuli and prior brand evaluation. *J. Target. Meas. Anal. Mark.* 15, 244–255. doi: 10.1057/palgrave.jt.5750049

Karniouchina, E. V., Uslay, C., and Erenburg, G. (2011). Do marketing media have life cycles? The case of product placement in movies. *J. Mark.* 75, 27–48. doi: 10.1509/jmkg.75.3.27

Khalilzadeh, M., Neghabi, H., and Ahadi, R. (2021). An application of approximate dynamic programming in multi-period multi-product advertising budgeting. *J. Ind. Manag. Optim.* 19:695. doi: 10.3934/jimo.2021202

Kim, K., Kwon, E., and Park, J. (2021). Deep user segment interest network modeling for click-through rate prediction of online advertising. *IEEE Access* 9, 9812–9821. doi: 10.1109/ACCESS.2021.3049827

Liu, X., Yu, C., Zhang, Z., Zheng, Z., Rong, Y., Lv, H., et al. (2021). Neural auction: end-to-end learning of auction mechanisms for E-commerce advertising, in *Proceedings of the 27th ACM SIGKDD conference on Knowledge Discovery & Data Mining* (New York, NY, USA: Association for Computing Machinery), 3354–3364. doi: 10.1145/3447548.3467103

Lou, K., Yang, Y., Wang, E., Liu, Z., Baker, T., and Bashir, A. K. (2021). Reinforcement learning based advertising strategy using crowdsensing vehicular data. *IEEE Trans. Intell. Transp. Syst.* 22, 4635–4647. doi: 10.1109/TITS.2020.2991029

Nyarko, J. (2023). Media diversification: redefining reliance on advertising revenue and autonomy implications. *Cogent Soc. Sci.* 9:2193382. doi: 10.1080/23311886.2023.2193382

Pahari, S., Bandyopadhyay, A., and Manna, A. (2024). Exploring the social media advertising avoidance behavior through the lens of avoidance motivation theory. *Kybernetes*, ahead-of-print. doi: 10.1108/K-02-2024-0309

Pardo, A. (2013). "Digital Hollywood: how internet and social media are changing the movie business" in Handbook of social media management: Value chain and business models in changing media markets. eds. M. Friedrichsen and W. Mühl-Benninghaus (Berlin, Heidelberg: Springer), 327–347.

Pavlou, P. A., and Stewart, D. W. (2000). Measuring the effects and effectiveness of interactive advertising: a research agenda. *J. Interact. Advert.* 1, 61–77. doi: 10.1080/15252019.2000.10722044

Pompper, D., and Choo, Y.-F. (2008). Advertising in the age of TiVo: targeting teens and young adults with film and television product placements. *Atl. J. Commun.* 16, 49–69. doi: 10.1080/15456870701647656

Qi, X., and Han, Y. (2023). Research on the evolutionary strategy of carbon market under "dual carbon" goal: from the perspective of dynamic quota allocation. *Energy* 274:127265. doi: 10.1016/j.energy.2023.127265

Song, L., Liu, L., Yang, Z., and Tso, K. F. (2025). How does binge-watching behavior affect advertising and video-on-demand platforms? Ad intrusiveness, irritation and attitudes via the psychological reactance theory lens. *J. Advert. Res.* 65, 4–33. doi: 10.1080/00218499.2025.2464280

Song, R., Meyer, J., and Ha, K. (2015). The relationship between product placement and the performance of movies: can brand promotion in films help or hurt moviegoers' experience? *J. Advert. Res.* 55, 322–338. doi: 10.2501/JAR-2015-012

Sun, W., Zhu, C., and Li, H. (2022). Evolutionary game of emergency logistics path selection under bounded rationality. *Socio Econ. Plan. Sci.* 82:101311. doi: 10.1016/j.seps.2022.101311

Tandberg, J. W. (2022). That Song from TikTok: how independent musicians develop their careers through the short-video platform. University of Agder. Available online at: https://uia.brage.unit.no/uia-xmlui/handle/11250/3020400 (Accessed April 2, 2025).

Vadakkepatt, G., Bryant, A., Hill, R. P., and Nunziato, J. (2022). Can advertising benefit women's development? Preliminary insights from a multi-method investigation. *J. Acad. Mark. Sci.* 50, 503–520. doi: 10.1007/s11747-021-00823-w

Williams, C. (2011). Research methods. *J. Business Econ. Res. (JBER)* 5.

Wilbur, K. C., Goeree, M. S., and Ridder, G. (2009). Effects of advertising and product placement on television audiences. *Work. Pap. Ser. Inst. Empir. Res. Econ.* doi: 10.5167/uzh-51901

Wu, T.-J., Xu, T., Li, L. Q., and Yuan, K.-S. (2020). "Touching with heart, reasoning by truth!" the impact of brand cues on mini-film advertising effect. *Int. J. Advert.* 39, 1322–1350. doi: 10.1080/02650487.2020.1755184

Zhou, Q., Yang, Y., and Ma, F. (2025). A Stackelberg-based deep reinforcement learning approach for dynamic cooperative advertising in a two-echelon supply chain. *Comput. Chem. Eng.* 196:109048. doi: 10.1016/j.compchemeng.2025.109048