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Research article

When engagement performs better: Revenue management on user-generated content platforms

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Abstract: User-generated content (UGC) platforms, such as YouTube and TikTok, motivate creators through revenue-sharing mechanisms. However, it remains unclear whether platforms should allocate revenue based on viewership or user engagement. Linear viewership-oriented models often overlook the crucial role of engagement, which directly influences both content exposure and advertising revenue. In this study, we developed a stylized model comparing the Viewership-oriented Model (VOM) and the Engagement-oriented Model (EOM). The analysis demonstrated that EOM encourages higher content quality and platform incentives to promote engaging videos. When the revenue-sharing rates were endogenously determined, EOM could yield Pareto improvements and generate a win–win outcome for platforms and creators, reinforcing its managerial relevance. Overall, the study highlights that engagement-based contracts enhance the effectiveness and sustainability for the long-term growth of UGC platforms, offering practical implications for platform design and revenue management.

Keywords: revenue sharing; engagement; user-generated content; creator economy; game theory
Mathematics Subject Classification: Primary: 91A10, 91A35; Secondary: 91B06

1. Introduction

User-generated content (UGC) refers to original content in various forms, such as text, images, videos, or audio, that is created and shared by users on online platforms rather than being professionally produced [1,2]. UGC platforms have become the linchpins of the creator economy, a sector experiencing significant growth and widespread attention [3]. These platforms are diverse, ranging from video-sharing sites (e.g., *YouTube, TikTok, and Vine*) to social media networks (e.g., *Facebook and LinkedIn*) and even niche communities like dating sites (e.g., *eHarmony and Match.com*). This diversity underlines UGC's rapid expansion and its significant market valuations [4]. With the growth and prevalence of social media platforms, many companies have increasingly engaged with users, encouraging them to generate content related to their products and services [5]. In particular, video-based UGC platforms like TikTok, Youtube, and Bilibili are becoming the most popular UGC platforms. These platforms are dominated by content created and uploaded by individuals known as *vloggers* or *video bloggers*. The profitability of these platforms is largely driven by advertising revenue, which is closely related to the viewership and engagement levels of the content. To incentivize content producers to produce high-quality videos, the platform adopts different revenue-sharing mechanisms. For instance, YouTube generated approximately $8.6 billion in advertising revenue in 2021, paying content creators around $1,800 per 1,000 ad views [6]. Moreover, YouTube also offers content creators 55% of advertising revenue as remuneration for making videos [7].

However, the UGC offers enormous opportunities for social media firms and leads to corresponding challenges. Compared to the previous traditional revenue-sharing modes, however, heated debates emerged a decade ago about which revenue-sharing mode generates and performs better, namely *viewership-oriented model* (VOM), which linearly shares based on content views and *engagement-oriented model* (EOM) which nonlinearly shares based on content engagement? Understanding the answer to this debate is crucial for managing revenue on UGC platforms within the creator economy. The debate remains unresolved despite these UGC platforms' practice of the above two revenue-sharing models.

In practice, several UGC platforms have already experimented with engagement-sensitive allocation schemes that resemble the EOM we study. For instance, TikTok has replaced its earlier Creator Fund with the *Creator Rewards Program*, under which payouts are influenced not only by the number of qualified views but also by engagement-related factors such as watch time, originality, and interaction rates [8, 9]. Likewise, Flip, a social commerce platform, recently launched a "Founding Creators Fund" of up to $100 million, explicitly tying grants and equity rewards to creators' engagement and follower metrics [10]. These real-world practices show that major platforms are moving beyond purely view-based sharing toward mechanisms that link rewards with engagement, providing concrete support for our focus on EOM.

There are some valuable observations and metrics in the UGC. In addition to the content quality, a video's views are also closely related to the video's exposure, which is affected by the promotion of the video. Video platforms use AI algorithms to recommend specific videos to specific user groups based on their data, such as age, gender, and browsing habits. According to statistics, more than 70% of YouTube video content users watch is recommended by AI algorithms [6]. The algorithms filter out high-quality videos that might be worth promoting and recommend them to users who may be interested. The promotion of videos is a process of matching supply and demand. However, these algorithms cannot always accurately make appropriate judgments about the quality of videos, which requires artificial traffic driving of videos. On the other hand, engagement metrics, such as views, likes, dislikes, and subscriptions, are also crucial indicators of a video's popularity and are closely related to its exposure and revenue. In comparison, studies have shown that revenue-sharing mechanisms significantly impact video quality and the profits of platforms and content creators [11], while the crucial role of engagement rates in revenue-sharing models has received less attention. Engagement affects video revenue in two main ways. First, videos with higher engagement receive more exposure because they reflect users' recognition of the video quality. Second, videos with higher engagement rates often have higher ad revenue rates. This means that even if two videos have the same number of views, they may not earn the same revenue due to differences in engagement. For example, the revenue per 1,000 views (RPM) varies from channel to channel on YouTube [12]. Unfortunately, researchers have ignored how engagement impacts video exposure and revenue. Here, we study a revenue-sharing model where the revenue rate is determined by engagement. By understanding the role of engagement in video promotion, the platform can generate higher profits and provide better services for users.

Motivated by these observations, we investigate the revenue management problem for UGC platforms. As a benchmark, we first investigate the advertising revenue-sharing model based on the VOM and compare the results with the EOM. We attempt to build a stylized model in which the platform independently drives traffic to a specific video. Thus, the platform needs to make decisions about video exposure to achieve a balance between advertising revenue and recommendation cost. Furthermore, the platform shares a part of the advertising revenue to content creators through revenue-sharing contracts to stimulate them to create high-quality videos. Therefore, we propose the following three research questions: (i) Compared with the VOM, are the platform and creator better off under the EOM? (ii) How does the EOM affect video quality, recommendation behavior, and the performance of platforms and content creators? (iii) How does the platform determine the appropriate commission rate?

Researchers investigating on UGC platform economics have primarily examined viewership-based revenue-sharing mechanisms. For instance, the researchers in [11] and [13] show that linear, view-based allocations can improve content supply and quality, but their effectiveness is constrained by external advertising revenues. These approaches, however, overlook the critical role of user engagement, measured by likes, comments, or subscriptions, which not only reflects user satisfaction but also directly enhances advertising value. The lack of engagement-based analysis leaves an important gap in understanding how platforms can design more effective incentive structures. We address this gap by explicitly modeling an engagement-oriented mechanism and comparing it with the traditional viewership-oriented approach, thereby providing new insights into the sustainability of revenue-sharing contracts.

By comparing the two revenue-sharing models, we find: (*i*) First, the revenue sharing commission can be used as a lever for the platform to control both video quality and exposures, while the platform can also increase profits for itself and content creators by using the tool wisely. The use of this tool is limited by external ad revenue, and platforms are less limited in the EOM compared to the VOM. (*ii*) Second, counterintuitively, the EOM can lead to higher profits for content creators when the sharing commission is smaller. This is because the EOM incentivizes content creators in terms of both views and engagement. This double incentive mechanism encourages content creators to create higher-quality videos and leads to higher exposure, allowing content creators to earn more even with smaller commission revenue. (*iii*) Third, our results show that the EOM can be a win-win policy for both platforms and content creators when the sharing commission is set appropriately. This model cannot only improve video quality and video promotion but can also enhance the user's experience on the platform compared to the VOM. In addition, when considering endogenous sharing commissions, if the platform has an incentive to improve quality, then both participants can achieve Pareto Improvements in the EOM.

The novelty of our work lies in explicitly incorporating user engagement into the revenue-sharing framework of UGC platforms, an aspect largely overlooked in the existing literature that primarily focuses on view-based allocations. By formalizing an EOM and comparing it with the traditional VOM, our study goes beyond existing models and provides new insights into platform design. The major contributions of this paper are threefold. First, we develop a stylized game-theoretic model that highlights how engagement-based contracts change the incentives of both platforms and creators. Second, we derive comparative results showing that, under suitable sharing rates, the EOM outperforms the VOM by generating higher quality content, stronger incentives, and even Pareto improvements. Third, we provide managerial implications by demonstrating that engagement-based mechanisms can lead to sustainable win–win outcomes for platforms, creators, and users. Taken together, these contributions advance the theoretical understanding of UGC platform economics and offer practical guidance for platform managers in designing effective revenue-sharing arrangements.

The remainder of the paper is organized as follows. In Section 2, we review the related literature. In Section 3, we provide some model preliminaries. We introduce the VOM and EOM in Sections 4 and 5, respectively. Then, we compare the two models in Section 6. In Section 7, we extend the primary model to verify the robustness of our conclusions when considering a symmetrical case and the endogenous commission rate. In section 8, we conclude and look forward to future research.

2. Literature review

We study revenue management on user-generated content platforms. In particular, we review works closely related to three streams of literature, i.e., multi-sided platforms, revenue sharing, and UGC.

