EXPLORING INFLUENCES ON USER ENGAGEMENT IN ONLINE PLATFORMS: THREE STUDIES ON USER-GENERATED CONTENT

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Exploring Influences on User Engagement in Online Platforms:

Three Studies on User-Generated Content

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CERTIFICATE OF ORIGINALITY

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Chen Zihan

Abstract

With the prevalence of online platforms, user-generated content (UGC) is developing rapidly, creating new jobs, markets and policy needs. UGC has evolved into a more dynamic form that demands users' attention and continuous consumption. While existing research has predominantly focused on the influence of sentiment on online user engagement, there is less understanding of how dynamic sentiment patterns influence subsequent discussions. Additionally, despite abundant research on internal factors on engagement in online communities, the impact of external event on user engagement in online communities remains unclear. Moreover, as regulations tightened, there is an increasing need to understand legitimate strategies for companies and platforms to foster positive UGC. My dissertation presents three studies that address these questions, enhancing our understanding of UGC in the modern digital era.

In the first study, I examine the effect of sentiment congruency on subsequent discussion by drawing on the priming theory. Utilizing a dynamic panel model, I empirically test my hypotheses using data from a popular online automobile forum in Asia. The empirical evidence demonstrates that higher sentiment congruency can motivate shorter response interval, more positive sentiment, and increased post volume in subsequent discussions. Additional exploration of contingent factors suggests that sentiment congruency effect is stronger in discussions that primarily comprise a higher proportion of inquiries and in relatively later discussion phases. This study highlights the importance of content and display sequence of user posts, providing valuable implications for platform designers aiming to boost trending topics in online discussions.

In the second study, I investigate the impact of public negativity on engagement within online fan communities. Leveraging natural experiment design and weighted regression

discontinuity in time model, I explore the public negativity effect using data from three online fan communities. The results suggest a decrease in comments and increase in likes when facing public negativity, suggesting reserved engagement within online fan communities. Moreover, I examine the common assumption of members' homogenous responses by exploring the moderating influence of member types, demographic characteristics, and status characteristics. This study highlights the potential risk associated with making engagement in online fan communities visible to the general public, providing valuable insights for celebrities, influencers, entertainment companies, and platform designers.

In the third study, I explore the emerging industry of digital serial publications, where publishers release creators' content incrementally, and consumers make rating decisions with each new update. Using an analytical model, I investigate how publishers can use preview strategies to increase the equilibrium of user rating when the market reaches a static state. I find that previews and rating equilibrium follow a U-shape pattern, and the optimal preview strategy depends on rating value and market scale.

Theoretically, these findings contribute to user-generated content (UGC) literature, particularly in terms of sentiment in UGC. They provide new insights into the dynamic sentiment patterns, influence of external events, and company strategies to enhance content generation. These insights deepen our understanding of the evolving landscape of UGC.

Key words: sentiment congruency; public negativity; online preview; iterative rating; online user engagement

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Introduction

In today's digital landscape, online platforms serve as primary sources for consuming various informational content, ranging from comments, reviews to vlogs, and livestreams. According to Forbes 2023 statistics, users spent an average of 145 minutes daily on social media, generating around 49 billion values for the social media app market in 2022 (Belle 2023).

User-generated content (UGC) is created by users on online platforms and shared for consumption by others (Tang et al. 2014). With the rise of ubiquitous social media platforms, UGC has evolved, allowing ordinary individuals to become content creators and monetize from it. The global influencer market, comprising over 200 million content creators, was valued at over 21 billion US dollars in 2023 (Howarth 2024). Notably, more than 46% of these individuals are full-time content creators who earn a living to support themselves and their families. Maintaining and growing their user base is crucial for brand collaborations, compelling them to continuously produce content to attract more users (Cheng and Zhang 2022). However, without attracting a sufficient user base, content creators struggle to survive in an increasingly competitive market.

Companies have capitalized on the evolving landscape of UGC by partnering with content creators to produce digital serial content, tailored to meet the needs of users with diminishing attention spans. The content varies from novels and mangas to short micro-series. Leveraging artificial intelligence, creators can frequently upload new content on a daily or weekly basis within limited budgets and small teams (Zhang 2023). However, as new content becomes regularly available on social media, competition intensifies. Unlike the traditional publishing industry, which often relies on one-time consumption, companies must work harder to continuously attract users to their serial content. Timely adjusting content according to user feedback is crucial to the success of digital serials (Xu et al. 2023). Thus, there is an urgent need to understand UGC within this rapidly developing digital context.

To create favorable first impressions and capture consumers' attention, some companies may manipulate the overall sentiment toward their products by leveraging social media bots or fake accounts (Lee et al. 2018b). However, in recent years, social media platforms have intensified their effort to combat manipulation, making such tactics costly. For example, X (formerly Twitter), has begun charging new users a small annual fee to reduce bots and fake accounts. Governments have also recognized the dangers of these bots and fake accounts and are pressing social media companies to take measures, such as banning anonymous postings (Kinnard 2023). Understanding how legitimate company strategies promote positive UGC is beneficial for business success and growth in a digital era with strict regulations.

Extensive research has been conducted on the sentiment within online communities, focusing on its impact on user ratings (Villarroel Ordenes et al. 2017), content consumptions (Oh et al. 2022), and sales (Cho et al. 2022; Khern-am-nuai et al. 2023). Recent studies have explored sentiment congruency across various dimensions, from post to comment (Kaakinen et al. 2020), from firm to consumer (Liu et al. 2022), and among online friends (Wang et al. 2018a). Yet, there is still a scarcity of research considering the dynamic formation of sentiment – examining shifts in users' sentimental expressions over multiple periods, spanning minutes, hours, or days online (Berger et al. 2021; Houben et al. 2015; Schweidel and Moe 2016). The influence of sentiment congruency, defined as the extent to which users express similar sentiments during discussions, on subsequent engagement remains an open question. The issue is vital for content creators and digital serial publishers, as frequent interactions with users who consume content can enhance the chances of ongoing discussions and viral potential of their content.

Despite extensive research on how internal factors influence engagement within online communities, there is a notable gap in examining the influence of external factors on content generation in online communities. A relevant study by Nian et al. (2021) investigated television programs as an external factor, analyzing how sentiment generated from these programs influence users' response to related product advertisments on social media. Online users are often categorized as either community members or general public. Given the transparency of social media platforms, members' engagement in online communities is exposed to and influenced by the general public (Lorenz 2020). However, the impact of external events that capture the attention of the general public on members' engagement within online communities remains underexplored.

As online regulation tightens, researchers are shifting their focus from manipulation to legitimate platform strategies that enhance content generation towards products and services. For instance, Huang et al. (2019) explored various push notification strategies on likes across genders on online platforms, proposing optimal performance feedback. Cao et al. (2023) investigated platform format strategies, offering managerial insights on how to increase likes across different content types. However, there is a lack of research concerning strategies in emerging digital markets, such as digital serial market, and how platforms and publishers can use them to garner positive comments from users, which is beneficial for their long-term goodwill.

My dissertation comprises three studies that delve into UGC within the evolving digital landscape. The first study investigates the effect of sentiment congruency in online discussion forums on users' subsequent discussions. The second study examines how an external event, specifically negative publicity, influence member engagement in online communities. The third study explores a novel UGC context – digital serial publication – investigating how publishers can employ preview strategies to foster the equilibrium of user rating through analytical modelling. Detailed overviews for each study are outlined below:

Study 1: *Propelling Trending Topics: Exploring the Impact of Sentiment Congruency on User Participation in Online Discussions*

The prevalence of the internet is continuing to rise, accompanied by growing user participation in online discussions. While abundant research has addressed the impact of sentiment on the spread of online information, few studies have explored dynamic sentiment patterns during online discussions. Drawing on priming theory, this study examines the effect of sentiment congruency – defined as the extent to which users express similar sentiments during discussions – on subsequent response interval, valence, and volume. Using a dynamic panel model, hypotheses are empirically tested across 28,791 threads with approximately 1.6 million posts from 101,358 users. My key findings include:

1) Sentiment congruency decreases subsequent response interval and increases response valence and volume.
2) The impact of sentiment congruency is more salient with a higher proportion of inquiries raised during a discussion and varies across different discussion phases.

This study tests robustness of its findings through alternative model specification and measurement. It also eliminates alternative explanations related to reciprocity, confirmative pressure, and content congruency, confirming the robustness of the main results. The consistency of these findings is further validated through an online experiment. Theoretically, these findings contribute to the literature on dynamic online discussions and priming by investigating sentiment congruency patterns, studying the priming effect on subsequent discussions using observational online data, and exploring underlying mechanisms. Practically, these findings provide insights into the display of user posts in online discussion across discussion purposes and over time.

Study 2: *Investigating the Effect of Public Negativity on Member Engagement in Online Fan Community*

With the rapid growth of social media, online fan communities significantly influence the fame and success of celebrities and influencers. While research on online communities mainly focus on internal factors, this study explores the impact of an external event – public negativity arising from a celebrity dropout event – on engagement within online fan communities. Public negativity is defined as collective criticisms by the public in response to events. Measuring public negativity is challenging due to its elusive nature and the potential confounding factors. To overcome these challenges, I employ a natural experimental design and utilize a weighted Regression Discontinuity in Time (RdiT) model. The study leverages a unique dataset consisting of 4,752 original posts from three online fan communities, captured 5 weeks before and after a celebrity dropout event that triggered public negativity. These communities are experiencing high, medium, and low level of public negativity after the dropout event. The study reveals the following findings:

1) The study observes a decrease in likes and an increase in comments after communities experienced public negativity, indicating reserved engagement.
2) The effect of public negativity does not vary among demographic and status characteristics. However, its effect on comments differs across member types.

Theoretically, this study adds a new perspective to online community literature, emphasizing the impact of an external factor on online community engagement. Additionally, it contributes to celebrity and influencer literature by quantifying the effect of public negativity and examining whether members generate a homogeneous response toward public negativity.

Practically, the findings provide insights for celebrities and influencers to connect with fans, help entertainment companies in assessing risk of grouping celebrities and influencers, and underscore the importance of creating private online environments for fan communities.

Study 3: Examining Relationship Between Previews and Ratings: Evidence from Digital Serial Publication

In the realm of digital content marketing, digital serial publications have gained popularity. However, this digital landscape also presents consumers with increased uncertainty in evaluating digital content. To reduce uncertainty, rating and preview are provided to offer indirect and direct product experiences, respectively. This study explores the relationship between preview and the equilibrium of user rating in digital serial context, where publishers release content gradually, and consumers can add new ratings with each update. Maintaining a high average rating is crucial for the survival and prosperity of digital serials. Thus, I also examine how publishers can employ preview strategies to maintain a high average rating when the market reaches a static state. Employing analytical models to describe the purchasing and rating process of digital serial publications, the study yields the following findings:

1) The relationship between preview and equilibrium of user rating follows a U-shaped pattern – equilibrium of user rating first decreases and then increases as the proportion content included in preview grows.
2) The optimal preview strategies depend on the rating value and market scale. In mass market, for a low rating value, optimal strategies include little or extensive content in preview; for a moderate rating value, providing abundant preview content is optimal; for a high rating value, offering all content for free is optimal. In the niche market, for a low rating value, optimal strategies include little or extensive content in preview; for

a moderate rating value, providing little preview content is optimal; for a high rating value, the optimal strategy is to provide no preview content.

Theoretically, these findings contribute to preview literature by emphasizing the proportion of content in the preview and its impact on long-term goodwill. They also add to digital serial publication literature by examining the impact of preview strategies on average ratings, considering variations with the rating value and market scale. Additionally, the study enriches online rating literature by incorporating an iterative rating process. Practically, these insights guide digital serial publishers in choosing optimal preview strategies and taking rating value and market scale into consideration.

Chapter 1

Propelling Trending Topics: Exploring the Impact of Sentiment Congruency on User Participation in Online Discussions

1.1 Introduction

In today's digital economy, people have become increasingly reliant on the Internet to communicate and spend large amounts of time gathering in online discussion platforms for knowledge exchange, experience sharing, and collaborative creativity. Illustratively, students engage in course discussion platforms to brainstorm ideas and reinforce learning experiences (Hill and Fitzgerald 2020; Huang et al. 2021); online users participate in discussion forums to share personal journeys (Kornfield and Toma 2020), and customers take part in firm-sponsored or third-party platforms to seek valuable information and provide feedback (Manchanda et al. 2015; Wang and Chaudhry 2018). On the other hand, the lifespan of discussion topics can be inherently short-lived (Fu and Stvilia 2016). Some stakeholders may attempt to manipulate the discussion series in order to foster buzz for the sake of visibility and advertising purposes.[1] Without sustaining discussions, users might quickly lose attention to the topics, leading to potential user attrition from the associated brand discussions or online platforms. It is thus important to understand how to facilitate continued user participation in online discussions.