The first relevant works mainly focus on multi-sided platforms. A critical issue in multi-sided platforms is how to lead supply and demand [14]. The choice of a charging model is related to the market efficiency of the platform's supply and demand matching [15]. Traditional charging models, such as fixed and unit transaction fees, are challenging to achieve on UGC platforms, so ad revenue sharing is the mainstream operating mode of UGC platforms. In an on-demand platform, the platform can achieve the allocation of supply and demand through pricing means and affect the profit and consumer surplus of the platform [16]. However, the role of pricing is limited in scenarios where the price is not involved, such as the UGC platform we studied, where most of the content is provided spontaneously by users and allowed to consume (watch) for free. Therefore, it is necessary to find new means to achieve supply and demand matching in this scenario. One possible solution is a platform-led matching process, the platform recommends specific videos to specific users. However, literature in this area focuses on developing more efficient recommendation algorithms [17–19]. However, the economic analysis of video recommendation is insufficient, so this paper studies the traffic-driving action of the platform to fill the theoretical blank in this regard. Platform advertising strategy and content production are other important research directions. Platforms need to make tradeoffs between ad revenue and content charges [20–23] and balance advertising volume and content volume [24, 25]. The researchers in [26] point out that the performance-based payment mechanism is gradually replacing the traditional pay-per-exposure mechanism in the advertising industry. User interaction with video is often taken as a performance standard for video quality, and the revenue-sharing model based on engagement rate is also a sharing model similar to performance-based payment. This paper treats advertising revenue as external revenue to the platform, focusing on internal revenue sharing between the platform and content creators. The researchers in [27] study the relationship between user engagement and the effectiveness of advertising, and their work suggests that advertising policies should depend on user engagement. While few researchers have touched on the connection between user engagement and advertising revenue, our research complements this insight by demonstrating that platforms can use user engagement to more effectively motivate content producers.

Traditionally, revenue sharing has become a common practice on many platforms, and the revenue-sharing mechanism of advertising is the main content of our research. Some scholars have designed several subsidy policies to cope with different market conditions [28–33]. Unfortunately, due to the limitations of application scenarios, the method they adopt is difficult to apply to online digital platforms. The researchers in [34] consider the tendency of both supply and demand sides of online platforms to be multi-homing, and their research shows that if one side is subsidized alone, it may not bring about an increase in profit. In the UGC platform, the platform doesn't need to subsidize both the supply and demand sides simultaneously because the platform does not directly obtain value from the demand side, and the revenue mainly comes from external advertisers. Therefore, compared with the traditional subsidy model, advertising revenue sharing is more feasible. In music streaming, two focal rules, pro-rata and user-centric, have been axiomatized and compared in terms of sustainability and incentives [35–37]. These studies show that allocation based on individual users' consumption (user-centric) can reshape incentives and the distribution of payouts relative to market-share (pro-rata) schemes. Our EOM is conceptually analogous: It shifts the basis of allocation from total view counts to realized engagement, thereby strengthening incentive alignment when engagement is informative of quality and advertising value. The researchers in [38] propose a dynamic framework for attributing revenues across creators on video-sharing platforms, illustrating how allocation schemes evolve with user behavior. The researchers in [39] study the interplay between subscription revenues and advertising strategies on YouTube, showing that monetization design influences both creator incentives and audience engagement. These studies shed light on platform-specific mechanisms, but still largely adopt viewership as the main basis for allocation. Empirical research by the researchers in [40] show that ad revenue sharing stimulates creators' creative efforts, leading to higher quality and more content. The researchers in [41] construct a game theory model to study the impact of a platform's advertising strategy on content generation, and their results also implied that revenue sharing should depend on viewer satisfaction, a metric that is represented in our model by engagement rates. Innovative revenue-sharing models are crucial to the success of platforms, yet disputes between platforms and users over the distribution of revenue sharing can arise [42]. Our research shows that if the platform considers altruism and sustainable operation, it is possible to apply non-optimal revenue share rates to achieve Pareto improvements for both participants. This paper contributes to the literature on revenue-sharing models for UGC platforms, which have been extensively studied in recent years. Researchers have primarily focused on the impact of view-based revenue-sharing models, such as the VOM, where content creators are compensated based on the number of views their videos receive. For instance, the researchers in [11] analyze the effects of linear ad commission models on content quality and creator profits, while the researchers in [13] emphasize the role of revenue-sharing in platform design and content creator incentives. However, a significant gap in the literature is the limited attention given to the role of user engagement in revenue-sharing models. Although some studies, such as [41], mention the importance of engagement, most existing models focus on view counts as the primary metric for content compensation. The engagement metrics, such as likes, shares, and comments, which reflect the quality and relevance of content, have not been adequately integrated into revenue-sharing frameworks. In contrast to these studies, our paper introduces a more comprehensive model by incorporating both viewership and engagement into the revenue-sharing structure. We propose the EOM, where the revenue share is determined not just by the number of views, but also by the level of user engagement. This approach enables a more nuanced understanding of how platforms can incentivize content creators to produce high-quality, engaging content. We further compare the EOM with the traditional VOM, showing that the EOM can lead to higher profits for both content creators and platforms, particularly when the sharing rate is optimized.

Another topic relevant to our research is user-generated content. Many researchers have studied the driving factors behind user-generated content. The incentive of honor to UGC content is temporary [43], and the herding effect is the main driving force of UGC content [44]. The researchers in [45] show that users are motivated to produce content based on intrinsic satisfaction and gaining status and reputation. The researchers in [46] argue that exposure and reputation are the main motivators for creators. In some studies, UGC does not generate value, but UGC creates value for related products [47]. In this study, we consider that UGC will bring direct value to the creator. The empirical research of the researchers in [48] shows that there is a critical value in the number of contributors(viewers). To enhance the value of UGC, some users can be directed to other UGC. This inspired us to consider studying the optimal exposure of a particular UGC. However, exposure is often overlooked in UGC-related theoretical models. We believe platforms can artificially expose and drain videos of different quality levels to obtain views and advertising revenue more efficiently. Therefore, we allow the platform to rationally decide the exposure of a particular video under the premise of considering the economy. Some studies examine how to incentivize the production of UGC in competitive scenarios. The researchers in [4] study the competition among UGC platforms, finding that the differentiation of UGC can affect a platform's market position and the intensity of competition. Conversely, we focus on how UGC platforms, in non-competitive settings, allocate resources effectively to guide users in watching videos, maximizing their profits. The researchers in [49] reveal that pure monetary incentives may not necessarily elicit a positive impact on UGC, as diverse types of contributors may exhibit varying responses to such incentives. This observation poses a challenge to the conventional, ubiquitous "one-rate-for-all" linear revenue-sharing mechanism. Concurrently, The researchers in [50] investigate into the moderating role of social connections on monetary rewards. Their findings indicate that users with a strong sense of social connections experience an augmentation in their motivation to contribute when receiving monetary incentives, whereas those with weaker social connections exhibit the opposite trend. User interaction, or user engagement, serves as a crucial manifestation of this sense of social connection. Based on this premise, we hypothesize that platforms may offer differentiated monetary rewards contingent upon user engagement. Indeed, several studies have already focused on users' engagement behavior. Engagement signals (likes, comments, and watch time) are strong predictors of future exposure and outcomes on video platforms [51]. The researchers in [52] document how YouTube's recommendation system relies heavily on engagement signals to personalize video exposure. This line of research underscores that engagement is not only a reflection of content quality but also a driver of advertising value and exposure. The content and its characteristics will affect the users' engagement [5]. The empirical research of the researchers in [53] show that the user's praising, commenting, and sharing behavior will affect the quality of the creators' published content. In this paper, the behavior of praise, comment and sharing is defined as the user's interactive behavior because, in essence, these behaviors reflect the user's feedback on the content. We attempt to reveal the nature of user engagement that motivates producers to produce high-quality content. The researchers in [54] construct a two-period game model to study the impact of user ratings and reviews on UGC advertising strategies. In the research framework of this paper, user ratings and reviews are considered as engagement. They looked at how these user interactions affected price and advertising strategies while we focused on how user interactions could be used to incentivize supply. In addition to the revenue-sharing mechanisms, researchers have examined the role of content promotion and view allocation policies on digital platforms. Some researchers analyze how bonus incentives influence streamer performance on live streaming platforms, emphasizing the importance of compensation schemes in driving content creation. Some researchers provide an in-depth examination of content promotion and view allocation policies, which closely aligns with our study, as they also explore the platform's role in determining content exposure. These works are particularly relevant to our analysis of platform strategies in maximizing creator engagement and content visibility.

In conclusion, our research contributes significantly to the extant body of literature on UGC platforms by addressing several pivotal gaps. First, we advance the traditional revenue-sharing paradigm by introducing a nonlinear framework, thereby broadening the conceptual boundaries of contract design. While researchers predominantly assume that platforms allocate revenue proportionally to content views using linear formulas [55], our approach innovatively ties revenue-sharing mechanisms to engagement rates. This model not only enriches the analytical comparison with conventional linear models but also provides a more nuanced understanding of revenue allocation strategies. Second, by establishing a direct link between engagement rates and content profitability, we underscore the critical role of engagement in enhancing the quality and visibility of content. Although empirical research has consistently demonstrated the positive impact of engagement on UGC output and quality, the underlying mechanisms remain underexplored. Our theoretical framework addresses this lacuna by elucidating how platforms can strategically optimize content quality and exposure through dynamic adjustments in commission rates based on engagement metrics. Our findings indicate that setting well-calibrated benchmarks fosters mutual benefits for platforms and content creators, driving sustainable growth on both sides. Last, we examine the platform's proactive role in traffic redirection, extending beyond its conventional function of mediating supply and demand. Unlike most researchers, who treat content exposure as a passive outcome, our analysis highlights the strategic agency of platforms in shaping visibility, whether through algorithmic prioritization or manual curation. By modeling these proactive exposure strategies, our research offers novel insights into revenue management for two-sided platforms, paving the way for more sophisticated approaches to content monetization and ecosystem governance.

3. Model preliminary

We analyze a game involving four key participants: External advertisers, the platform, video bloggers, and users. Using a stylized model, we investigate how users engage with and interact with content. Our primary focus is on the creative efforts of content creators, the platform's promotional activities, and how these behaviors are influenced by the revenue-sharing model. Specifically, we assume a monopoly video UGC platform that attracts and promotes creator-generated videos. In turn, content creators must decide how much effort to invest in producing their content.