Many previous studies have examined the antecedents of user participation in online discussions, including individual characteristics (Kane et al. 2014; Wasko and Faraj 2005), social needs (Dewan et al. 2017; Wang et al. 2018a), free services (Yan et al. 2022) and platform design features (Huang et al. 2019). Recent research has focused on the effect of information content (Lee et al. 2018a; Yang et al. 2019). However, there is a lack of research documenting the role of sentiment patterns in the discussion process.

[1] https://cacm.acm.org/news/253085-mass-scale-manipulation-of-twitter-trends-discovered/fulltext

One typical feature of online discussions is that users participate in the discussions by referring to previous opinions, and their posts are displayed in sequence with an order indicator (i.e., 1st floor, 2nd floor, etc.). This is differentiated from a mere social media setting, where users can simply like friends' posts with a motivation to build social connections (Berger 2014). It is also distinguished from online review platforms where users may not necessarily read through previous posts before they write a review, as they can write their own opinions based on personal product usage experience and overall rating indexes (Moe and Schweidel 2012). In contrast, reading previous posts to understand others' opinions is an inevitable endeavor and thus a unique feature of the online discussion context. Previous research has already verified the existence of dependency among user opinions such that the later posts are influenced by the content presented in previous posts (Ma et al. 2015; Wang et al. 2018a). However, those studies neglect the effect of post patterns during the discussion process. The fundamental question about how the similarity or conflicts among user posts across a discussion sequence influence user participation in subsequent discussions remains underexplored.

Based on the results from lab experiments, previous literature on priming suggested that when primes and targets are congruent in terms of sentiment, subjects tend to have a quicker response (Bargh et al. 1996; Fazio et al. 1986; Hermans et al. 1994) and more positive attitude toward content (Tanford et al. 2020; Yi 1990). Consequently, this positive sentiment influences consumer behavior (Minton et al. 2017). Peng et al. (2020) studied the effect of content congruency on a question-and-answer platform and find that the congruency between an answer's content and contextual cues (including emotional intensity) had an impact on answer helpfulness. Nevertheless, there is little understanding of how the congruency of previous user posts, especially in their sentiment, influences evolution of subsequent discussions. To address this gap, this study attempts to investigate the role of sentiment congruency in online discussions.

In this study, I conceptualize sentiment congruency as the extent to which users express similar sentiment during their discussions. I quantify sentiment congruency by considering discussion sequence and comparing pairwise sentiment between adjacent posts throughout the discussion process. The dependent variables of interest are users' response interval, valence, and volume in subsequent discussions. Prior work has mostly examined overall discussion valence and volume (Chen and Berger 2013; Stieglitz and Dang-Xuan 2013). However, a trending discussion requires not only more posts or more positive word-of-mouth, but also users' continuous and timely participation in the discussion over time. A faster response speed attracts the attention of new users and maintains the attention of old users, which facilitates a more time-efficient discussion (Zhang and Peng 2015). A more positive sentiment might indicate a positive attitude toward a discussion topic and associated brand, which strengthens following engagement in the platform and purchase intention of the discussed brand (Prendergast et al. 2010; Rui et al. 2013). In addition, a larger response volume helps to bump up the thread to the front of topic lists, which increases discussion visibility across time (Susarla et al. 2016).

I empirically evaluate the effect of sentiment congruency in online discussions using the data from a large online automobile forum in Asia, covering the period from January 2018 to October 2018. Each discussion follows a typical thread structure, where an initiator posts a message, and subsequent users participate by replying to previous posts. Posts are sequentially displayed in chronological order, enabling us to examine the formation of sentiment congruency over time.

Leveraging panel data structure, this research examines the effect of sentiment congruency from previous discussions on the discussion outcomes. To enhance the validity of our findings, I estimate alternative model specification and measurement. Furthermore, considering that the effect of sentiment congruency in the discussion process might be confounded with social influence such as reciprocity effect and confirmative pressure, as well as congruency of discussion content, this study examines various mechanisms and alternative explanations of the relationships. I also conduct an experimental study in a hypothetical online discussion context. To gain deeper insights into the influence of sentiment congruency, we also explore its heterogenous effects across different discussion purposes and phases.

The results suggest that sentiment congruency positively drives subsequent discussions, by decreasing response interval by 15.1%, increasing the proportion of positive response by 1.674, and increasing response volume by 13.6%, with one standard deviation increase of sentiment congruency. Moreover, I find that the impacts of sentiment congruency depend on the proportion of inquiries in the discussion thread and phases of the discussion process.

This research offers several contributions to literature. First, it contributes to the literature on dynamic online discussions by identifying sentiment congruency between user posts as an important antecedent of user participation in online discussions. While prior work has proven the influence of discussion sentiment itself (Lee et al. 2018a; Yang et al. 2019), little is known about the role of discussion patterns centered around sentiment congruency in online discussions. Leveraging the sequence of user posts in an online forum, this study adds to the literature by investigating sentiment congruency patterns, namely by comparing adjacent user posts and evaluating their effect on subsequent discussions. Second, this study contributes to the literature on priming. The effect of sentiment congruency has been examined in laboratory settings (Fazio 2001; Fazio et al. 1986; Spruyt et al. 2002). In this study, I empirically verify the influence using observational data from an online forum. Furthermore, previous literature primarily focuses on the priming effect on response speed. This study extends the investigation of priming effect on subsequent discussions regarding response interval, valence, and volume. The findings enrich the understanding of discussion behaviors in multiple aspects. Third, this study further explores the mechanisms underlying the effects of sentiment congruency on online discussions. The findings suggest that the impacts of sentiment congruency can go beyond the social influence and discussion content and vary across discussion purposes and phases. These additional findings lend insights into platform designers and managers on where and when to foster the sentiment congruency of user posts in order to propel online discussions effectively.

1.2 Literature Review

1.2.1 Dynamics of Online Discussion

In an online discussion, users exchange opinions, feelings, or experiences regarding a topic in an online community. There is a considerable body of research that has examined the influence of discussion sentiment on the spread of online information. Vosoughi et al. (2018) found that people like to share novel news and that users' perception of information is associated with the sentimental content presented in replies. It is worth noting that, in their study, Vosoughi et al. (2018) demonstrated that emotional content-related factors influence the spread of online news, beyond the impacts of user characteristics and network structure. Akcura et al. (2018) investigated the diffusion of online news on Twitter and demonstrated that the characteristics of users, users' conversations, news content, and sentiment together impact the diffusion volume and valence in social media. Using advertising messages from Facebook, Lee et al. (2018a) found that emotional messages related to brand personality are associated with a higher level of consumer engagement with a message, such as likes, comments, and shares. Yang et al. (2019) pointed out that discussion valence plays a significant role in influencing commenting behavior on social media. Leveraging content characteristics, Berger and Milkman (2012) examined how sentimental valence influences online content virality. Yu et al. (2020) further explored online content diffusion based on discrete emotion components.

While sentiment has been proven to influence user engagement in online platforms, these prior studies have largely overlooked the impact of information patterns, specifically the role of sentiment congruency. Previous literature on online user-generated content (UGC) has focused on the sequential influence of discussion valence and demonstrated the dynamic pattern therein. For example, subsequent participation behaviors are influenced by previously posted valence (Moe and Schweidel 2012; Wang et al. 2018a). Wang et al. (2018a) investigated how friend ties influence online rating generation and found that online users are socially nudged and tend to follow friends' previous rating patterns. Moe and Schweidel (2012) found that previously posted ratings influence not only whether to participate in online discussion but also what to post in online discussion. A study by Wang and Chaudhry (2018) highlighted the information similarity in firms' responses to customer reviews and suggested that tweaking a similar response to positive reviews does not have a constructive influence on customer impressions. Still, less is known about the effect of sentiment congruency on subsequent participation behaviors. One exception is the work of Peng et al. (2020), who investigated congruence between question and answer in an online disease forum. Their results suggested that if the language attributes (i.e., emotional intensity) of the answer's content are congruent with those of the preceding question, perceived helpfulness of an answer will increase. Unlike their study with a focus on the comparison between question and answer, sentiment congruency in this study considers similarity between adjacent posts. Given the unique feature that replies are displayed in a time-based sequence in the online forum, it is crucial to uncover how such sentiment congruency, measured by a weighted aggregation of pairwise sentiment similarity between adjacent replies within a current period of time, affects the evolvement of subsequent discussions.

1.2.2 Response Interval, Valence, and Volume in Discussions

Active participation by online users is vital to maintaining value-adding interactions and the visibility of online discussions (Chen et al. 2017). To gauge user participation in online discussions, I examine three outcome variables, i.e., response interval, valence, and volume.

The nature of trending topics tends to be fast-paced and constantly evolving, with new information and opinions emerging rapidly. Previous literature has suggested that speed is a defining feature of information diffusion (Van den Bulte 2000). A faster response indicated a more efficient diffusion (Zhang and Peng 2015). In social media, previous studies used the duration between a message and its next diffusion to evaluate its overall performance (Stieglitz and Dang-Xuan 2013; Zhang and Peng 2015). Active participation in online discussions requires staying informed and responding quickly to new developments. Timely responses in a discussion thread can generate excitement and a sense of "buzz" around the conversation. To measure the efficiency of the discussion process, this study examines the time difference between active discussion periods, which I call the "response interval". A shorter response interval indicates more active participation in the discussion, as it suggests that participants are engaged and responding promptly to new information.

Previous literature in user-generated content has indicated that review valence is a key feature of online word-of-mouth (Chevalier and Mayzlin 2006). A broad stream of literature confirmed the impact of rating information and discussion valence on online discussion and sales (Chevalier and Mayzlin 2006; Oh et al. 2022; Stieglitz and Dang-Xuan 2013; Sun 2012). Specifically, positive word-of-mouth indicated higher subsequent sales, whereas negative word-of-mouth suggested lower subsequent sales (Rui et al. 2013). In the online discussion context, response valence reflected users' attitude toward the platform or discussed product, which is crucial to facilitate subsequent discussion and even purchase behavior (Prendergast et al. 2010). Therefore, this study examines response valence as the second outcome to gauge user participation in online discussions. I quantify response valence as the proportion of positive (negative) sentiment in the subsequent discussions.

Besides, previous literature has suggested that review volume is a defining feature of online word-of-mouth (Chevalier and Mayzlin 2006). In the online discussion studies, the volume of user posts indicated the overall level of user participation in the discussion (Ibrahim et al. 2017; Le 2018). More importantly, response volume increased the visibility of a discussion topic (Lappas et al. 2016; Mamykina et al. 2011; Susarla et al. 2016). In the online discussion context, whenever there is a new response from an online user, the discussion thread that the user participated in will pop up at the front of the forum, which can grab more visibility and attract user attention. As such, this study examines response volume as the third outcome, measured by the number of user posts in online discussions.

1.3 Theoretical Background and Hypotheses

In this section, I hypothesize the effects of sentiment congruency in previous discussions on subsequent discussions in terms of response interval, valence, and volume.

1.3.1 Sentiment Congruency and Response Interval

Priming has examined the phenomenon where response to a target is facilitated when the sentiment tone of prime and target are congruent with each other (Fazio 2001; Klauer 1997). azio and colleagues (Fazio et al. 1986) initiated the study of priming one sentiment and found a sentiment congruency effect. In their experiments, a prime valence word was presented for 200 ms, followed by a target valence word presented after a 100 ms delay. Participants were asked to classify the valence of words as quickly and accurately as possible. Their results suggested that participants classify a target stimulus faster with congruent valence pairs (i.e., positive prime – positive target, negative prime – negative target) compared to incongruent valence pairs (i.e., positive prime – negative target, negative prime – positive target). Similar results were yielded in later research (Bargh et al. 1992; Bargh et al. 1996) and the effect of sentiment congruency was extended from words to visual contexts (Hermans et al. 1994; Spruyt et al. 2002).

One possible explanation for the sentiment congruency effect is the spread of activation mechanism (Collins and Loftus 1975; Fazio 2001; Fazio et al. 1986). It suggests that the activation of valence in prime words could spread to words with similar valence. As a result, if the valence of the target word is congruent with the valence of the prime word, the target becomes more accessible. Another possible explanation is the response competition mechanism (Klauer and Musch 2003; Wentura 1999). It indicates that subjects must choose one or the other valence when facing incongruency valence. Consequently, subjects inhibit the influence of incongruent primes. Such suppression slows down the subject's response time when the valence of prime and target is incongruent. Researchers suggested both spread of activation mechanism and response competition mechanism play an important role in producing the sentiment congruency effect (Fazio 2001).

In the context of online discussion, the above-mentioned research indicated that users would respond faster in discussion with congruent sentiment rather than incongruent sentiment. In other words, when users read a post followed by another post with the same sentimental valence in the discussion thread, they will easily process the information and give a faster response. Given this logic, I argue that a discussion with higher sentiment congruency between user posts will receive faster responses, i.e., shorter response intervals, in the subsequent discussions. Hence, I posit:

Hypothesis 1: Previous discussions with higher sentiment congruency will shorten the response interval in the subsequent discussions.

1.3.2 Sentiment Congruency and Response Valence

Previous researchers have found that responses triggered by sentimental context can subsequently influence people's attitudes (Edell and Burke 1987; Yi 1990). In the context of advertising, Edell and Burke (1987) have suggested that subjects' feelings experienced during advertisement exposure significantly contribute to their attitude toward advertisement and brand. Similarly, Yi (1990) further found that sentimental context influences not only subjects' attitudes toward the advertisement, but also their purchase intention. Specifically, placing an advertisement in a positive context (vs. a negative context) results in more favorable brand evaluations. However, priming in previous literature was manipulated by valence in the context (i.e., either positive tone or negative tone). There is a lack of evidence for how people will react to the congruency of sentiment in the context.

In online discussions, incongruent sentiment usually implies users' disagreement on a topic, inferring negative attitudes. Villarroel Ordenes et al. (2017) investigated the sentiment incongruence across sentences within text-based reviews. They argued that incongruent sentiment is negatively associated with the user's overall product evaluation (Villarroel Ordenes et al. 2017). The more incongruent sentiment in reviews, the less likely a user has a positive overall rating toward the product. Peng et al. (2020) examined the effect of sentiment intensity, the proportion of expressed emotion in an online forum. They found that congruence in sentiment intensity between question and answer positively influences users' perceived helpfulness of the answer. While it is hard to predict whether congruent negative user posts in the discussion can still motivate positive attitudes in the following, since congruent sentiment can be perceived as more helpful, I posit a positive relationship, such that users will favor the subsequent discussions if the previous discussions have higher overall sentiment congruency among adjacent posts. Hence:

Hypothesis 2: Previous discussions with higher sentiment congruency will strengthen the response valence in the subsequent discussions.

1.3.3 Sentiment Congruency and Response Volume

Sentiment congruency in the previous discussions might also increase response volume in the subsequent discussions. Previous research has suggested that discomfort appears when a newly acquired message disconfirms the knowledge user previously acquired in an online discussion (Zhang and Watts 2016). Moreover, researchers have indicated that discomfort negatively influences users' willingness to participate (Chen and Berger 2013). That is, when viewing a discussion thread where the sentiments of posts are always different from each other, users might feel uncomfortable, which in turn reduces users' willingness to participate in the following discussions. Further, research on the credibility of online word-of-mouth have suggested that users tend to give more credit to word-of-mouth that is congruent across different sources (Cheung et al. 2009; Metzger et al. 2010). Therefore, the more congruent opinions previous users give, the more credible the discussion is, and the more likely the user will add to the discussion. In line with the above arguments, I posit:

Hypothesis 3: Previous discussions with higher sentiment congruency will increase the response volume in the subsequent discussions.

1.4 Empirical Setting and Methods

1.4.1 Research Context and Data

The research data is collected from autohome.com.cn, an influential automotive website in Asia. The website aims to facilitate automobile buying and ownership experience for auto customers. It provides automobile information and meanwhile organizes online forums for user communication. The website has approximately three million daily active users.

The users of the online forum of Autohome are those interested in automobile topics or who intend to make an automobile purchase. According to a report, over 50% of customers refer to information from automotive websites to make automobile purchase decisions (iResearch 2018). Moreover, a previous report has indicated that customers trust information from automotive forums more than information from e-commerce platforms (PERCENT Technology 2015). In each forum, users can engage in discussions by posting opinions, experiences, and feelings related to automobile topics. An initiator begins a discussion thread by posting the initial message. Other users then join in the discussion by replying to previous posts in this thread and the replies are typically displayed in a time-based sequence. The collection of posts comprises a thread. Meanwhile, platform managers maintain the discussion environment by promoting high-quality threads and removing inappropriate content.

This dataset consists of discussions from Geely Boyue forum between January 2018 and October 2018. I remove data from 3,610 incomplete threads without a title. I also remove 361 threads where initial posts are deleted by platform managers, which suggests the topics of those discussion threads might be malicious. I focus on the threads that last more than two hours for time series calculation. Therefore, the final sample ensures an overall informative and rational online discussion environment capable of revealing sentiment congruency in user posts. The final sample consists of 28,791 threads, containing approximately 1.6 million posts from 101,358 users.

To construct a panel data structure, I divide user posts by time (hours). I focus exclusively on active discussion hours, defined as those hours during which at least one user post occurs within a given hour. The average thread discussion lasted for 16 hours, ranging from 3 hours to 757 hours. On average, the response interval between two discussion sessions is 26 hours. Generally, each session receives approximately 3 replies, ranging from 1 to 322 replies. Regarding the sentiment of user replies, 91% is neutral, with 8.6% of positive sentiment and 0.4% of negative sentiment.

1.4.2 Main Variables

Sentiment congruency. To measure sentiment congruency (*SENC*), I first use the Jieba toolkit for word segmentation. I adopt sentiment dictionaries in Chinese from the Linguistic Inquiry Word Count (LIWC) program (Pennebaker et al. 2007). Recent research has indicated that LIWC linguistic features are helpful for revealing information in online articles (Clarke et al. 2020). I retrieve the positive and negative words of each post and construct a vector consisting of three components: the percentage of positive, negative, and neutral (=1-positive-negative) words. I then calculate the similarities between each pair of adjacent posts in terms of their overall sentiment using the cosine similarity measure. Previous studies have suggested that using cosine similarity to classify sentiment results in higher classification accuracy (Bhattacharjee et al. 2015; Thongtan and Phienthrakul 2019). Then, I assign a softmax weight for each adjacent pair. The softmax weight is a normalized exponential function (Gao and Pavel 2017; Peng et al. 2017; Wang et al. 2018b) that enables the conversion of numeric weights into a probability distribution ranging from 0 to 1. The logic behind softmax weight is the assumption that users' attention to the similarities between the adjacent posts follows an exponential decay, i.e., $e^{(-\frac{i-1}{n_t-1})}{}_j$. Here n_t indicates the total number of user replies by time *t* (it assumes that each thread has n_t*+1* posts with one initial post and n_t replies by time *t*), and *I* indicates the similarity between the *i*th reply and its previous one, and *j* is the index of the thread. In this case, the similarity between the first two posts receives the most attention from users without discounting weight, while the weight decreases exponentially according to the sequence of posts. Such decay patterns have been shown in different online environments, such as in online citations and video evolution (Avramova et al. 2009; Della Briotta Parolo et al. 2015). I normalize the exponential decay values to form a softmax weight, i.e., $w_{j,i} = \frac{e^{(-\frac{i-1}{n_t-1})}{}_j}{\sum_{i=1}^{n_t} e^{(-\frac{i-1}{n_t-1})}{}_j}$, with *i=1,2,...,* n_t. I then aggregate the similarity values of adjacent pairs by time *t* by taking the softmax weight. As a result, the sentiment congruency of thread *j* by time *t* is a product of softmax weights and cosine similarities, which is specified as follows:

$$SENC_{jt} = \sum_{i=1}^{n_t} w_{j,i} \times Cosine(A_{j,i}, A_{j,i-1}) \tag{1}$$

where $Cosine\left(A_{j,i}, A_{j,i-1}\right) = \frac{\overrightarrow{A_{j,i}} \cdot \overrightarrow{A_{j,i-1}}}{\|\overrightarrow{A_{j,i}}\| \|\overrightarrow{A_{j,i-1}}\|}$ is the cosine similarity of sentiment vectors between *i*th reply and *(i-1)*th reply. $A_{j,i}$ represents a three-dimensional sentiment vector of the

i^{th} reply in thread j. Note that, in particular, $A_{j,0}$ represents the sentiment vector of the initial post in the thread j.

Subsequent Discussions. As stated above, this study focuses on three aspects to quantify subsequent discussions – response interval, valence, and volume. A shorter response interval represents faster subsequent discussions. It is measured by the time (hour) difference between two adjacent discussion sessions. Response valence is operationalized as the percentage of positive (negative) sentiment in the subsequent discussion session. I evaluate the influence on positive and negative sentiment separately. Response volume is calculated as the number of replies in the subsequent discussion session.

1.4.3 Summary Statistics

Table 1 summarizes the descriptions and statistics of the main variables. On average, a discussion thread receives 3 replies within an hour, 8.6% of the content is positive, occurring the next day (i.e., after 26.11 hours). The average sentiment congruency is 0.92, probably because I include the neutral word dimension in the calculation. A high level of sentiment congruency might result from people's preference to be objective regarding automobile discussions. Nevertheless, I observe a 0.09 standard deviation in the sentiment congruency measure.

Table 1 also includes the statistics used in additional analyses (i.e., initiator's response, manager response, cumulative valence, content congruency, and proportion of inquiries), which will be used to further examine the alternative mechanisms of the effect of sentiment congruency and examine how it varies across discussion purposes and discussion phases. I will explain the operationalizations of these variables and the moderating results in a later section. Additionally, I check the variance inflation factors (VIFs) of the key independent variables according to Equation 2. All VIFs are lower than the threshold of 10 (Myers and Myers 1990), suggesting that multicollinearity does not represent a serious issue for the main analysis.

Table 1. Descriptive Statistics and Correlations

	Var	Description	Mean	Std.D.	Obs.	Correlation										
						1	2	3	4	5	6	7	8	9	10	11
1	$Interval_{j,t}$	Number of hours from time *t-1* to time *t* in thread *j.*	26.11	154.16	432,400	1.00										
2	$Pos_{j,t}$	Proportion of positive sentiment posted by users in thread *j* from time *t-1* to time *t.*	8.56	14.92	461,191	-0.02*	1.00									
3	$Neg_{j,t}$	Proportion of negative sentiment posted by users in thread *j* from time *t-1* to time *t.*	0.38	2.45	461,191	0.002	-0.05*	1.00								
4	$Replies_{j,t}$	Number of replies in thread *j* from time *t-1* to time *t.*	3.42	6.87	461,191	-0.03*	0.18*	-0.01*	1.00							
5	$SENC_{j,t}$	Sentiment congruency of thread *j* by time *t.*	0.92	0.09	461,191	0.01*	-0.38*	0.02*	-0.19*	1.00						
6	$1st\ Reply_{j,t}$	Number of replies from the initiator in thread *j* from time *t-1* to time *t.*	0.99	4.10	461,191	-0.02*	0.20*	-0.01*	0.77*	-0.19*	1.00					
7	$Class_{j,t}$	The class of thread *j* from time *t-1* to time *t*, where 1 indicates the thread is labeled as high-quality thread on or before time t, and 0 otherwise.	0.49	0.50	461,191	-0.01*	0.32*	-0.03*	0.17*	-0.59*	0.14*	1.00				
8	$PosAgg_{j,t}$	Cumulative proportion of positive sentiment in thread *j* by time *t.*	9.95	8.89	461,191	-0.01*	0.50*	-0.04*	0.21*	-0.89*	0.21*	0.66*	1.00			
9	$NegAgg_{j,t}$	Cumulative proportion of negative sentiment in thread *j* by time *t.*	0.36	0.87	461,191	0.01*	-0.07*	0.36*	-0.03*	0.05*	-0.02*	-0.11*	-0.13*	1.00		
10	$CONC_{j,t}$	Content congruency of thread *j* by time *t.*	0.16	0.17	461,191	-0.01*	-0.24*	-0.02*	-0.15*	0.42*	-0.12*	-0.49*	-0.47*	-0.05*	1.00	
11	$Inquiry_{j,t}$	Proportion of inquiries in thread *j*'s posts from time *t-1* to time *t.*	0.06	0.21	461,191	0.06*	-0.09*	0.02*	-0.04*	0.07*	-0.03*	-0.08*	-0.08*	0.04*	-0.04*	1.00
Multicollinearity Check (VIF)										4.80	1.09	1.93	5.67	1.05	1.44	1.02

*Note. Correlations are displayed in * if p-value < 0.05.*

1.4.4 Model Specification

Based on this data set and panel data structure, I estimate the following dynamic panel model (Moral-Benito 2013; Wilkins 2018):

$$y_{j,t} = \alpha y_{j,t-1} + \beta SENC_{j,t-1} + \gamma X_{j,t-1} + \eta_j + \mu_t + \epsilon_{j,t} \tag{2}$$

where j indexes the thread, t indexes the sequence of the time. The outcome variable $y_{j,t}$ represents subsequent discussion behaviors, including response interval, valence, and volume. The coefficient β captures the influence of the sentiment congruency effect. μ_t denotes a set of hour-fixed effects. Specifically, I divide 24 hours into four dummy variables and control them: morning (6am-12pm), afternoon (12pm-18pm), evening (18pm-24pm), and night (0am-6am). Additionally, I control an indicator variable on whether the current time belongs to weekday or weekends. Also, I control the sequence of the time since the initiator posted. η_j represents thread-specific fixed heterogeneity. I include lagged outcome variables $y_{j,t-1}$ in the model. Specifically, I control for lagged response interval, lagged response valence, and lagged response volume. Lagged response interval is operated as lagged time difference between previous adjacent hours. Lagged response valence is measured as the percentage of positive and negative sentiment by time *t-1*, as sentiment changes continuously through discussions. Lagged response volume is calculated as lagged number of replies from time *t-2* to time *t-1*.