We consider the decision sequence (see Figure 1). First, the vlogger decides to create a video with a quality rating q and upload it to the platform. Subsequently, the platform determines the video exposure η. The recommended users can observe the video on the home page and decide whether to watch and engage. Specifically, user engagement refers to the general term of the interactive behaviors, including like, share, and comment behavior, that users spontaneously perform after watching the video because of recognition of the video quality. To maintain tractability, we assume that the platform determines video exposure prior to observing user engagement outcomes. This assumption enables us to focus on the comparative incentive effects of VOM and EOM without modeling the full dynamics of recommendation algorithms. We acknowledge that in practice, platforms often adopt a sequential process in which preliminary engagement signals (e.g., watch time, likes, and comments) are used to adjust subsequent exposure. Incorporating such a feedback mechanism would require a multi-stage game-theoretic framework, which we leave as a valuable direction for future research.

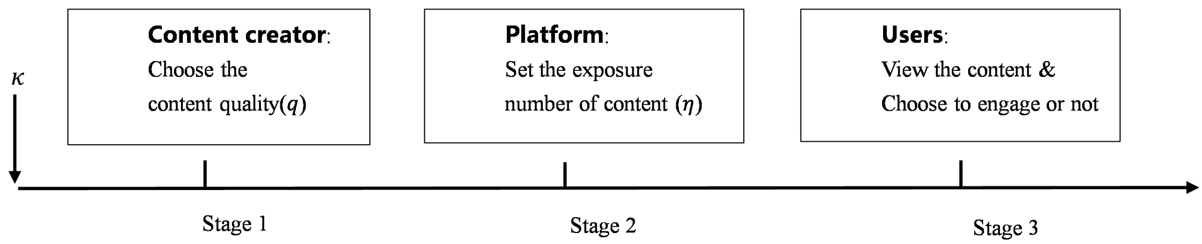

Figure 1. Decision sequence.

There are three types of users, namely *watch-and-engage* users who will interact with other users while watching videos, *watch-only* users who will only watch the videos without engagement, and *not-watch* users who will do neither. The behavior of these users watching the video and interacting is shown in Figure 2.

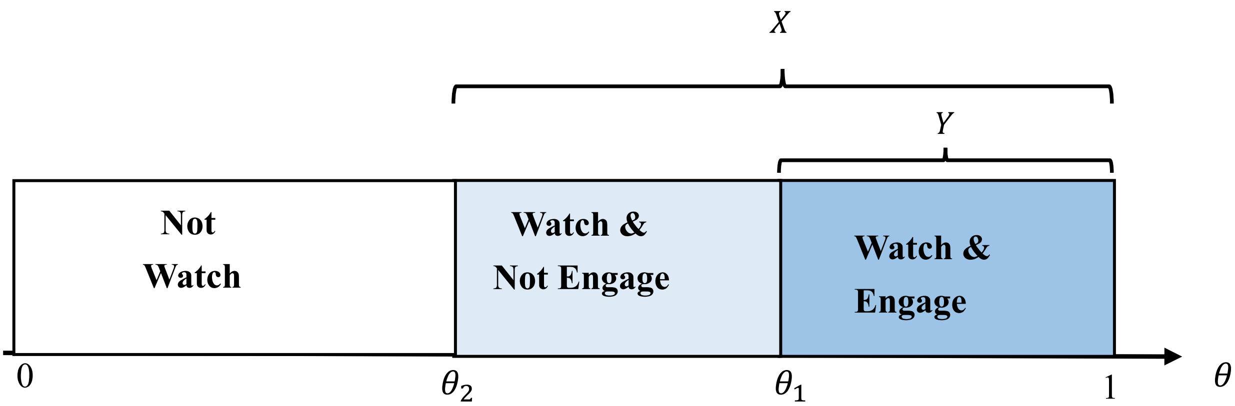

Figure 2. User behavior selection.

There may be potential negative utility of advertising for users. However, in our model, we do not explicitly account for this effect for several reasons. First, our focus is on UGC platforms, such as YouTube or TikTok, where advertising is typically non-intrusive and non-compulsory. Ads are often placed unobtrusively, such as in banners or at the end of videos, and users are not forced to engage with them. Second, since UGC platforms give users control over the content they watch, we believe the negative impact of advertising is minimal. Users are more likely to tolerate or even appreciate ads, especially when they are creatively integrated. Last, researchers, such as those in [26], focus on traditional media platforms with mandatory ads, which differ significantly from the voluntary, user-controlled ad experience on UGC platforms.

Users will estimate the quality of a video before watching it. The actual quality of the video consists of the basic quality and the quality related to the vlogger's efforts [11]. Due to individual differences and preferences for video types, we assume that the utility that user groups derive from the base quality of a particular video is heterogeneous. The video's basic quality, independent of the vlogger's effort, is represented by θ, which follows a uniform distribution $U(0, 1)$. Moreover, the video blogger will devote time, money, and other resources during the production process, all of which will affect the final quality level of the video. We use q to represent part of the video quality affected by the video blogger's efforts. Users will perceive the actual quality of the video while watching the video and taking interactive actions. That is, the higher quality video leads to higher user utility. When a user watches a video, he or she will spend an amount of time equal to the length of the video. Even if the user does not finish watching a particular video, it takes a certain amount of time for the user to confirm the actual quality of the video. Other videos cannot be watched during this period, so some costs will be generated for the user to watch a specific video. We use c_1 to represent the time and opportunity costs of a user watching a video. Similarly, users will consume corresponding time and opportunity costs when engaged, so we use c_2 to represent them uniformly. Thus, the utility of *watch-and-engage* users is:

$$\mathcal{U}_A = \theta + q - c_1 - c_2. \tag{3.1}$$

We denote by $\mathcal{U}_B$ the utility of a user who only watches the video without engaging (e.g., does not like, comment, or share). We model this utility as

$$\mathcal{U}_B = \zeta\theta + \zeta q - c_1. \tag{3.2}$$

If a user decides to watch a video without any engagement, he will undoubtedly save a certain amount of time, but he will also lose some of the fun due to the lack of user engagement. To capture this loss of utility, we use $\zeta \in (0, 1)$ to represent the proportion of utility users retain by watching a video without engagement. This discount effect affects both the utility that users get from the basic quality (θ) and the perceived actual quality of the video (q). Finally, c_1 denotes the consumption cost (e.g., time or attention) incurred by watchers. Under these assumptions, a passive watcher's net utility $\mathcal{U}_B$ may be lower than the utility of a watcher who also engages, $\mathcal{U}_A = \theta + q - c_1 - c_2$, depending on ζ and c_2.

Proposition 3.1. *Users type $\theta_i, i \in \{1, 2, 3\}$ and the proportion of users $\mathcal{X}$ and $\mathcal{Y}$ satisfy*

(i) $\theta_1 = \frac{c_2 - q - \zeta q}{1-\zeta}$, $\theta_2 = \frac{c_1 - \zeta q}{\zeta}$, $\theta_3 = c_1 + c_2 - q$,
(ii) $\mathcal{X} = 1 - \frac{c_1 - \zeta q}{\zeta}$, $\mathcal{Y} = 1 - \frac{c_2 - q + \zeta q}{1-\zeta}$.

The proposition fundamentally delineates the decision-making process by which users determine whether to engage actively with a video or merely view it passively. This decision hinges on the video's perceived quality, the vlogger's exerted effort, and the associated costs. Among these factors, the time and opportunity cost c_1 incurred by passive viewing, coupled with the absence of interactive engagement, enable users to circumvent the additional time and opportunity cost c_2 associated with interactive behaviors. We refer to these user choices as Watch & Not Engage (see Figure 2). The proposition introduces three key cutoff points, $\theta_i, i \in \{1, 2, 3\}$, which represent thresholds in the decision-making process for different types of users. The proportion of users who will watch and engage $\mathcal{X}$ or only watch $\mathcal{Y}$ depends on how the costs and quality balance for each group. The proposition outlines how different factors, base quality (θ), vlogger effort (q), and user costs (c_1, c_2), affect user decisions to engage with or simply watch a video. As the vlogger's efforts (q) increase, more users are likely to engage, but higher costs (c_1, c_2) reduce the likelihood of both watching and engagement. The cutoffs $\theta_i, i \in \{1, 2, 3\}$ help to classify user behavior based on these trade-offs.

4. VOM

We build the profit function of the platform first and then the vlogger's profit function according to the game's reverse order. The core issue for platforms to make decisions is to determine the exposure of a video after the vlogger uploads it. We use η to indicate the final promotion volume of the video by the platform. Thus, the profit optimization problem of the platform is:

$$\begin{aligned} &\sup_{\eta>0} \Pi_{p_1}(\eta) = \sup_{\eta>0} \left((m - w_1)\eta\mathcal{X} - \frac{\alpha\eta^2}{2} \right), \\ &\text{s.t. } w_1 = \kappa. \end{aligned} \tag{4.1}$$

The marginal gain per content view, denoted by m, reflects the platform's external advertising revenue. Platforms such as YouTube leverage diverse advertising formats. For example, YouTube employs pre-roll ads (displayed before video playback), display ads (embedded within the viewing page), and overlay ads (running concurrently with video content) [56]. Although these formats vary, they share a common characteristic: Users are exposed to advertisements while watching videos, and advertisers are charged based on the number of ad impressions. Therefore, it is reasonable to posit that platform revenue is directly tied to the number of video views, irrespective of ad type.