$X_{j,t-1}$ denotes a vector of lagged thread-level controls of threads, users, and the product. For thread-related factors, I control the average reply characters from time *t-2* to time *t-1* and whether the thread is labeled as a high-quality thread by platform manager by time *t-1*. I also control the proportion of inquiries asked in replies from time *t-2* to time *t-1*. For user-related factors, I control the proportion of users shown personal information from time *t-2* to time *t-1*. I further control log-transformed number of replies from initiators from time *t-2* to *t-1*. For product-related factors, I control SUV sales rank and the total sales rank of the focal automobile in the previous month.[2] Considering response interval and volume are positive, I transform the variable (plus 1) via natural logarithm. The normality of the response interval (skewness = 1.61, kurtosis = 5.88) and response volume (skewness = 1.94, kurtosis= 6.94) after the log transformation met the standard (Hair et al. 2010). In addition, I standardize the sentiment congruency in the estimation. I implement the OLS estimator as previous simulation results indicate that the OLS estimator does not suffer from non-negligible bias in β, especially when the sample size is large (Moral-Benito 2013).

1.5 Main Results

1.5.1 Main Effects of Sentiment congruency

Table 2 displays the results of the main analyses using OLS estimation. The first column of Table 2 estimates the effect of sentiment congruency on subsequent response interval. The result suggests sentiment congruency has a significant negative impact on the subsequent response interval. In other words, the higher the sentiment congruency, the shorter the response interval to previous discussions. Specifically, a one-unit (i.e., one standard deviation from the mean) increase in sentiment congruency decreases the response interval between discussions sessions by 15.1%. This result supports Hypothesis 1, suggesting discussions with congruent sentiment are easier for users to access and respond to the content than those with incongruent sentiment.

In regard to Hypothesis 2, I examine the effect of sentiment congruency on response valence regarding positive and negative content, respectively, in Model 2 and Model 3 of Table 2. Results show that sentiment congruency only has a significant effect on response valence in the positive aspect, while its influence on subsequent negative discussion content is insignificant. In particular, a one-unit increase in sentiment congruency significantly increases

[2] Due to data limitation, I only collected the sales rank data of the focal automobile by month.

the proportion of positive content in the subsequent discussion by 1.674. Since the sentiment congruency can positively influence the subsequent positive content but have no impact on subsequent negative content, overall, I believe that higher sentiment congruency will strengthen the response valence in the subsequent discussions, supporting Hypothesis 2.

Intriguingly, results of response valence in Model 2 suggest a negative trend in online discussions. The positive discussion content will become less with longer response waiting time (Model 2: Coef. = -0.119, $p < 0.01$). Moreover, the results suggest that the discussions tend to deviate from previous discussion valence. The more positive the previous discussions are, the less likely the subsequent discussion valence will be positive (Model 2: Coef. = -0.114, $p < 0.01$). In contrast, the more negative the previous discussions are, the more likely the subsequent discussion valence will be positive (Model 3: Coef. = -0.504, $p < 0.01$).

Finally, I investigate the effect of sentiment congruency on discussion volume. The results are shown in Model 4 of Table 2. The estimating coefficient of sentiment congruency, $SENC_j$, is positive and significant (Coef. = 0.136, $p < 0.01$). It suggests that grouping similar sentiments in replies, compared to displaying replies with contradictory sentiments next to each other, motivates user participation. With a one-unit increase in sentiment congruency, the subsequent discussion volume will increase by 13.6% within one hour, supporting Hypothesis 3.

Table 2. Main Results: Sentiment Congruent Effect on Response Interval, Valence, and Volume

	(1)	(2)	(3)	(4)
	Model 1	Model 2	Model 3	Model 4
DV	Log($Interval_{j,t}$)	$Pos_{j,t}$	$Neg_{j,t}$	Log($Replies_{j,t}$)
$SENC_{j,t-1}$	-0.151***	1.674***	0.022	0.136***
	(0.012)	(0.208)	(0.020)	(0.007)
Log($Interval_{j,t-1}$)	0.070***	-0.119***	0.004	-0.024***
	(0.004)	(0.023)	(0.004)	(0.001)
$PosAgg_{j,t-1}$	0.002	-0.114***	0.003	0.004***
	(0.002)	(0.028)	(0.002)	(0.001)
$NegAgg_{j,t-1}$	-0.001	0.050	-0.504***	-0.003
	(0.007)	(0.063)	(0.053)	(0.003)
Log($Replies_{j,t-1}$)	-0.433***	1.405***	-0.037***	0.248***
	(0.006)	(0.069)	(0.008)	(0.004)
Constant	1.511***	7.105***	0.495***	0.791***

	(0.060)	(0.396)	(0.048)	(0.015)
Controls	Included	Included	Included	Included
FE	Included	Included	Included	Included
Log likelihood	-617224	-1.608e+06	-914645	-291167
No. of Threads	28,791	28,791	28,791	28,791
No. of Obs.	403,609	403,609	403,609	403,609

*Notes. *** p<.01, ** p<.05, * p<.1. Robust standard errors clustered by threads in parentheses.*

1.6 Mechanisms and Additional Analyses

In this section, I provide several robustness checks and validate the main results. First, I examine alternative model specification and measurement. Second, I eliminate the alternative explanation that the effect of sentiment congruency draws from the reciprocity effect by examining interaction effects between sentiment congruency and replies from the initiator and platform manager respectively. The third extension discusses how users respond to previous sentiments during discussions to rule out the alternative that the effect of sentiment congruency is related to confirmative pressures online. Fourth, I show the main results remain valid after controlling for the effect of content congruency. The fifth extension further eliminates endogeneity by conducting an experimental study. Finally, I explore how main results vary across discussion purposes (i.e., proportion of inquiries) and discussion phases.

1.6.1 Alternative Model Specification and Measurement

To ensure the robustness of the main findings, I first test the models under a different specification. While the main results are based on OLS estimation, in this section I implement system generalized method of moment (GMM) estimation. Popularized by Arellano and Bover (Arellano and Bover 1995), system GMM estimation uses lagged and lagged differences of endogenous variables as instruments to eliminate endogeneity concerns. Estimation results are reported in Table 3, which suggests that the findings from the main analysis are robust to the alternative model specification.

Table 3. Alternative Model: System GMM

	(1)	(2)	(3)	(4)

DV	Model 1 Log($Interval_{j,t}$)	Model 2 $Pos_{j,t}$	Model 3 $Neg_{j,t}$	Model 4 Log($Replies_{j,t}$)
$SENC_{j,t-1}$	-0.929***	3.516***	0.040	0.206***
	(0.291)	(1.269)	(0.182)	(0.059)
$Log(Interval_{j,t-1})$	0.538**	0.793	-0.028	-0.004
	(0.218)	(0.662)	(0.106)	(0.040)
$PosAgg_{,t-1}$	-0.244***	0.811***	-0.031	0.040***
	(0.058)	(0.233)	(0.036)	(0.012)
$NegAgg_{,t-1}$	-0.112	0.037	0.132	0.003
	(0.129)	(0.362)	(0.115)	(0.022)
$Log(Replies_{j,t-1})$	-2.953***	7.792***	-0.630*	1.118***
	(0.827)	(2.350)	(0.376)	(0.184)
Constant	24.054***	-18.298	4.356	-2.301**
	(5.710)	(20.044)	(3.096)	(1.107)
Controls	Included	Included	Included	Included
FE	Included	Included	Included	Included
Hansen Test	0.077	0.979	0.926	0.462
No. of Threads	28,791	28,791	28,791	28,791
No. of Obs.	403,609	403,609	403,609	403,609

*Notes. *** p<.01, ** p<.05 , * p<.1. Robust standard errors clustered by threads in parentheses.*

Second, following the measurement of sentiment congruency used by Peng et al. (2020), I consider a different measurement of sentiment congruency. Specifically, sentiment congruency by time *t* is operationalized as the average of absolute difference in adjacent sentiment by time *t*, i.e., the difference of percentage of sentimental words (positive words minus negative words) by time *t*. To ease the interpretation of results, I multiply this absolute difference by -1, such that a higher value of sentiment congruency implies a greater congruence of sentiments between adjacent posts. I rerun models with OLS estimation with this alternative measurement in Table 4. The effects of sentiment congruency on discussion interval, valence, and volume are consistent with that in the main results. In addition, the effect of sentiment congruency on negative discussion content (Model 3) is negative and significant. The results provide further support that higher sentiment congruency is associated with more positive (and less negative) response valence.

Table 4. Alternative Measurement: Sentiment congruency

DV	(1) Model 1 Log($Interval_{j,t}$)	(2) Model 2 $Pos_{j,t}$	(3) Model 3 $Neg_{j,t}$	(4) Model 4 Log($Replies_{j,t}$)
$SENC_{j,t-1}$	-0.013***	0.238***	-0.005***	0.008***

	(0.001)	(0.017)	(0.002)	(0.001)
Log(Interval$_{j,t-1}$)	0.071***	-0.132***	0.004	-0.025***
	(0.004)	(0.023)	(0.004)	(0.001)
Pos$_{j,t-1}$	0.0003*	-0.007**	-0.00003	0.001***
	(0.0002)	(0.003)	(0.0003)	(0.0001)
Neg$_{j,t-1}$	-0.0004	0.009	-0.042***	-0.001**
	(0.001)	(0.009)	(0.004)	(0.0003)
Log(Replies$_{j,t-1}$)	-0.430***	1.370***	-0.037***	0.246***
	(0.006)	(0.069)	(0.008)	(0.004)
Constant	1.387***	8.524***	0.322***	0.897***
	(0.057)	(0.330)	(0.044)	(0.013)
Controls	Included	Included	Included	Included
FE	Included	Included	Included	Included
Log likelihood	-617403	-1.608e+06	-915390	-291727
No. of Threads	28,791	28,791	28,791	28,791
No. of Obs.	403,609	403,609	403,609	403,609

*Notes. *** p<.01, ** p<.05, * p<.1. Robust standard errors clustered by threads in parentheses.*

1.6.2 Does the Effect of Sentiment Congruency Draw from Reciprocity?

Although users are either typically strangers or online acquaintances in the current research context, one concern is that the reciprocity effect may cause the sentiment congruency effect. Previous research has suggested that user reciprocity might facilitate discussions (Chen et al. 2017; Joyce and Kraut 2006; Lakhani and Von Hippel 2004). In online forums, it indicates that users are more likely to post if a discussion thread involves reactions from the initiator and/or platform manager. If this is the case, the significant and positive effect of sentiment congruency on discussion volume in the main model may not hold after taking the effect of reciprocity into consideration.

To test whether reciprocity is an alternative explanation, I consider two types of reciprocity: response from the thread initiator and response from the platform manager. The rationale behind this test is that if reciprocity influences sentiment congruency, I should observe that users generate more replies after viewing responses from the initiator and manager. I operationalize response from the initiators at time *t-1*, $1st\ Reply_{j,t-1}$, as the number of replies written by the initiator at time *t-1*. Further, I operationalize response from the manager at time *t-1*, $Class_{j,t-1}$, as a binary variable indicating whether the discussion is labelled as a high-quality thread on or before time *t-1*. I rerun the model in Equation 2 with

OLS estimation by adding interaction terms between $SENC_{j,t-1}$ and $1st\ Reply_{j,t-1}$ and between $SENC_{j,t-1}$ and $Class_{j,t-1}$, respectively.

As shown in column (1) and column (2) of Table 5, the effect of sentiment congruency on response volume is still positive and significant after controlling the main and moderation effect of response from initiators and platform managers. The findings from the main analysis are still robust even if I take reciprocity effect into consideration. Furthermore, the results from Model 1 show a negative and significant effect of $1st\ Reply_{j,t-1}$, suggesting that the response from initiators actually will inhibit further discussions (Coef. = -0.098, p<0.01). This finding is consistent with research on incentive hierarchies (Goes et al. 2016), stating that user participation will decrease after reaching a goal in a hierarchy. In online forums, the goal can be receiving gratitude or appreciation from the initiator. There is no statistically significant effect of the interaction term between $SENC_{j,t-1}$ and $1st\ Reply_{j,t-1}$. The results from Model 2 show that the effect of $Class_{j,t-1}$ on subsequent discussion volume is insignificant, whereas the coefficient of the interaction term between $SENC_{j,t-1}$ and $Class_{j,t-1}$ is positive and significant (Coef. =0.101, p<0.01). In this sense, the positive effect of sentiment congruency on response volume will be enhanced when the discussion thread is labeled as high quality by platform managers.

Table 5. Robustness Check – Reciprocity Effects

	(1) Model 1	(2) Model 2
DV	$Log(Replies_{j,t})$	$Log(Replies_{j,t})$
$SENC_{j,t-1}$	0.136***	0.063***
	(0.007)	(0.008)
$1^{st}\ Reply_{j,t-1}$	-0.098***	-0.098***
	(0.004)	(0.003)
$Class_{j,t-1}$	-0.047***	0.004
	(0.013)	(0.014)
$SENC_{j,t-1} \times 1^{st}\ Reply_{j,t-1}$	0.001	
	(0.002)	
$SENC_{j,t-1} \times Class_{j,t-1}$		0.101***
		(0.007)
$Log(Interval_{j,t-1})$	-0.024***	-0.024***
	(0.001)	(0.001)

$PosAgg_{j,t-1}$	0.004***	0.004***
	(0.001)	(0.001)
$NegAgg_{j,t-1}$	-0.003	-0.006**
	(0.003)	(0.003)
$Log(Replies_{j,t-1})$	0.248***	0.248***
	(0.004)	(0.004)
Constant	0.790***	0.796***
	0.015	(0.015)
Controls	Included	Included
FE	Included	Included
Log likelihood	-291167	-290941
No. of Threads	28,791	28,791
No. of Obs.	403,609	403,609

*Notes. *** p<.01, ** p<.05, * p<.1. Robust standard errors clustered by threads in parentheses.*

1.6.3 Does the Effect of Sentiment Congruency Draw from Confirmative Pressure?

In this section, I assess whether sentiment congruency is associated with confirmative pressure users face online. While users in online forums participate in the discussions mainly for exchanging information instead of making friends, they are still likely to agree with each other simply due to confirmative pressure. That is, users are more likely to conform with previous discussion valence and post a positive opinion of the product if previous discussions are overall positive with high sentiment congruency.

To examine this alternative explanation, I rerun the model in Equation 2 with OLS estimation by including interaction effects between sentiment congruency and discussion valence. The results in Table 6 demonstrate that after accounting for the main and interaction terms between sentiment congruency and discussion valence, the positive effect of sentiment congruency on subsequent positive content still holds. Consistently, the effect of sentiment congruency on subsequent negative content is still insignificant. Meanwhile, I find no significant interaction effects of sentiment congruency and previous discussion valence on subsequent discussion valence. The effects of sentiment congruency do not vary across different sentiments in the previous discussions indicating that the observed effect of sentiment congruency is irrelevant to confirmative pressures. The main effects of previous discussion valence are negative in columns (1) and (2) (Coef. =-0.118 and -0.510, respectively, p<0.01), suggesting users' tendency to deviate from the previous discussion valence. In comparison, the positive effect of sentiment congruency on subsequent positive discussion content is stronger than the negative influence of previous discussion valence. The findings demonstrate that sentiment congruency and previous discussion valence independently influence subsequent discussion valence.

Table 6. Robustness Check – Confirmative Pressures

DV	(1) Model 1 $Pos_{j,t}$	(2) Model 2 $Neg_{j,t}$
$SENC_{j,t-1}$	1.810***	-0.009
	(0.226)	(0.031)
$PosAgg_{j,t-1}$	-0.118***	0.004*
	(0.030)	(0.002)
$NegAgg_{j,t-1}$	0.080	-0.510***
	(0.065)	(0.048)
$SENC_{j,t-1} \times PosAgg_{j,t-1}$	-0.008	0.002*
	(0.010)	(0.001)
$SENC_{j,t-1} \times NegAgg_{j,t-1}$	0.050	-0.010
	(0.037)	(0.031)
$Log(Interval_{j,t-1})$	-0.118***	0.004
	(0.023)	(0.004)
$Log(Replies_{j,t-1})$	1.408***	-0.038***
	(0.068)	(0.008)
Constant	7.062***	0.504***
	(0.391)	(0.049)
Controls	Included	Included
FE	Included	Included
Log likelihood	-1.608e+06	-914640
No. of Threads	28,791	28,791
No. of Obs.	403,609	403,609

*Notes. *** p<.01, ** p<.05, * p<.1. Robust standard errors clustered by threads in parentheses.*

1.6.4 Does the Effect of Sentiment Congruency Draw from Content Congruency?

In the hypotheses, I argue that the effect of sentiment congruency comes from the priming of congruent valence pairs between prime and target. However, as previous literature suggested, the distinction between sentiment congruency and content congruency might be muddy (Minton et al. 2017). Therefore, it is possible that the congruency effect on subsequent responses is driven by similar content, rather than similar sentiment.

To test whether content congruency is another explanation, I include content congruency in the model. I quantify content congruency by the content similarity across user posts and construct this variable in a similar manner to sentiment congruency. Specifically, I first apply the cosine similarity to calculate the degree of shared words between each pair of adjacent posts in the sequence of a discussion. I then aggregate the similarity values of adjacent pairs by time t while taking the same softmax weight described above (i.e., $w_{j,i} = \frac{e^{(-\frac{i-1}{n_t-1})}{}_j}{\sum_{i=1}^{n_t} e^{(-\frac{i-1}{n_t-1})}{}_j}$). Thus, content congruency of thread *j* by time *t* is a product of softmax weights and cosine similarities by time *t*, which is specified as follows:

$$CONC_{j,t} = \sum_{i=1}^{n_t} w_{j,i} \times Cosine(B_{j,i}\ , B_{j,i-1}) \tag{3}$$

where $Cosine\left(B_{j,i}\ , B_{j,i-1}\right) = \frac{\overrightarrow{B_{j,i}} \cdot \overrightarrow{B_{j,i-1}}}{\|\overrightarrow{B_{j,i}}\| \|\overrightarrow{B_{j,i-1}}\|}$ is the cosine similarity of words between i^{th} reply and $(i\text{-}1)^{th}$ reply. Before conducting cosine similarity, I process the words in each reply using the Jieba toolkit for word segmentation and deleting punctuation in each reply. I standardize content congruency, and rerun the model in Equation 2 with the same model specification by OLS estimation.

The estimation results are reported in Table 7. After controlling content congruency, the main results remain the same: sentiment congruency shortens response interval (Coef. = -0.153, p<0.01), and increases subsequent positive discussion (Coef. = 1.682, p<0.01) and discussion volume (Coef. =0.136, p<0.01). Notably, after controlling for content congruency, the effect size of sentiment congruency on response interval (i.e., -0.153 vs. -0.151), valence (i.e., 1.682 vs. 1.674), and volume (i.e., 0.136 vs. 0.136) almost does not change relative to the effect size in the main results (Table 2).

Interestingly, the results suggest that content congruency negatively influences subsequent response valence and volume but positively influences subsequent response interval. This might be related to the ignored object and the negative priming effect (Frings et al. 2015; Tipper 1985). When searching for information in online forums about an automobile, users expect to find valuable information on automatic attributes. The repeated information may cost them more time to filter out new information and deter their motivation to join further discussions. Moreover, users tend to discuss more neutrally when content similarity is high. Content congruency has negative effects on both positive and negative sentiment in subsequent discussions. These findings align with research by Chen et al. (2018), which highlighted the benefit of multidimensional rating systems in terms of informativeness and overall satisfaction.

Table 7. Robustness Check: Content Congruency

	(1)	(2)	(3)	(4)
	Model 1	Model 2	Model 3	Model 4
DV	$Log(Interval_{j,t})$	$Pos_{j,t}$	$Neg_{j,t}$	$Log(Replies_{j,t})$
$SENC_{j,t-1}$	-0.153***	1.682***	0.023	0.136***
	(0.012)	(0.210)	(0.020)	(0.007)
$CONC_{j,t-1}$	0.064***	-0.491***	-0.062***	-0.003
	(0.021)	(0.082)	(0.014)	(0.004)
$Log(Interval_{j,t-1})$	0.070***	-0.117***	0.004	-0.024***
	(0.004)	(0.023)	(0.004)	(0.001)
$PosAgg_{j,t-1}$	0.003**	-0.120***	0.002	0.004***
	(0.001)	(0.028)	(0.002)	(0.001)
$NegAgg_{j,t-1}$	0.006	-0.004	-0.511***	-0.003
	(0.007)	(0.065)	(0.054)	(0.003)
$Log(Replies_{j,t-1})$	-0.435***	1.420***	-0.035***	0.248***
	(0.006)	(0.068)	(0.008)	(0.004)
Constant	1.496***	7.223***	0.510***	0.791***
	(0.055)	(0.395)	(0.048)	(0.015)
Controls	Included	Included	Included	Included
FE	Included	Included	Included	Included
Log likelihood	-617160	-1.608e+06	-914631	-291166
No. of Threads	28,791	28,791	28,791	28,791
No. of Obs.	403,609	403,609	403,609	403,609

*Notes. *** p<.01, ** p<.05, * p<.1. Robust standard errors clustered by threads in parentheses.*

1.6.5 Experiment

Although I implement panel structure data and additional GMM estimation to justify causal relationships, the endogeneity concern might not be fully addressed. In order to further assess the causal impact of sentiment congruency on users' subsequent discussions, I further examine the relationships by a laboratory experiment, where participants viewed hypothetical online discussions and decided whether they want to join the discussion further. By manipulating sentiment congruency at two levels (high versus low sentiment congruency) while controlling discussion valence at the same level, I can directly examine the causal effect of sentiment congruency on subsequent discussions.

Method and Procedure. Three hundred ninety-one undergraduate students (73% female, M_{age}= 19.6) from a University in Asia participated in this experiment in exchange for extra credit. They were randomly assigned to either the high sentiment congruency condition or the low sentiment congruency condition in a between-subjects design. Participants were asked to imagine themselves as regular users of an online forum who have interests in *camera-related* topics. They read a discussion thread about the selection of cameras, where the sentiment congruency of replies was manipulated. In the high sentiment congruency condition, replies with similar sentiments were shown next to each other, while in the low sentiment congruency condition, a reply was followed by another reply with opposite sentiment. I kept the entire length of discussions the same and the overall sentiment neutral in both conditions. That said, the only difference between high sentiment congruency and low sentiment congruency conditions were the sequence of replies.

The measurements are collected in the following order: dependent variables, attention check, manipulation checks, and control variables. Willingness to participate is measured by asking participants to indicate their willingness to reply using a nine-point scale (1 = not at all willing; 9 = strongly willing). I revise and adopt the three items from Ziegele et al. (2018) and Van Zomeren et al. (2004) to measure this variable. The attention check question asks participants to either write down their reply or write “NA”. Participants who leave the answer blank are considered to fail the attention check. The manipulation check for sentiment congruency is measured by adapting three items from Aaker and Keller (1990) and Lanseng and Olsen (2012). Manipulation check for valence is measured using three items adopted from Lei et al. (2021) and MacKenzie and Lutz (1989). All items in manipulation checks are measured on a nine-point scale with a smaller number indicating lower sentiment congruency and valence. Finally, I collect participants' familiarity with the camera discussed in the thread and the online forum, as well as their demographic information such as gender and age.