We define w_1 as the per-view revenue allocated to content creators by the platform. In our foundational model, we assume w_1 equals κ, ensuring a linear relationship between the platform's payout and the number of views. Before the engagement, the platform establishes this revenue-sharing parameter κ, thereby rendering the linear commission model synonymous with w_1 and κ. Let η represent the number of video impressions the platform chooses to generate. The platform determines how many recommendations it will present to users likely to exhibit interest in the video. We operate under the assumption that the pool of potential viewers is sufficiently large for the platform to decide how many referrals to make without being constrained by the overall user base size. This assumption is particularly applicable to dominant market players like YouTube, which have significant user reach.

We introduce a quadratic term $\frac{\alpha\eta^2}{2}$ to capture the platform's expenditure on video promotion. As the number of targeted users increases, so does the complexity and cost of matching content with user preferences. Even with the advancements in big data analytics, accurately aligning supply with demand becomes increasingly expensive as the platform scales its user base and expands its content offerings. Additionally, there is an opportunity cost associated with promoting one video over others, which we incorporate into the model by assuming promotion costs grow quadratically with the number of users targeted. In our framework, the platform's revenue share allocated to content creators is solely dependent on the number of views. Specifically, the platform grants the vlogger a commission of $\eta\mathcal{X}\kappa$. Considering that this model adopts a linear sharing rate primarily aimed at incentivizing viewership, it is termed the viewership-oriented linear sharing model, hereafter referred to as the linear sharing mode.

Next, we construct the vlogger's earnings function. In the current digital landscape, many individual content creators collaborate with economic entities, such as multi-channel networks (MCNs), on the platform. Whether a vlogger independently produces content or hires a team for video production, the core issue remains the same: Determining the appropriate level of investment in video creation and the anticipated quality necessary to generate revenue from the platform or external sources. In this paper, we model and optimize content quality, where creators must balance expected returns with associated costs, irrespective of whether they have a team supporting them.

In this model, the operational activities of any involved team are regarded as components of an integrated system. When a team exclusively supports a vlogger, with revenue distributed under a predefined contract, the vlogger and the team are effectively treated as a single vertically integrated entity. Moreover, we emphasize the platform's role in promoting potentially high-performing videos, thereby excluding direct revenue streams from external advertising or sponsorship agreements. As a result, content creators are presumed to concentrate exclusively on optimizing video quality to maximize their earnings through the platform.

$$\begin{aligned}
&\sup_{q>0} \Pi_{u_1}(q) = \sup_{q>0}\left(w_1\eta\mathcal{X} - \frac{\beta q^2}{2}\right), \\
&\text{s.t. } w_1 = \kappa.
\end{aligned} \tag{4.2}$$

Among them, the creative incentives that content creators get from the platform are related to the video's number of views. We assume that the cost of the vlogger increases twice as the video quality increases and denote β as the cost coefficient of the vlogger. Therefore, the cost of making a video for a vlogger is $\frac{\beta q^2}{2}$. The following NASH equilibrium can be obtained by solving this game by reverse induction.

$$q^* = \frac{2\kappa(m-\kappa)(\zeta - c_1)}{(\alpha\beta + 2\kappa^2 - 2\kappa m)\,\zeta}, \quad \eta^* = \frac{\beta(m-\kappa)(\zeta - c_1)}{(\alpha\beta + 2\kappa^2 - 2\kappa m)\,\zeta}. \tag{4.3}$$

Assumption 4.1. $m \le \sqrt{2\alpha\beta}$, $c_2 \le 1 - \zeta$.

Assumption 4.1 ensures that the number of users engaging with the content remains positive. It is essential to guarantee that the proportion of interacting users is strictly greater than zero (i.e., $\mathcal{Y} > 0$). This is because we exclude videos that are only passively viewed, as interaction is central to our analysis. Moreover, when the interaction ratio $\mathcal{Y} = 0$, the income share w_1 drops to zero, making it impossible for content creators to earn revenue, which would be an unrealistic scenario. Hence, maintaining a positive $\mathcal{Y}$ is critical, while, the condition $c_2 < 1 - \zeta$ ensures a positive interaction ratio even when video quality is at its lowest ($q = 0$). In other words, when this condition holds, videos will receive some level of interaction when their quality exceeds zero. The underlying rationale of $c_2 < 1 - \zeta$ is a comparison between the costs and benefits of user engagement. This condition suggests that for interaction to occur, users must find sufficient value in engaging with the content. In essence, the enjoyment or benefits derived from interacting with a video should outweigh the time and opportunity costs incurred.

Lemma 4.2. *Let* $2\underline{\kappa} = m - \sqrt{m^2 - 2\alpha\beta}$ *and* $2\bar{\kappa} = m + \sqrt{m^2 - 2\alpha\beta}$*. The willingness of participants to engage in activities on a UGC platform must satisfy the following conditions:*

(i) If $m \geq \sqrt{2\alpha\beta}$*, then there exist* $\underline{\kappa}, \bar{\kappa} \in (0, m)$ *such that* $\kappa \leq \underline{\kappa}$ *or* $\kappa \geq \bar{\kappa}$*.*
(ii) Otherwise, for all κ*, this condition holds.*

The incentive rationality must be met as we should obtain meaningful equilibriums. Specifically, we ensure that the vlogger is willing to invest in generating content under a certain quality (i.e., $q > 0$), and the platform has the motivation to promote it (i.e., $\eta > 0$). Lemma 1 establishes that a strictly positive equilibrium exists under the condition that m is compared to $\sqrt{2\alpha\beta}$. Here, m represents external revenue, while $\sqrt{2\alpha\beta}$ is a threshold. If m surpasses this threshold, it indicates exceptionally high external revenue; conversely, if m falls below the threshold, it reflects moderate external revenue.

Lemma 1(i) further demonstrates that, when external revenue is exceedingly high, both parties lack the incentive to participate when the sharing parameter κ lies within the range $\underline{\kappa} < \kappa < \bar{\kappa}$. These values, symmetrically distributed around $\frac{m}{2}$, indicate that a revenue-sharing rate near half of the external revenue proves unsatisfactory for both. High external revenue forces both the vlogger and the platform to exert considerable effort, escalating costs to the point where they outweigh potential profits, resulting in disengagement from both sides; neither high-quality content is produced nor is the video promoted. However, when κ falls outside this range, i.e., either $\kappa < \underline{\kappa}$ or $\kappa > \bar{\kappa}$, the effort from one party is tempered, controlling costs and allowing both to secure positive profits.

On the other hand, with moderate external revenue, the gap between revenue and costs remains manageable. Ensuring that, regardless of the platform's choice of κ, the vlogger remains incentivized to create content, and the platform is willing to promote it. This scenario of moderate external revenue reflects typical market conditions. Thus, we assume $m \leq \sqrt{2\alpha\beta}$ in the primary model and explore the symmetrical case where $m > \sqrt{2\alpha\beta}$ in Extension 7.1.

Proposition 4.3. *Assume that 4.1 holds. Then, the following conditions are satisfied:*

(i) When $\kappa < \frac{m}{2}$, q_1^* *and* Π_{u_1} *increase with* κ*; otherwise,* q_1^* *and* Π_{u_1} *decrease with* κ*.*
(ii) When $\kappa < m - \frac{\sqrt{2\alpha\beta}}{2}$, η_1^* *and* Π_{p_1} *increase with* κ*; otherwise,* η_1^* *and* Π_{p_1} *decrease with* κ*.*

Proposition 4.3 illustrates that when the platform's revenue-sharing rate is less than half of its external revenue, increasing the rate positively impacts video quality. This suggests that the platform can strategically leverage the revenue-sharing rate to incentivize creators to produce higher-quality content, thereby enhancing profitability without necessarily increasing exposure. However, this approach has inherent limitations. When the sharing rate remains below half of external revenue, incremental increases effectively boost both creator motivation and platform profits. Yet, as the rate approaches or exceeds half, its marginal benefits diminish. At higher sharing rates, creators may become discouraged, reducing their effort and lowering overall profitability. Furthermore, the platform faces higher operational costs, which dampen its willingness to promote videos, leading to reduced exposure and diminished profits for both the platform and creators. The platform's profit grows with the sharing rate only up to a certain threshold, where the balance between costs and returns is optimized. Beyond this threshold, the returns decrease, and further increases in the sharing rate become counterproductive. Therefore, a rational platform would exercise caution when considering additional increases in commissions, prioritizing sustainability and long-term profitability.

In summary, the revenue-sharing rate is the platform's tool for balancing content quality and profit, though its effectiveness is capped by external revenue. It remains advantageous only when it stays below half of the external revenue. As external revenue increases, the platform gains more flexibility in using this lever to optimize both quality and profitability, making external revenue a key determinant in this strategy.

5. EOM

In this section, we introduce a revenue-sharing model, referred to as the Engagement-Oriented sharing model (EOM), where the commission is determined by user engagement with the content. The decision-making sequence of the game remains unchanged, where only the profit structure for both participants is modified, while user behavior follows the same pattern described earlier in section 3. We analyze the profit structure for both participants by backward induction. After receiving the video, the platform determines the level of exposure it will provide while keeping the other fundamental assumptions intact, except altering the revenue-sharing commission. The platform's profit in this model can be expressed as follows:

$$\begin{aligned} \sup_{\eta>0} \Pi_{p_2}(\eta) = \sup_{\eta>0} \left((m - w_2)\eta\mathcal{X} - \tfrac{\alpha\eta^2}{2}\right), \\ \text{s.t.} \quad w_2 = \tfrac{\kappa\mathcal{Y}}{\mathcal{X}}. \end{aligned} \tag{5.1}$$

We propose a commission to reflect the video's engagement rate, which is defined as the proportion of interactions relative to total viewership. Specifically, we define w_2 as $\frac{k\mathcal{Y}}{\mathcal{X}}$, where $\mathcal{Y}$ represents the number of users engaging with the content and $\mathcal{X}$ the total number of views. In this model, the engagement rate $\mathcal{Y}$ (and watch rate $\mathcal{X}$) is not an exogenous parameter but a function of the creator's chosen strategy quality q, i.e., $\mathcal{Y} = \mathcal{Y}(q)$. The engagement depends on the interaction between the creator's effort (which is influenced by their strategy q) and the platform's policy (determined by the parameter κ). This introduces a non-linear relationship between w_2 and κ. Setting w_2 as a multiple of the engagement rate offers two clear advantages for the platform: First, it incentivizes content creators to produce highly interactive videos, enhancing user engagement; second, engagement rates provide a more accurate measure of video quality than view counts, which are more susceptible to manipulation. Platforms like Bilibili already use similar methods, where videos with higher engagement, despite similar view counts, may generate higher revenue. Similarly, YouTube's revenue per 1,000 views (RPM) varies across channels [12]. In this model, the sharing parameter κ remains fixed and exogenously determined, but the commission fluctuates from κ to $\frac{k\mathcal{Y}}{\mathcal{X}}$, depending on the engagement. Since $\mathcal{Y}$ is a function of the creator's strategy $q(\kappa)$, the resulting revenue-sharing commission w_2 is non-linear with respect to κ. We refer to this structure as an engagement-based revenue-sharing model. In this framework, content creators decide on the quality level of their videos, and thus, we construct the content creator's profit function accordingly.

$$\begin{aligned} \sup_{q>0} \Pi_{u_2}(q) = \sup_{q>0} \left(w_2\eta\mathcal{X} - \tfrac{\beta q^2}{2}\right), \\ \text{s.t.} \quad w_2 = \tfrac{\kappa\mathcal{Y}}{\mathcal{X}}. \end{aligned} \tag{5.2}$$

After comparison, it can be seen that only the commission changed, w_2, has the first item in the profit expression. $w_2 n\mathcal{X}$ is a payout of the platform, which is also the vlogger's earnings. The following Nash equilibrium can be obtained by backward induction,

$$q_2^* = \frac{\kappa m\zeta\,(2 - c_2 - 2\zeta) - 2\kappa^2\zeta\,(1 - c_2 - \zeta) - \kappa m c_1(1 - \zeta)}{(\alpha\beta + 2\kappa^2 - 2\kappa m)\,(1 - \zeta)\zeta}, \tag{5.3}$$

$$\eta_2^* = \frac{\alpha\beta\,[m\,(\zeta - c_1)\,(1 - \zeta) - \zeta\kappa\,(1 - c_2 - \zeta)] - \kappa m(m - \kappa)\,[\zeta c_2 - c_1(1 - \zeta)]}{\alpha\,(\alpha\beta + 2\kappa^2 - 2\kappa m)\,(1 - \zeta)\zeta}. \tag{5.4}$$

Lemma 5.1. *Under the EOM, the participation conditions of both players in the game are consistent with VOM.*

Lemma 5.1 reveals the commonness of the two revenue-sharing modes. Looking back on our discussion of Lemma 4.2, we can conclude that changing the revenue-sharing model will not affect the willingness of both players to participate. What can affect the platform and ' willingness to participate is the platform's external rate of return m, the sharing parameter κ, and the cost structure of both participants. Here, we still keep the assumption that $m \leq \sqrt{2\alpha\beta}$ unchanged and discuss the case under $m > \sqrt{2\alpha\beta}$ in extension 7.1.

Proposition 5.2. *If assumption 4.1 holds, then the following will be satisfied,*

(i) When $\kappa < m/2$, the video quality q_2^* and the profit of creator Π_{u_2} increase in κ; when $\kappa \geq m/2$, the comparative statics of q_2^* and π_{u2} with respect to κ are generically ambiguous.

(ii) When $\kappa > m/2$, the exposure η_2^* and the platform's profit Π_{p_2}decrease in κ; when $\kappa \leq m/2$, the comparative statics of η_2^* and π_{p2} with respect to κ are generically ambiguous.

As stated in Proposition 5.2, when the revenue-sharing rate is relatively low, both video quality and the platform's profit improve as the rate increases. This highlights that, even in an engagement-oriented revenue-sharing model, the sharing rate remains a powerful lever for enhancing video quality and profitability. However, there are two key differences to consider. First, the effective range of this tool is broader. In the traditional model, platform profit begins to decline once the sharing rate surpasses a certain threshold. In contrast, the EOM offers a wider range where increasing the rate continues to boost platform profit, providing greater flexibility for the platform to maximize returns. A similar pattern applies to increasing video exposure. Second, the EOM may maintain effectiveness even beyond typical limits. In traditional models, when the sharing rate exceeds half the external revenue, both video quality and content creators' profits usually decline, as higher commissions dampen motivation. However, in the engagement-oriented model, this adverse effect may not occur. Under certain conditions, even a sharing rate exceeding the conventional range can still positively impact video quality and profit. We emphasize that for $\kappa \geq m/2$ the comparative statics $\partial q_2^*/\partial\kappa$ and $\partial\pi_{u2}^*/\partial\kappa$ are not determinate under the baseline assumptions (their signs depend on other model parameters and interaction terms), and likewise for $\kappa \leq m/2$ the comparative statics $\partial\eta_2^*/\partial\kappa$ and $\partial\pi_{p2}^*/\partial\kappa$ are not determinate; accordingly, Proposition 3 reports only the parameter regions where definitive monotonicity can be established.

Streaming platforms have favored the traditional viewership-based model for its simplicity and ease of implementation. Its mathematical straightforwardness has also made it a popular choice among researchers. In comparison, the EOM is more intricate and less intuitive. Since engagement generally accounts for a smaller proportion of viewership, the EOM results in lower commissions for creators.

This raises new questions: Will higher expenditures place additional financial strain on the platform? And will increased revenue-sharing rates genuinely motivate creators to produce better content?

6. Comparison of VOM and EOM

In this section, we will conduct a comparative analysis of the VOM and the EOM, focusing on how each contract impacts the profits of both the platform and content creators. Since the EOM is considered an improvement over the traditional VOM, we aim to determine whether the EOM can more effectively incentivize creators and lead to a Pareto improvement for the overall system. In both models, the platform's profit and video exposure rise and fall together, while the content creator's profit and video quality follow the same pattern. This reflects the profit-driven behavior of both parties. As both are assumed to be rational, each participant seeks to maximize their respective profits. As a result, preferences for one model over the other will vary based on the profit outcomes. We propose the following insights based on a comparative evaluation of the platform's profits under the two models.

Proposition 6.1. *Assume that Assumption 4.1 holds. If* $\kappa > \frac{m^2-\alpha\beta}{m}$*, then* $\Pi^*_{p_2} > \Pi^*_{p_1}$*. Otherwise,* $\Pi^*_{p_2} \leq \Pi^*_{p_1}$.

Proposition 6.1 elucidates the platform's differing preferences between the two revenue-sharing models. It demonstrates that when external revenue falls within a moderate range, the engagement-based model becomes more profitable only when the revenue-sharing rate surpasses a specific threshold. Below this threshold, the linear model proves more advantageous. In both cases, the sharing rate acts as an incentive for content creators to produce higher-quality content, which in turn drives increased profitability, referred to as the incentive effect. However, the sharing rate also incurs costs for the platform, introducing what is known as the cost effect. When the sharing rate is low, the incentive effect predominates, and the linear model, offering higher payouts, better stimulates content creation. In such cases, the cost savings of the engagement-based model are insufficient to compensate for the stronger incentive effect provided by the linear model, thus rendering the latter more favorable.

As the sharing rate exceeds the threshold, the cost effect begins to dominate. The engagement-based model becomes more cost-efficient, requiring lower payouts to creators, thereby amplifying its cost advantage. Additionally, as previously discussed, the engagement-based model offers a broader range of incentives, while the linear model's efficacy in motivating creators diminishes as the sharing rate increases. Consequently, once the sharing rate surpasses a certain level, the engagement-based model becomes more profitable than the linear model, owing to its superior cost-efficiency and broader incentive scope.

Let $\overline{c_1} = \frac{\zeta c_2 \kappa m^2 - 2\alpha\beta\zeta\left[m(1-\zeta)-\kappa(2-c_2-\zeta)\right]}{\left[2\alpha\beta(\kappa-m)+\kappa m^2\right](1-\zeta)}$ and $\overline{c_2} = \frac{2\alpha\beta(m-2\kappa)(1-\zeta)}{\kappa\left(m^2-2\alpha\beta\right)}$. Under the assumption 4.1, from the side of the producer, we have the following proposition,

Proposition 6.2. *Assume that Assumption 4.1 holds. Then the following conditions are satisfied:*

(i) When $\kappa \geq \frac{2\alpha\beta m}{2\alpha\beta+m^2}$*, the EOV mode dominates the VOM mode for the content creator.*

(ii) When $\frac{m}{2} < \kappa < \frac{2\alpha\beta m}{2\alpha\beta+m^2}$*, there exist* $\overline{c_1} \in \left(0, \frac{\zeta c_2}{1-\zeta}\right)$ *and* $\overline{c_2} \in (0, 1-\zeta)$ *such that either* $c_2 \leq \overline{c_2}$ *or* $c_2 > \overline{c_2}$ *and* $c_1 > \overline{c_1}$*, where the EOV mode dominates the VOM mode for the content creator.*

(iii) Otherwise, the VOM mode dominates the EOV mode for the content creator.