Reliability and Manipulation Check. Eighteen participants who failed the attention check are excluded from the analyses (N=373). I first test the reliability of major variables in the study. Cronbach's alpha for willingness to participate was above 0.9. Besides, Cronbach's alpha of manipulation check is 0.919 for sentiment congruency and 0.863 for valence. Both dependent variables and manipulation checks suggest satisfactory reliabilities (Nunally and Bernstein 1978). I then average items for each measure to form an overall score.

Results of manipulation checks show that perceived sentiment congruency in the low-level condition was significantly lower than that in the high-level condition (M_{low} = 3.93 vs. M_{high} = 5.39, F(1,371) =72.92, p<0.001), suggesting valid manipulation of the variable of interest. Manipulation checks on valence reveal that there is no significant difference in perceived valence of discussions between the two experimental groups (M_{low}= 4.94 vs. M_{high}= 5.06, F(1,371) =1.37, p=0.243), ruling out the confounding influence of valence.

Experiment Results. Figure 1 displays the means for perceived willingness to participate under different sentiment congruency conditions. I use one-way analysis of variance (ANOVA) with the willingness to participate as the dependent variable. The results show that moving from low to high sentiment congruency significantly increased users' willingness to participate in the discussion (M_{low}= 4.28 vs. M_{high}= 4.73, F(1,371) =4.77, p=0.030).

I also explore whether the effect holds when controlling for the perceived valence of the discussion. To examine it, I conduct Analysis of Covariance (ANCOVA) with valence as a continuous covariate. The result suggests that the difference in willingness to participate between low and high sentiment congruency is marginally significant in light of including valence (F(1,370) =3.71, p=0.055). A higher sentiment congruency level results in a higher willingness to participate in the discussion. Therefore, the experimental results further support that the effect of sentiment congruency on discussion volume exists, and it is not derived from the effect of discussion valence.

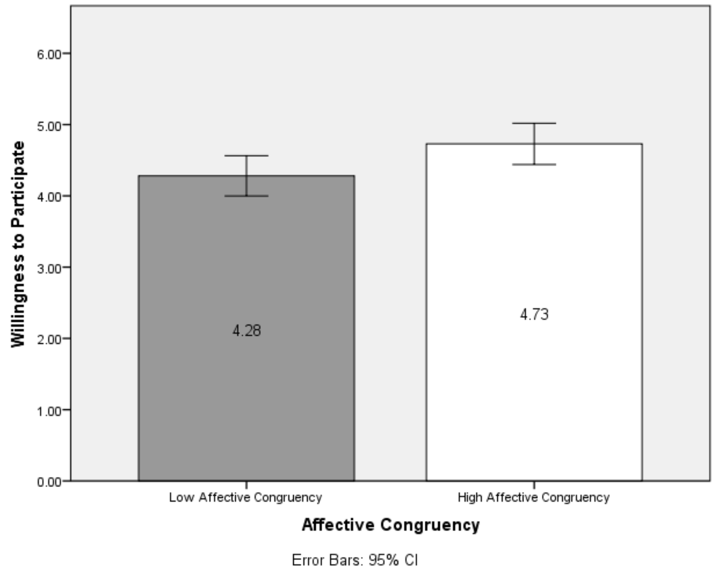

Figure 1. Effect of Sentiment Congruency on Online Discussions

1.6.6 Contingent Influence of Sentiment Congruency

This chapter aims to empirically identify the existence of the sentiment congruency effect in the process of online discussions. Leveraging panel data structure, I propose models that clearly identify the sentiment congruency effect. In this section, I explore the conditions under which the sentiment congruency effect is more salient.

First, I investigate the moderating role of discussion purposes. Previous studies have shown that discussion topic influences participation behaviors (Blau and Barak 2012; Chen and Berger 2013; Thomson 2006). As per the research review by Berger (2014), users are motivated to participate in online communication for different purposes, such as information acquisition, emotion regulation, and social bonding. Users' expectations of the discussion content under different purposes could vary. For instance, users who seek information may prefer to read and participate in the discussions with more inquiries and answers; therefore, the impact of the sentiment congruency effect could differ.

I classify whether a reply is for an inquiry by looking into the reply content. Specifically, a reply is coded as an inquiry if it includes at least one word, phrase, or symbol indicating a question (e.g., how, may I ask, seek advice).[3] I then calculate the proportion of questions asked from time *t-1* to time *t*, $Inquiry_{j,t}$. A higher value indicates a higher proportion of inquiries involved in the discussion thread *j* from time *t-1* to time *t*. Table 1 shows that, on average, 6% of users ask follow-up questions in subsequent discussions.

I examine the moderating effect of discussion purposes by adding interaction terms $SENC_{jt-1} \times Inquiry_{j,t-1}$ in the main models with OLS estimation. Estimation results are reported in Table 8. The results suggest that a higher proportion of inquiries in the previous discussions strengthens the sentiment congruency effect on subsequent response interval, valence, and volume. Specifically, the coefficient of $SENC_{j,t-1} \times Inquiry_{j,t-1}$ on response interval is significantly negative (Coef. = -0.028, p<0.01), demonstrating that the discussion interval can be further shortened if the discussion is mainly for question-and-answer and has a high level of congruency in sentiment. In addition, the coefficient of $SENC_{j,t-1} \times Inquiry_{j,t-1}$ on positive discussion content and volume are significantly positive, suggesting that the positive effect of sentiment congruency on discussion valence and volume will be larger when the discussion includes a higher proportion of questions.

To sum up, these results suggest that the sentiment congruency effect becomes more salient with a higher proportion of inquiries during discussions. Discussions with a high degree of sentiment congruency, usually indicating consistent opinion expression, may be helpful to users who want to access knowledge and gain information. As a result, it facilitates subsequent discussions. These results shed light on platform managers' strategy on where to spread out the

[3] A reply is classified as an inquiry if the content includes at least one word, phrase, or symbol about: "Do you", "Have you", "What", "How", "What to do", "Seek advice", "Please", "Ask", "May I ask", "?".

sentiment congruency effect in online discussions, particularly in the discussion sessions with high volume of information inquiries.

Table 8. Results of Moderating Effects: Proportion of Inquiries

DV	(1) Model 1 Log($Interval_{j,t}$)	(2) Model 2 $Pos_{j,t}$	(3) Model 3 $Neg_{j,t}$	(4) Model 4 Log($Replies_{j,t}$)
$SENC_{j,t-1}$	-0.150***	1.625***	0.021	0.135***
	(0.012)	(0.208)	(0.020)	(0.007)
$Inquiry_{j,t-1}$	0.030***	-0.703***	0.067***	-0.013***
	(0.011)	(0.108)	(0.025)	(0.004)
$SENC_{j,t-1} \times Inquiry_{j,t-1}$	-0.028**	1.111***	0.024	0.018***
	(0.012)	(0.144)	(0.025)	(0.004)
$Log(Interval_{j,t-1})$	0.070***	-0.116***	0.004	-0.024***
	(0.004)	(0.023)	(0.004)	(0.001)
$PosAgg_{j,t-1}$	0.002	-0.115***	0.003	0.004***
	(0.002)	(0.028)	(0.002)	(0.001)
$NegAgg_{j,t-1}$	-0.001	0.050	-0.504***	-0.003
	(0.007)	(0.063)	(0.053)	(0.003)
$Log(Replies_{j,t-1})$	-0.433***	1.395***	-0.038***	0.248***
	(0.006)	(0.069)	(0.008)	(0.004)
Constant	1.511***	7.099***	0.495***	0.790***
	(0.060)	(0.396)	(0.048)	(0.015)
Controls	Included	Included	Included	Included
FE	Included	Included	Included	Included
Log likelihood	-617221	-1.608e+06	-914644	-291160
No. of Threads	28,791	28,791	28,791	28,791
No. of Obs.	403,609	403,609	403,609	403,609

*Notes. *** p<.01, ** p<.05, * p<.1. Robust standard errors clustered by threads in parentheses.*

Second, I investigate the moderating effect of discussion phases. The insights derived from this analysis will be crucial to understanding when to implement a strategy in online platforms (Hock and Raithel 2020; Lambrecht and Misra 2017). A study by Hock and Raithel (2020) indicated that the faster a company responds to public negativity, the more the firm’s value remains in subsequent weeks. In the context of crowdfunding, Li et al. (2022) found that the initial herd of funders leads to overfunding. Considering online discussions, it is important to know when grouping replies with similar sentiments together generates greater benefit to the forum.

To evaluate the moderating effect of discussion phases, I create a series of dummy variables, $Phase_{jtk}$, to indicate the quantile to which discussions from time *t-1* to time *t* of thread *j* belongs. *k=1,2,3,4* is an indicator of the quantile from time *t-1* to time *t*. For instance, the value of $Phase_{jt1}$ is equal to 1 if the discussion session from *t-1* to time *t* of thread j belongs to the first quantile among all discussion sessions and 0 otherwise. Similarly, $Phase_{jt2}$, $Phase_{jt3}$, and $Phase_{jt4}$ indicate whether the discussion session of thread j belongs to the second, third, or fourth quantile, respectively.

I investigate the moderating effects of $Phase_{jtk}$ by including $Phase_{jtk}$ and interaction terms of $SENC_{jt-1} \times Phase_{jtk}$ in the main models with OLS estimation. I construct a subsample of the data used in the main analysis in order to observe four quantiles for each thread. Thus, I drop the threads in which the number of discussion sessions is smaller than four.

The results are shown in Table 9. These results suggest that the effects of sentiment congruency vary with different phases during the discussion process. Specifically, relative to the last phase (the reference phase), the effects of sentiment congruency on response interval are smaller in early phases. The interaction effects of sentiment congruency with the first three phases are all significantly positive, which will weaken the impact of sentiment congruency on shortening response interval.

Second, I find that the effect of sentiment congruency on subsequent positive discussion content is least salient at the beginning of the discussion (i.e., 3.259-2.566 = 0.693). The positive influence of sentiment congruency increases gradually with the development of discussion process. The effect of sentiment congruency will be 370% higher in the last discussion phase relative to the first discussion phase (i.e., 3.259-0.693/0.693 = 3.703). However, the influence of sentiment congruency on negative discussion valence is unchanged across discussion phases. This result suggests that while users tend to demonstrate different opinions in the initial discussions, they show support for each other’s ideas and reach a sentimental consensus (i.e., increasing positive sentiment) in later discussion phases.

Finally, the later the discussion, the larger the positive effect of sentiment congruency on discussion volume. The effect of sentiment congruency on response volume is strongest in the last discussion phase, which is 367% higher relative to the effect of sentiment congruency in the first discussion phase (i.e., (0.201 - (0.201- 0.158)) / (0.201- 0.158) = 3.674).

Overall, the findings suggest that the sentiment congruency effects vary with different phases. The priming is relatively less important in early discussions when users attempt to gain more relevant information from different perspectives. However, higher sentiment congruency helps to better gather and summarize information, and thus facilitates discussions in the later phases of the discussion process.