Proposition 6.2 reveals that the EOM may be more profitable for content creators. EOM ties the revenue-sharing rate to user engagement, which is typically less than 1, and the actual commission earned by creators is lower than in the linear model. In other words, content creators might prefer a model that offers a smaller commission under the right conditions.

The reason for this preference lies in the EOM's ability to more effectively incentivize creators to produce high-quality content. User interactions serve as a more accurate reflection of user approval and preferences, which in turn better correlate with content quality. While the traditional linear model incentivizes creators by rewarding views, the engagement-based model goes further by also rewarding user engagement. This double incentive mechanism links profit margins directly to engagement rates, stimulating higher-quality content creation. As the quality improves, the platform allocates greater exposure, ultimately leading to increased traffic and higher profits for the content creator. According to Proposition 6.2, for a video blogger to achieve higher profits under the engagement rate-based model, the sharing parameter κ must be sufficiently large ($\kappa \geq \frac{2\alpha\beta m}{2\alpha\beta+m^2}$). A smaller κ fails to provide adequate motivation for the blogger. Due to the double incentives of engagement and views, this model proves more profitable than the linear model, which focuses solely on views. Additionally, Proposition 6.2(ii) indicates that when κ is moderate $\left(\frac{m}{2} < \kappa < \frac{2\alpha\beta m}{2\alpha\beta+m^2}\right)$, certain additional conditions must be satisfied for the engagement rate-based model to remain more profitable. These conditions pertain to user interaction behavior and viewing costs.

The first condition relates to the user's engagement cost, typically representing the time required for interaction. High interaction costs can reduce engagement rates, making it essential for the platform to minimize barriers and ensure seamless, accessible interaction. If the interaction cost is too high ($c_2 > \overline{c_2}$), the platform must compensate by ensuring that the cost of watching the video ($c_1 > \overline{c_1}$). This cost is influenced by the video's length; if the video is too short relative to the interaction time, the resulting low interaction rate may diminish sharing rates and overall profitability.

In summary, when κ is large, no additional conditions are necessary, as users are sufficiently incentivized. However, when κ is moderate, it is essential to ensure either low interaction costs or that the video length aligns well with the interaction time to maintain profitability.

Corollary 6.3. *When the dominant condition of the producer is satisfied, both participants of the game achieve Pareto improvement under the EOV.*

Corollary 6.3 demonstrates that under certain conditions, the engagement rate-based revenue-sharing model can provide greater profits for both participants compared to the traditional linear model, resulting in a "win-win" scenario. Achieving Pareto improvement aligns with the dominant conditions for the model. This occurs because the platform can easily secure higher profits from the engagement rate-based model by ensuring the sharing parameter κ is sufficiently large. Moreover, the video blogger may face some cost constraints (c_1, c_2). Thus, it is only necessary to ensure that the blogger's preference conditions are met for both parties to benefit from the engagement-based model. In Figure 3, we apply the conditions from Propositions 5.2 and 6.1, as well as the conclusions from Section 7.1, to illustrate the dominant regions for both models. The left side represents the case where $m \leq \sqrt{2\alpha\beta}$, and the right side shows $m > \sqrt{2\alpha\beta}$. The region favoring the engagement rate-based model (the Pareto region) covers a larger area, indicating that this model is the preferable choice for most parameter combinations.

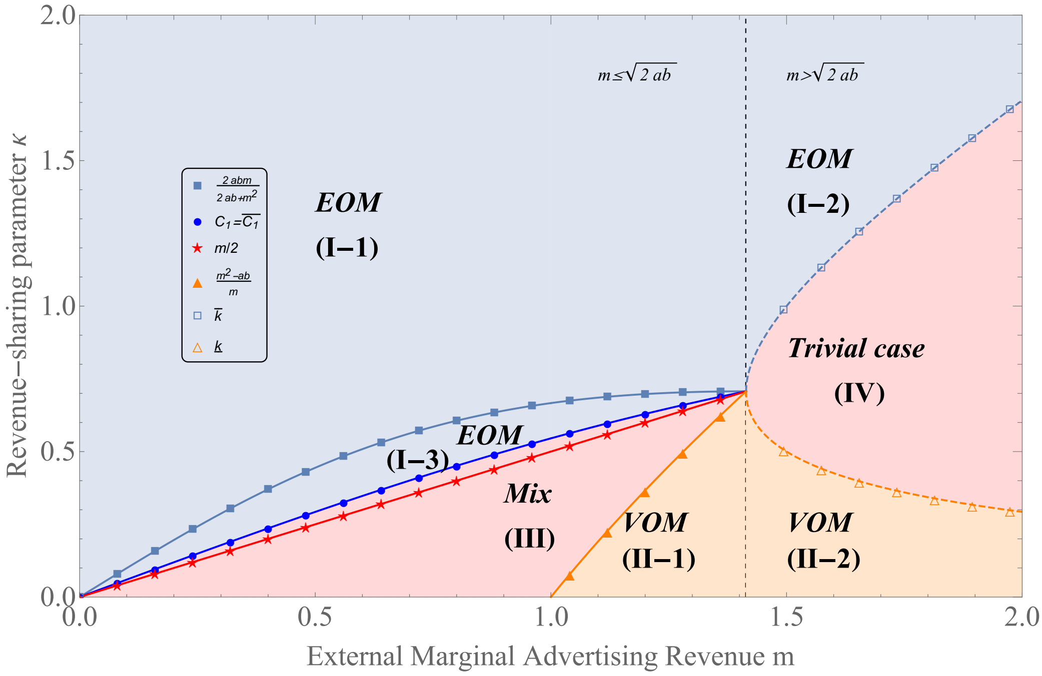

Figure 3. Pareto dominant region of two modes ($\zeta = 0.8$, $c_1 = 0.2$, $c_2 = 0.1$, $\alpha = 1, \beta = 1$).

Comparison of the VOM and the EOM reveals distinct benefits for content creators and consumers. In the VOM, creators are compensated based solely on the number of views their content receives. This model incentivizes content creators to produce videos that attract more views. However, it does not account for the quality of user engagement, such as likes, shares, and comments, which could reflect deeper levels of viewer interaction and content quality. In contrast, the EOM ties revenue sharing to user engagement metrics, thus encouraging creators to produce content that generates higher levels of interaction. This creates a dual incentive structure where creators are motivated not only by viewership but also by engagement, which leads to higher-quality content. As we show in Proposition 6.2, even at lower commission rates, the EOM can result in higher profits for content creators due to the enhanced exposure and engagement generated by this incentive structure. From the consumers' perspective, the EOM offers a significant advantage over the VOM. Since the platform promotes content that is more engaging and of higher quality, consumers benefit from better recommendations, leading to a more satisfying viewing experience. The interaction-based rewards ensure that the content recommended to users is not only popular but also more likely to meet their interests, thus improving the overall user experience.

Corollary 6.4. *When the conditions of (i) or (ii) of Proposition 6.2 are satisfied, both the quality q^* and the exposure η^* of the video in the EOV model, and the consumer surplus of the users are improved.*

Corollary 6.4 further establishes that the engagement rate-based sharing model provides stronger incentives for content creators. The mechanism behind this effect is that the platform uses κ to boost video views. A higher κ encourages creators to produce higher-quality content, which motivates the platform to increase the video's exposure. Greater exposure leads to more views, and higher quality enhances the video's interaction rate, both of which drive profitability for content creators. Thus, the parameter κ acts as a double incentive by encouraging both video exposure and interaction rates. This incentive mechanism creates a virtuous cycle where improved video quality leads to increased views, which further raises engagement rates, resulting in higher profits for the platform and creators, achieving Pareto improvements.

Additionally, Corollary 6.4 shows that as Pareto improvements are achieved, video quality and promotion efforts improve, meaning more users watch better-quality videos. This results in a higher consumer surplus. Therefore, when certain conditions are met, the engagement rate-based revenue-sharing model benefits all three parties: The platform, content creators, and consumers, leading to a three-win outcome. As we discuss in Proposition 6.1 & 6.2, when the platform sets the revenue-sharing parameter κ optimally, both the platform and creators can achieve higher profits compared to the VOM, and consumers enjoy higher-quality content. This triple win is particularly evident when the platform's external revenue is within a certain range, allowing it to adjust the commission rates without sacrificing profitability. This is further demonstrated in Corollary 6.4, where we show that the EOM can lead to Pareto improvements, benefiting all three participants simultaneously. These findings highlight the significant potential of the EOM to create a more sustainable and mutually beneficial ecosystem for all parties involved, as it fosters both content quality and user engagement.

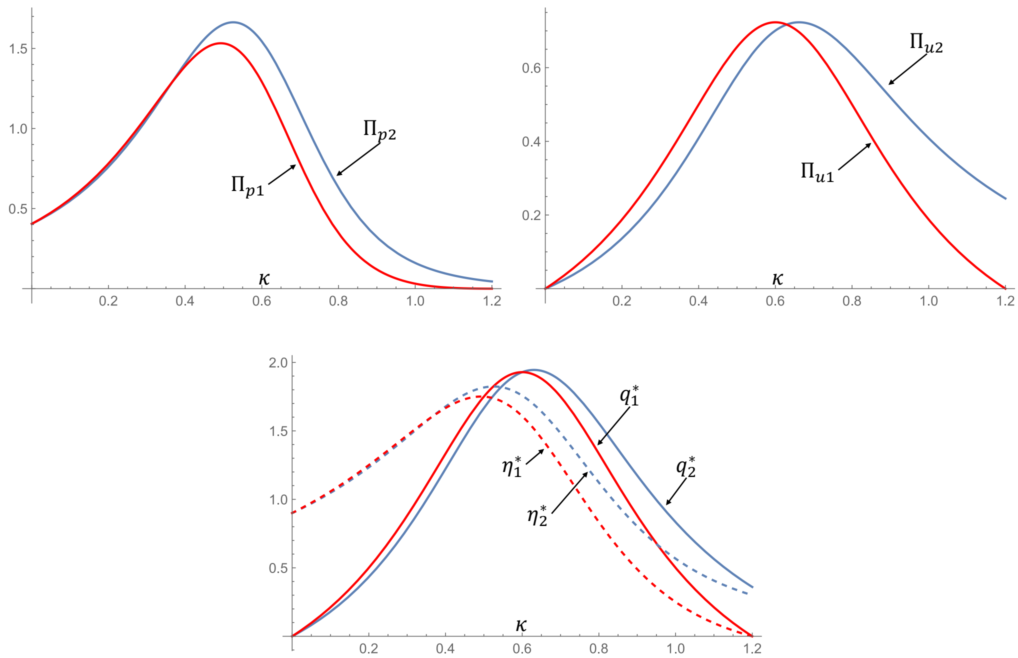

Figure 4. Impact of parameter κ on (a) platform profit, (b) creators' payoff, and (c) equilibrium outcomes ($m = 1.2$, $\zeta = 0.8$, $c_1 = 0.2$, $c_2 = 0.1$, $\alpha = 1, \beta = 1$).

To further validate the effectiveness of the proposed EOM and to complement the metrics reported above, we study the sensitivity of key outcomes with respect to the parameter κ. Figure 4 shows the impact of parameter κ on (a) platform profit, (b) creators' payoff, and (c) equilibrium outcomes (equilibrium content quality and equilibrium exposure) under the two operating modes considered in this paper. All three plots exhibit an inverted-U shape with respect to κ. This behavior agrees with our analytical arguments in Sections 4 and 5: When κ is very small, incentives are insufficient to elicit high-quality contributions or extensive exposure, whereas when κ is excessively large, adverse effects (e.g., excessive competition or inefficient allocation) reduce overall performance. The intermediate range of κ therefore yields the best trade-off, producing the maximal platform profit and creators' payoff. Importantly, the figure also shows that for sufficiently large κ, the EOM outperforms the alternative operating mode for platform profit and creators' payoff, which corroborates the theoretical comparative statics discussed in Section 6. We have added this discussion to make explicit how the simulation trends align with our theoretical predictions. Finally, these additional metrics and plots provide a more comprehensive evaluation of the mechanism and strengthen the simulation evidence supporting our conclusions.

7. Extensions

In the preliminary model, we assume the platform's external ad revenue is within a moderate range ($m \leq \sqrt{2\alpha\beta}$). In this part, we relax this assumption and study the more extreme case when the external ad revenue is above the threshold $\sqrt{2\alpha\beta}$.

7.1. Symmetrical Case: $m > \sqrt{2\alpha\beta}$

Assumption 7.1. $m > \sqrt{2\alpha\beta}$, $c_2 \leq 1 - \zeta$.

According to Lemma 1, if $m > \sqrt{2\alpha\beta}$, $\kappa < \underline{\kappa}$ or $\kappa > \bar{\kappa}$ must be satisfied to obtain a meaningful equilibrium solution, so we come to the following propositions.

Proposition 7.2. *If assumption 7.1 holds, then the following will be satisfied,*

(i) When $\kappa < \underline{\kappa}$, the video quality q^* and the exposure η^* are positively correlated with κ. when $\kappa > \bar{\kappa}$, the video quality q^* and the exposure η^* are negatively correlated with κ;

(ii) When $\kappa < \underline{\kappa}$, the profits of both participants are positively correlated with κ. When $\kappa > \bar{\kappa}$, the profits of both participants are negatively correlated κ.

(iii) When $\kappa < \underline{\kappa}$, both participants are better off in the engagement rate-based revenue-sharing model. When $\kappa > \bar{\kappa}$, both participants are better off in the linear model.

Proposition 7.2(i) and 7.2(ii) demonstrate that the sharing parameter κ remains an effective lever for the platform to adjust both video quality and the profits of both parties. When κ is small, increasing it can enhance video quality and promotion efforts, benefiting both participants. This conclusion aligns with our findings in the primary model. Interestingly, when external revenue m is substantial, the effective range of κ is identical across both models, suggesting that the ability to adjust profit and quality via κ is not influenced by the different sharing models. This contrasts slightly with the primary model, likely because when $m > \sqrt{2ab}$, Lemma 2(2) shows that the platform cannot choose κ freely within the range $\underline{\kappa}$ to $\bar{\kappa}$. This constraint narrows the effective range of κ, making it consistent for both models.

Proposition 7.2(iii) further shows that when external revenue is large ($m > \sqrt{2ab}$), the two models have distinct application ranges. Specifically, with a small sharing rate κ, the linear revenue-sharing model generates higher profits for both parties. However, when κ is large, the engagement rate-based model becomes more profitable. This outcome is due to the difference between the incentive effect and the cost effect. With a small κ, the engagement rate model's cost advantage is not pronounced enough compared to the linear model. Consequently, the linear model, with its higher commissions, provides stronger incentives, resulting in higher video quality and profits for both parties.

Conversely, when κ is large, the engagement rate-based model has a significant cost advantage over the linear model. Additionally, its "double incentive" mechanism further enhances motivation, leading to greater benefits for both parties. These findings are consistent with our comparative analysis in the primary models, confirming that the incentive mechanism of the engagement rate-based model remains robust, even with substantial external ad revenue. The conclusions of this proposition are illustrated in the right part of Figure 3.

7.2. Endogenous κ Revenue-Sharing Decision

In the benchmark model, we assume that the revenue-sharing parameter κ is exogenously given. In this section, we relax this assumption by allowing the platform to first set the sharing commission κ that maximizes its profit in the linear mode. After the platform has chosen the commission, the content creator decides on the quality of the video. Finally, the platform determines the exposure level. We then analyze how this endogenous decision-making process can lead to an optimal κ and achieve a Pareto improvement based on specific profit conditions for both participants in the engagement-oriented mode.

Let the commission in the linear mode be $w_1 = \kappa_1$, while in the engagement-oriented mode, the commission is expressed as $w_2 = \kappa_2 \frac{y}{\chi}$. For simplicity, we standardize the cost factors α and β to 1, which does not alter the conclusions of the benchmark model. The platform typically holds a strong bargaining position over content producers when setting the commission. While the platform aims to optimize its own profits, it also considers the profit of the creator, given their cooperative relationship. The goal is to maximize the creator's profit as much as possible, without sacrificing the platform's own gains.

Keeping all other assumptions unchanged, we calculate the platform's optimal revenue-sharing parameters κ_1 and κ_2 for both models, based on the derived Nash equilibrium.

$$\kappa_1^* = \frac{2m - \sqrt{2}}{2}, \quad \kappa_2^* = \frac{A - \sqrt{B}}{2\zeta(1 - \mathrm{c}_2 - \zeta)}. \tag{7.1}$$

Let $B = \mathrm{c}_1^2 m^2 (1-\zeta)^2 - 2\mathrm{c}_1 m^2 (1-\zeta)^2 \zeta + \left(-\mathrm{c}_2{}^2 \left(m^2 - 2\right) + 2\mathrm{c}_2 \left(m^2 - 2\right)(1-\zeta) + 2(1-\zeta)^2\right)\zeta^2$, $A = m\left(\zeta\left(2 - \mathrm{c}_2 - 2\zeta\right) + \mathrm{c}_1\zeta - \mathrm{c}_1\right)$. Given $\kappa_1 = \kappa_1^*$, we obtain the maximum profit $\Pi_{p_1}^*\left(\kappa_1^*\right)$ that platform can achieve in the linear mode. It is straightforward to prove that when $\kappa_2 = \kappa_2^*$, then $\Pi_{p_2}^*\left(\kappa_2^*\right) > \Pi_{p_1}^*\left(\kappa_1^*\right)$, indicating that the profit ceiling of the platform under the EOM surpasses that under the VOM. However, it is noteworthy that the platform can attain a higher profit under the engagement-oriented mode than under the linear mode, even without setting $\kappa_2 = \kappa_2^*$.

Proposition 7.3. *If $m \leq \sqrt{2}, \xi_1, \xi_2 \in (0, m)$ exist, when $\xi_1 < k_2 < \xi_2$, no matter what value k_1 is, the platform can obtain higher profit under engagement rate-based revenue-sharing model, i.e.,*

$\Pi_{p2}(\boldsymbol{\kappa}_2) > \Pi^*_{p1}\left(\boldsymbol{\kappa}^*_1\right)$. *Similarly,* $\boldsymbol{\eta}_1, \boldsymbol{\eta}_2 \in (\mathbf{0}, \boldsymbol{m})$ *exist, when* $\boldsymbol{\eta}_1 < \boldsymbol{\kappa}_2 < \boldsymbol{\eta}_2$*, no matter what value* κ_2 *is, the producer can obtain higher profit under engagement rate-based revenue-sharing model, i.e.,* $\Pi_{u2}(\kappa_2) > \Pi^*_{u1}\left(\kappa^*_1\right)$.