Table 9. Results of Moderating Effects: Discussion Phases

	(1)	(2)	(3)	(4)
	Model 1	Model 2	Model 3	Model 4
DV	Log($Interval_{j,t}$)	$Pos_{j,t}$	$Neg_{j,t}$	Log($Replies_{j,t}$)
$SENC_{j,t-1}$	-0.108***	3.259***	0.047**	0.201***
	(0.013)	(0.222)	(0.022)	(0.008)
$SENC_{j,t-1} \times Phase_{j,t1}$	0.126***	-2.566***	-0.014	-0.158***
	(0.009)	(0.116)	(0.013)	(0.004)
$SENC_{j,t-1} \times Phase_{j,t2}$	0.103***	-1.252***	0.010	-0.091***
	(0.009)	(0.103)	(0.012)	(0.003)
$SENC_{j,t-1} \times Phase_{j,t3}$	0.125***	-0.626***	0.009	-0.056***
	(0.008)	(0.096)	(0.012)	(0.003)
$Phase_{j,t1}$	-0.839***	-0.185	-0.100***	0.168***
	(0.013)	(0.208)	(0.018)	(0.008)
$Phase_{j,t2}$	-0.785***	-0.599***	-0.016	0.098***
	(0.009)	(0.131)	(0.014)	(0.005)
$Phase_{j,t3}$	-0.569***	-0.241***	0.004	0.062***
	(0.007)	(0.084)	(0.012)	(0.003)
Log($Interval_{j,t-1}$)	0.021***	-0.113***	0.002	-0.015***
	(0.003)	(0.022)	(0.004)	(0.001)
$PosAgg_{j,t-1}$	0.007***	-0.133***	0.003*	0.000
	(0.001)	(0.028)	(0.002)	(0.001)
$NegAgg_{j,t-1}$	-0.012*	0.036	-0.460***	-0.002
	(0.006)	(0.062)	(0.053)	(0.003)
Log($Replies_{j,t-1}$)	-0.378***	1.216***	-0.033***	0.232***
	(0.005)	(0.071)	(0.008)	(0.005)
Constant	0.021***	-0.113***	0.002	-0.015***
	(0.003)	(0.022)	(0.004)	(0.001)
Controls	Included	Included	Included	Included
FE	Included	Included	Included	Included
Log likelihood	-600461	-1.563e+06	-891161	-284333
No. of Threads	20,409	20,409	20,409	20,409
No. of Obs.	391,611	391,611	391,611	391,611

*Notes. *** p<.01, ** p<.05, * p<.1. Robust standard errors clustered by threads in parentheses.*

1.7 Discussion

1.7.1 Summary of Results

In this chapter, I investigate whether and how sentiment congruency influences subsequent discussions using data from a popular automobile forum in Asia. In particular, I quantify sentiment congruency by taking into account the sequence of user posts as well as the pairwise sentiment similarity between adjacent posts and examine its impacts on response interval, valence, and volume. The findings demonstrate that sentiment congruency facilitates users' subsequent discussions by reducing response interval and increasing response valence and volume. I examine the validity of the findings with numerous tests to extend the understanding of the sentiment congruency effect in the online discussion process. I find that the effect of sentiment congruency is more salient with higher proportion of inquiries raised during a discussion thread. In addition, the sentiment congruency effect varies with different discussion phases.

1.7.2 Theoretical Contribution

This study contributes to literature in several ways. First, it extends the literature on dynamic online discussions from the perspective of sentiment congruency across the sequence of user posts. While recent research has focused on the effect of UGC sentiment (Lee et al. 2018a; Yang et al. 2019) and abundant evidence indicates the dynamics of user opinions (Ahn et al. 2016; Wang et al. 2018a), little is known about how the evolving pattern of UGC sentiment across a sequence influences subsequent online discussions. In this study, I focus on the sentiment congruency of the linguistic features between adjacent user posts over a given time period. I also consider the decay of attention weights over time in constructing the features. As such, this study deepens the understanding of the role of the sequential display of sentiment, and more specifically, the congruence patterns within the textual sentiment information, in influencing users' subsequent discussions.

Second, I contribute to the literature on priming. Previous priming literature only revealed findings regarding people's response toward congruent sentiment in the laboratory setting (Fazio 2001; Fazio et al. 1986; Spruyt et al. 2002). I empirically tease out the sentiment congruency effect from field data. Leveraging linguistic features, findings in this study explain the effects of sentiment congruency patterns on user discussion behaviors. While previous researchers focused on how priming influences response speed, I extend to investigate sentiment congruency effects on subsequent discussions, i.e., response interval, valence, and volume, in an online discussion context. Moreover, I rule out several alternative explanations for the effects of sentiment congruency. The results show that sentiment congruency takes effect beyond the reciprocity effect from thread initiators and platform managers, overall discussion sentiments, and congruency of discussion content.

Lastly, I further delve into the mechanisms of the relationships between sentiment congruency and users' subsequent discussion behaviors by investigating the moderating effects of discussion purposes and discussion phases. The findings suggest a nuanced picture of the sentiment congruency effect in different circumstances. That is, the effects of sentiment congruency on discussion interval, valence, and volume are further strengthened when the proportion of inquiries in previous discussions is higher. In addition, the moderating effect of discussion phases suggests that the sentiment congruency effect varies with different discussion phases. In general, the effects of sentiment congruency on subsequent discussions become stronger at the later phases of the discussion process, such that a trending topic is more easily formed when the discussion develops to a later stage and participants hold consistent opinions. The findings enrich the understanding of the effects of sentiment congruency across discussion purposes and time.

1.7.3 Practical Implication

Given the intense competition among online discussion platforms that provide similar services, the massive amount of information contained on each platform, and users' limitations in processing capacity (Li et al. 2018; Lucky 1989; Marr 2019), how to attract user attention and stimulate discussions is a critical yet unsolved question for platform designers, managers, and thread initiators. This research provides important practical implications to these stakeholders for facilitating user participation and thus propelling trending topics in online discussions.

The findings in the main analysis suggest that higher sentiment congruency facilitates more subsequent discussions, represented by shorter response intervals, higher response valence, and larger response volume. These findings demonstrate the necessity and benefit of considering the pattern of user posts on online platforms and shed light on the sequential design of how to present user posts. The results of additional analyses suggest that sentiment congruency among user posts can take effect isolated from discussion sentiments. Users tend to deviate from previous discussion valence; however, a discussion thread with congruent sentiments can motivate users to post positively. Simply creating fake content may not be workable in some situations and probably will hurt the seller's reputation and decrease consumers' purchase intentions (Clarke et al. 2020; Lappas et al. 2016; Ma and Lee 2014). Alternatively, the platform designers and managers can consider implementing and making use of display features so as to group user posts with similar sentiment next to each other. For instance, change the display sequence by taking advantage of the vote up or down features. The findings suggest that changing the display of replies might be a better strategy for firms to generate positive word-of-mouth than manipulating sentiment in the discussion. The effect size of sentiment congruency on subsequent discussion positivity is higher than that of previous positive discussions (Table 6 Model (1)).

Furthermore, I explore contingent factors answering where and when for platform managers and/or thread initiators to implement this displaying feature. These findings suggest that the effect of sentiment congruency is more salient when the proportion of inquiries in the discussion is high. It also provides another solution to the platform designers: if there are many questions asked in one thread that cause users to react differently to the same exhibition of replies, then bifurcating them into different spin-off threads may be a better choice. It also reveals the optimal timing of grouping posts with similar sentiment. Basically, the sentiment congruency becomes more beneficial at the later phase of the discussion process.

Lastly, I roughly estimate the economic impact of sentiment congruency in online discussions on product sales using the estimates from my model and public statistics. A back-of-the-envelope calculation suggests that one standard deviation increase in sentiment congruency facilitates approximately 15,016 monthly automobile purchases (= 13.6% * 170,286 replies per month * 109 views per reply * 0.0006 users per view * 0.0027 purchase rate per user per month * 3,672 automobile forums).[4] It contributes to 0.12% of monthly sales for an average automobile and 0.02% of monthly sales for the automobile of interest.[5] The results provide side support that a higher sentiment congruency benefits the automakers by increasing their revenue gained from users' participation in online forums.

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[4] According to https://club.autohome.com.cn/#pvareaid=3311253, there are 3,672 automobile forums. In our data, on average a forum has 170,286 replies in a month, with 109 views per reply. An average user has a 0.06% probability to view a reply and a 0.27% probability to purchase an automobile after viewing the reply. The purchase information is indicated from text mining analysis. If the initial post includes the words "pick up", I consider a consumer purchase after viewing the forum. I only keep those users who pick up the automobile within one year by removing users whose post includes the word "year".

[5] According to https://xl.16888.com/style-202201-202202-11.html, the monthly purchase of an average automobile during our observation window is 3,276. According to https://xl.16888.com/s/126952-2.html, the average monthly purchase of the automobile related to our forum is 21,904. Note that there are only 583 automobile sales available online. Therefore, I only provide a conservative estimation when calculating the effect of estimation on the percentage of sales.

1.7.4 Limitations and Future Research

I conclude by summarizing some caveats and limitations of this paper. First, the empirical study takes advantage of the fact that most users in online discussion forums read previous posts that are sequentially displayed (the user posts are displayed by time order in the context of this study) before they decide whether or not to post their own opinions. While this is commonly observed in professional discussion forums, such as the automobile discussion platform in the context of this study and other knowledge-sharing platforms, the assumption might not hold for the platforms where users have a low commitment to the relevant online community. In the online review context, users may simply write a review based on their product experiences. In addition, the main purpose of users posting on social media is to build or maintain social relationships with specific individuals. Therefore, reading and understanding posts from all users may not be strong motivation in that context. Nevertheless, my results shed light on the benefit of implementing display features of online platforms, such that online review platforms could also benefit from a display of reviews that indicate higher sentiment congruency.

While the sequential display in the online forum provides an elegant structure to evaluate the impact of congruency patterns, it does not incorporate complex user activities, such as direct commenting, liking, or sharing others' posts. It would be interesting to enrich the structure of sentiment congruency measures based on multilayer user reactions and evaluate their impact on subsequent discussions if such data becomes available for future research.

Third, my research is mainly based on empirical data. While showing the positive effect of sentiment congruency on subsequent discussions, my research is based on users who read and write replies. That is, a limitation of this research is the lack of data on viewers who only read previous replies but do not add to the discussions. Unlike in an experimental setting where participants are required to give their evaluation, online users might not post their opinions even if they think positively after viewing congruent sentiments. Therefore, my research only provides a conservative measurement of the sentiment congruency effect. The actual effect of sentiment congruency might be even more positive than what I had observed in my results. Moreover, I reduce such concern by examining the sentiment congruency effect in an experimental setting as an additional analysis. The results remain the same as observational data suggested.

Fourth, my research focuses on understanding how sentiment congruency in user posts influences subsequent discussions. Therefore, I conduct analyses at the hour level and controlled for a series of thread-, user-, and time-related factors. I also apply regressions with GMM estimation to evaluate the relationships. The research findings provide integrated guidance regarding the influence of sentiment congruency as a whole. Taking this as a starting point, future studies could manipulate the information sequence by, for example, creating contradictory sentiments in user posts to evaluate the impact of individual messages on subsequent discussion generation outcomes.

Finally, due to the limitation of the dataset, I use discussion information from one automobile brand in the analyses. Although offering a back-of-the-envelope calculation on the economic impact of sentiment congruency, there is not enough sales data for the corresponding automobiles. One interesting extension could be to conduct a thorough analysis of the marketing impact of sentiment congruency in online discussions.

Chapter 2

Investigating the Effect of Public Negativity on Member Engagement in Online Fan Community

2.1 Introduction

In the digital age, online fan communities significantly influence the fortunes of celebrities and influencers (Hollingsworth 2020; Soo 2023). While a member of an online fan community may appear negligible, the collective support of fans can swiftly amass millions in revenue for their beloved figures, reshaping the dynamics of fame and success.[6] A noteworthy example is the two-day virtual fan gathering of BTS, a renowned Korean Pop Music (K-pop) group, which attracted over a million global fans and generated more than $70 million in merchandise and ticket sales (Chung and Koo 2023).

Given its public nature, member engagement in online fan communities depends not only on how members bond with each other but also crucially on the eye of the public. When the general public supports the community, it thrives and prospers; however, if differences between the general public and community arise, it leads to a downward spiral for the community. While a number of studies in information systems (Arazy et al. 2011; Arazy et al. 2013; Campbell et al. 2009), marketing (De Valck 2007; Dineva and Daunt 2023; Husemann et al. 2015), and management (Faraj et al. 2011; Hinds and Bailey 2003) have documented conflicts within a community, there is still limited knowledge regarding how these communities deal with external sentiment factors.

According to public opinion literature, *public negativity* refers to the collective expression of criticism by the public in response to specific events or related parties (Hibbing and Theiss-Morse 1998; Kuhnen and Niessen 2012). Initially, the general public might casually browse

[6] https://www.washingtonpost.com/lifestyle/kidspost/why-do-some-athletes-make-millions-because-fans-support-them/2017/07/26/f743ae7e-70b6-11e7-8f39-eeb7d3a2d304_story.html

and consume online information for entertainment, especially in news related to the entertainment industry (Jackson 1999; Schindler and Bickart 2005). Negative information about celebrities and influencers often grabs public attention, leading to a negative impression and public pressure on those public figures involved (Akcura et al. 2018; Jackson 1999; Kintu and Ben-Slimane 2020). Public scrutiny extends beyond celebrities, impacting ordinary users who grapple with public pressure and judgement of their online lives (Auxier 2020; Mcnamara 2022). Therefore, following a negative event involving a celebrity or influencer, the general public may continue to closely observe and form negative judgments about the associated online fan communities. Past research on subjective norms have revealed that individuals with minority opinions often conform to the majority's viewpoint to avoid social isolation, especially when the opinion aligns with an important reference group (Cialdini and Goldstein 2004; Stafford and Cocanougher 1977). As online fan communities value public recognition on social media, members in online fan communities might conform to public opinion, especially in the face of public negativity directed at celebrities and influencers they love. They take this step to mitigate the negative impact on their public image, leading to more reserved engagement within their communities.