Proposition 7.3 provides valuable managerial insights into the potential advantages of engagement-oriented revenue-sharing models over traditional linear models. By carefully designing the sharing parameter κ_2, platforms can create conditions where both the platform and content creators achieve higher profits, surpassing the profit ceiling of linear models and achieving Pareto improvement. This underscores the importance of refining revenue-sharing mechanisms to balance the interests of platforms and creators. Specifically, platforms should dynamically adjust κ_2 within optimal intervals to incentivize creators to enhance user engagement while ensuring sustainable profitability for the platform. To achieve this, detailed analysis of user interaction behaviors and content creation costs is essential for identifying critical parameter ranges, enabling data-driven and adaptive decision-making. Moreover, the EOM's emphasis on fostering deeper user interactions (e.g., comments, likes, and shares) demonstrates its potential to create greater value for both stakeholders, offering a compelling alternative to viewership-based models. By leveraging this approach, platforms can foster a collaborative content ecosystem that supports long-term sustainable growth and innovation.

Corollary 7.4. *Let* $\underline{\kappa_2} = \max\{\xi_1, \boldsymbol{\eta}_1\}, \overline{\kappa_2} = \min\{\xi_2, \boldsymbol{\eta}_2\}$. *When* $\kappa_2 \in \left(\underline{\kappa_2}, \overline{\kappa_2}\right)$,

(i) Both participants may achieve Pareto improvement under EOM,
(ii) Quality of content improves under EOM.

Corollary 3 outlines the conditions that κ_2 must meet to achieve pareto improvement in the engagement-oriented mode. If the platform adopts a purely self-interested approach and sets $\kappa_2 = \kappa^*_2$, it will earn a maximum profit, denoted as $\Pi^*_{p2}\left(\kappa^*_2\right)$, under this model. However, this approach reduces the content producer's profit compared to the linear mode, even though the platform's profit increases. In this scenario, content producers are worse off.

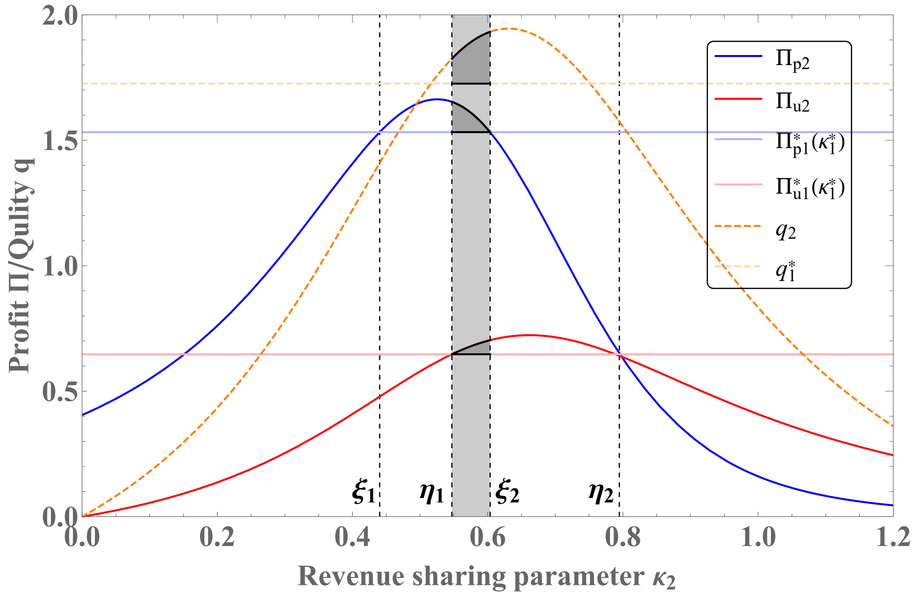

Figure 5. Pareto equilibrium interval of k_2 ($m = 1.2, \zeta = 0.8, c_1 = 0.2, c_2 = 0.1, \alpha = 1, \beta = 1$).

Alternatively, if the platform selects a κ_2 within the pareto interval $\left(\underline{\kappa_2}, \overline{\kappa_2}\right)$, shown as the shaded area in Figure 5, it can boost the content producer's profit, though this would mean not maximizing its own profit. Such sacrification is feasible, as supporting content producers can lead to improved content quality. Essentially, by choosing a non-optimal sharing rate, the platform can enhance content quality and achieve Pareto profit improvement for both parties in the EOM compared to the VOM. This emphasizes the robustness of our conclusions from the benchmark model, as shown in Figure 5.

8. Conclusions

In this paper, we address the fundamental problem of how UGC platforms should design revenue-sharing mechanisms to balance creator incentives, platform performance, and user experience. To this end, we develop a stylized model to examine how different allocation rules affect the operations of UGC platforms and the incentives of content creators. By comparing the VOM with the EOM, we highlight the conditions under which engagement-based contracts can outperform view-based arrangements. Our analysis shows that EOM not only provides stronger incentives for improving content quality and platform exposure, but also creates the possibility of win–win outcomes and Pareto improvements when revenue-sharing rates are properly set. These findings underscore the practical significance of adopting engagement-oriented mechanisms, offering both theoretical contributions to the literature on platform economics and managerial implications for sustainable platform design. In addition to these core findings, our extended analysis reveals that the sharing parameter serves as a managerial tool to fine-tune incentives, though its effectiveness is moderated by external advertising revenues. We also show that EOM can enhance user experience and consumer surplus, even under relatively low commission levels. These insights provide a broader understanding of how engagement-based mechanisms reshape the economics of content platforms.

First, we find that the revenue-sharing commission, represented by the revenue-sharing parameter, κ is a tool for the platform to enhance both content quality and exposure. This mechanism can improve profits for the platform and content creators. Our results indicate that the platform's external revenue can limit the effectiveness of this tool; however, the EOM enables for greater flexibility compared to the traditional VOM. Notably, we observe that a more generous compensation plan does not always benefit creators due to potential slackness, suggesting that a moderate revenue-share rate may be optimal.

Second, counterintuitively, the EOM can yield higher profits for content creators even at lower commission levels than the VOM. By incentivizing engagement, the EOM encourages creators to produce higher-quality content, thus driving both views and engagement. This double incentive effect motivates creators to enhance video quality, resulting in greater exposure and higher revenue at a lower share rate. Our findings illustrate that this nonlinear revenue-sharing model offers a more effective incentive structure.

Third, our analysis demonstrates that the EOM can create a win-win scenario for both parties when the revenue-sharing parameter is appropriately set. In comparison to the traditional linear VOM, the EOM fosters improved content quality and increased traffic, benefiting user experience on the platform and enhancing consumer surplus. This trend holds even when the platform's external revenue is exceptionally high. Our results elucidate why creators often seek "likes" and "subscriptions" from viewers, as these interactions boost traffic and increase potential earnings. Enhanced engagement leads to higher commissions, incentivizing creators to invest more effort into video production, which in turn elevates the platform's advertising revenue, creating a virtuous cycle. Moreover, when considering an endogenous revenue-sharing parameter, it appears that if the platform aims to enhance content quality, both parties can achieve Pareto improvements within the EOM by making minor sacrifices in the platform's profits, reinforcing the robustness of our conclusions.

To conclude, we (i) tackle the problem of optimal revenue-sharing in UGC platforms, (ii) propose and analyzes an engagement-oriented mechanism alongside the conventional view-based rule, (iii) contribute by highlighting the theoretical and managerial implications of explicitly incorporating engagement, and (iv) demonstrate that EOM outperforms VOM by generating stronger incentives, higher quality, and potential Pareto improvements. This concise summary highlights the significance of our contribution and provides a clear foundation for future research on platform design and digital content economics.

The proposed framework, which broadens the scope of classical problems associated with UGC platforms, opens avenues for intriguing future research. In the future, researchers could investigate the impact of network externalities on content viewing and engagement, exploring how these factors influence platform promotion. Additionally, it may be worthwhile to examine how platforms can design suitable revenue-sharing arrangements amid competition between platforms or producers. The potential for content creators to establish direct connections with advertisers necessitates further investigation into how such advertiser-dominated behaviors may affect the revenue-sharing strategies of platforms. An interesting extension of our model would be to incorporate UGC creators' nonmonetary utility, such as social recognition and intrinsic satisfaction from content engagement. This would offer a more holistic view of creator behavior and better reflect the motivations present in the UGC creation ecosystem. Moreover, we have simplified the platform's exposure decision by assuming that it precedes user engagement. In reality, many platforms adopt a sequential process in which initial engagement signals inform subsequent exposure decisions. Incorporating such feedback into a two-stage or multi-stage game-theoretic framework would provide a more realistic characterization of platform operations. We leave this promising extension for future research.

Author contributions

Run Tang conceived the study, selected the research question, and designed the modeling framework (Conceptualization; Methodology). Zhengyang Wang developed the solution approach, carried out the theoretical analyses, and implemented and ran the numerical experiments (Methodology; Formal analysis; Software; Validation; Visualization). Yangyang Peng led manuscript revision, drafted the conclusions, coordinated submission, and served as the corresponding author (Writing–review & editing; Writing–original draft; Project administration). Ziyuan Zeng drafted sections of the manuscript and performed language and grammar editing (Writing–original draft; Writing–review & editing). Tong Zhang contributed to model analysis and numerical experiments (Formal analysis; Investigation; Validation). Yingjun Shen contributed to model analysis and numerical experiments (Formal analysis; Investigation; Validation). All authors discussed the results, provided critical feedback, and approved the final version of the manuscript.

Use of Generative-AI tools declaration

The authors declare that no Artificial Intelligence (AI) tools were used in the preparation of this manuscript.

Data availability statement

The corresponding author can provide the datasets created and examined in this study upon reasonable request.

Conflict of interest

The authors have stated that they do not have any conflicts of interest.

Ethical approval

This paper has not been published before, and it is not under consideration for publication anywhere else.

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