On the other hand, public negativity might strengthen the engagement within the community. It can increase the community's ingroup favoritism in the presence of public negativity (Balliet et al. 2014; Voci 2006), reduce its negative impact on beloved celebrities and influencers (Chang et al. 2013), and prompt members to take actions against those holding opposite perspectives in the general public (Balliet et al. 2014; Nauroth et al. 2015; Phadke and Mitra 2020). Moreover, online fan community members, who are deeply engaged with celebrities and influencers, tend to rationalize and decouple their support for these public figures, even in the face of wrongdoing (Wang and Kim 2020). These reasoning strategies may further increase engagement by enhancing support among members in online fan communities when dealing with public negativity directed at their beloved public figures.

This study delves into the impact of public negativity on engagement in online fan communities, where the engagement activities are visible to the public. I examine two types of engagement: total number of comments and likes. Recent research has highlighted the distinct and important roles that comments and likes play as forms of engagement on social media (Yang et al. 2019; Yang et al. 2020). Leveraging a natural experiment, I empirically measure how online fan communities respond to varying levels of public negativity.

Yet, within online communities, members who share common interests and beliefs may experience shifts in attitude and internal conflicts due to negative events. These internal factors can become intertwined with the influence of public negativity. Moreover, the impact of public negativity may differ among member types, demographics, and statuses.

This paper aims to address the following questions:

1) What is the impact of public negativity on engagement in online fan communities, in terms of comments and likes?
2) Does the impact of public negativity vary among different member types, demographics, and statuses?

To provide answers, I analyze a unique dataset consisting of 4,752 original posts across three online fan communities on a leading social media platform in China. These online fan communities were subject to varying levels of public negativity stemming from the same event – an unexpected dropout of a celebrity from the celebrity group. Influenced by Confucian culture, trustworthiness is highly valued in Chinese society (Koehn 2001). When a celebrity unexpectedly breaks a promise, the general public, in line with Confusion values, tends to view both the involved celebrities and online fan communities supporting them negatively. This negative perception is supported by the decreasing stock price of the entertainment company after the dropout event (Bollen et al. 2011; Phillip 2014). Moderated and populated by fans of the respective celebrity or celebrity group, each community features original posts in the form of Fan Pages that detail information about the schedules and activities of the celebrity or celebrity group. Only a few members who are administrators can create original posts. Other members engage through comments and likes. The data collection spans from 10th April 2014 to 19th June 2014, capturing the number of comments and likes for each original post, along with content, emotion, format, and time characteristics.

Empirically investigating the impact of public negativity presents practical challenges. First, tracing public negativity is complex, as the general public often observes content without actively participating in online fan communities. Even when the general public comments on social media, they tend to use coded language to avoid interference from members of online fan communities. Second, it is difficult to estimate the influence of public negativity, as its effect is likely confounded with other internal factors within online fan communities.

To overcome these challenges, I utilize a natural experimental design and employ a weighted Regression Discontinuity in Time (RDiT) model. RDiT is a technique supported by previous literature for recovering a causal effect of interest (Hausman and Rapson 2018). The identification strategy of this study hinges on the observation of a famous event that went viral on social media. By examining the members' engagement within online fan communities during a short window around the event, I can estimate the direction and magnitude of public negativity. Moreover, I use Baidu search index as a weighting factor in the model. This index reflects the daily public attention directed toward the favored celebrity or celebrity group in these online fan communities. It follows the methodology used in prior research facing similar challenges (Anderson 2014). I also conduct additional analyses to eliminate alternative explanations related to internal factors. Further details regarding the research design are discussed in section 2.4.

I report two main findings. *First*, I uncover a nuanced pattern of engagement when online communities encounter public negativity. In response to public negativity, online fan communities tend to decrease comments yet increase likes. This effect becomes more pronounced with higher levels of public negativity. It indicates that the reserved engagement in online fan communities is likely driven by the fear of public judgment.

Secondly, I explore heterogeneity based on members' characteristics, including their member types, demographics, and statuses. The public negative effect on comments is amplified among members who favor dropout celebrity less. I reason that they might fear that their comments will be misinterpreted by the general public, leading to negative influences on the remaining celebrities and celebrity group. Furthermore, the effects of public negativity do not differ across members' demographic and status characteristics, indicating that the impact of public negativity is consistent across characteristics irrelevant to online fan communities.

This study contributes to literature in several ways. Firstly, it adds to the online community literature by providing a new perspective on antecedents of engagement in online communities. While previous research has predominately focused on internal factors within communities, I highlight that an external factor, public negativity, also plays an important role in shaping engagement in online communities. This public negativity effect stems from the public nature of online communities, where engagement in communities is easily observed by the general public.

Secondly, this study contributes to celebrity and influencer literature by quantifying the impact of public negativity on online fan communities. Public negativity is often challenging to observe or measure. However, this study overcomes this challenge by utilizing a natural experiment design and an RDiT model, specifically focusing on an event where a celebrity unexpectedly dropped out of a celebrity group and incorporating daily public attention weights.

Thirdly, this study adds to celebrity and influencer literature by exploring the heterogenous effect of public negativity on online fan communities. Previous literature has often assumed that customers share the same response to negative news of celebrities (Chung et al. 2013; Halonen - Knight and Hurmerinta 2010; Hock and Raithel 2020). This study contributes by examining whether and how members' response to public negativity varies across member characteristics. Consequently, my findings identify member characteristics that are more susceptible to the effect of public negativity.

The remainder of this chapter is structured as follows. Section 2.2 provides background and reviews of relevant literature on online community and celebrity and influencer studies. In section 2.3, the research context is introduced. Section 2.4 covers the research design and measures. Section 2.5 presents and summarizes the impact of public negativity on engagement. Session 2.6 delves into robustness checks and additional analyses to eliminate alternative explanations and explore moderating effects of member characteristics. Session 2.7 concludes the chapter.

2.2 Background and Literature Review

Online communities have experienced significant expansions in recent years. According to a report by GWI (Beer 2020), 76% of online users have engaged in online communities in 2019. Another source, TRT World (Balkiz 2021), reported that people spent an average of 7 hours per day online, with a large amount of the time dedicated to social media. This trend is particularly noticeable in fan communities, where 70% members stated that their engagement in fan communities are integral to their daily routines (Amazon Ads 2023).

With the rapid growth of celebrity and influencer marketing, fan communities are flourishing online. Some of these communities, such as those on Discord (discord.com), Facebook Groups (facebook.com/creators/tools/groups), and Daum Cafe (top.cafe.daum.net), tend to be more private. In contrast, communities on Twitter (twitter.com), Instagram (instagram.com) and Weibo (weibo.com) are relatively more public, allowing the general public to view member engagement within online fan communities. Nowadays, many online fan communities are moving to private environments to freely express themselves and interact with members.

This study examines the effect of public negativity on member engagement within online fan communities. The research is broadly related to two streams of prior literature. First, I contribute to the online community literature by incorporating the perspective of an external factor, i.e., public negativity. Second, I benefit celebrity and influencer literature by quantifying the influence of public negativity on member engagement and examining whether this effect varies across member characteristics.

2.2.1 Online Community Engagement

Online community refers to a group of individuals engaging in social interactions about their shared interests through the internet (Kim et al. 2008; Manchanda et al. 2015; Williams and Cothrel 2000). These communities take diverse forms, including brand communities (Algesheimer et al. 2005; Muniz Jr and O'guinn 2001), support communities (Moon and Sproull 2008; Peng et al. 2020) and fan communities (Cheng and Zhang 2022; Kim and Kim 2017). Beyond serving as informative platforms, online communities facilitate engagement among members (Manchanda et al. 2015; Ren et al. 2012). From the members’ perspective, these engagements play a crucial role in forming connections (Szmigin et al. 2005), fostering a sense of belonging (Zhou 2011), and delivering enjoyment (Wasko and Faraj 2005). For companies, these engagements contribute to increasing product loyalty (Hur et al. 2011), driving innovations (Porter and Donthu 2008), and enhancing economic gains (Manchanda et al. 2015). The engagement value persists, regardless of whether the community is organized by companies (Lykourentzou et al. 2022; Moon and Sproull 2008).

Engagement was initially conceptualized by organizational behavior researchers as a psychological state in which group members are motivated to invest cognitive and emotional effort in work performance (Rich et al. 2010). With the emergence of online communities, previous marketing and information system literature has adopted the concept of engagement to explain online community-oriented behaviors (Hollebeek 2011; Ray et al. 2014; Ren et al. 2012). Following Ray et al. (2014), I define engagement in online community as "the enthusiasm of members for contributing to their community". Specifically, my focus is on members' comments and likes accumulated under original posts within online fan communities.

While previous researchers have treated comments and likes as interchangeable measures of engagement (Hughes et al. 2019; Lee et al. 2018a), recent studies have suggested a differentiation between the two. Commenting and liking in an online community exhibit variations in the level of involvement and emotional expression (Yang et al. 2019; Yang et al. 2020). Commenting requires deliberate effort in composing a message, indicating a higher level of involvement (Kim and Yang 2017). On the other hand, liking requires a lower level of involvement, characterized by a habitual action—simply clicking the like button (Alhabash et al. 2019; Yang et al. 2020). Moreover, while liking simply indicates favoritism toward a post, commenting allows for expression of complex and diverse emotions (Abbasi et al. 2018; Yin et al. 2014), as text can convey emotions at the granular level and evoke an emotional response through speech acts.

Online community literature has highlighted numerous antecedents of engagement, such as member characteristics, including conflicts among members (Arazy et al. 2011; Tsai and Bagozzi 2014; Zhou 2011) and members' attachment to the community (Kuem et al. 2020; Ren et al. 2012), post valence and content characteristics (Hughes et al. 2019; Yang et al. 2019), and platform design (Cao et al. 2023; Dewan et al. 2017). However, previous research has predominately focused on internal factors within the community, leaving the impact of external factors relatively underexplored.

This study delves into the external impact of public negativity on engagement in online fan communities. Public negativity refers to the collective expression of criticism by the public in response to specific events or related parties (Hibbing and Theiss-Morse 1998; Kuhnen and Niessen 2012). While this phenomenon exists widely, it has received limited attention from researchers. One recent exception is the work of Kuhnen and Niessen (2012), where they examined how public negativity affects CEO payment. However, to the best of my knowledge, none of these studies have explored public negativity faced by online communities.

From the social influence perspective, public negativity might influence members' engagement in a community through two mechanisms: compliance and identification, which often refer to subjective norms and social identity (Abrams and Hogg 1990; Balliet et al. 2014; Tsai and Bagozzi 2014). Subjective norms refer to situations where individuals are influenced by opinions of other people that are important to them (Ajzen 1991; Stafford and Cocanougher 1977). A similar phenomenon is observed by public opinion researchers, who describe it as a "spiral of silence", where people are often hesitant to speak up due to potential public backlash (Noelle - Neumann 1974; Scheufle and Moy 2000). In the context of online communities facing public negativity, members might confirm negative public opinions, even if they don't necessarily agree, leading to reduced interactions with other members. Social identity encompasses a sense of belonging to a community (McLeod 2008). When confronted with a threat to their identity outside the community, members might post comments to increase engagement within the community and defend against public negativity (Balliet et al. 2014; Nauroth et al. 2015). In both cases, the public nature of online communities creates a social context in which engagement in communities can be swayed by public opinion.

2.2.2 Celebrity and Influencer

A celebrity is a widely-known individual recognized by a specific group of people (Schlecht 2003), while an influencer is someone who has significant influence over a particular target audience (Kadekova and Holienčinova 2018; Sudha and Sheena 2017). These two concepts are not entirely separate. Nowadays, individuals with public recognition and social media influence hold substantial marketing value (Nistor and Selove 2023).

In today's digital age, social media visibility plays a pivotal role in evaluating the fame of celebrities and influencers (Hung 2020; Turner 2013). However, this increased visibility also means that negative information about them can spread rapidly online, regardless of its veracity (Akcura et al. 2018; Tandoc Jr et al. 2020). Consequently, it has become increasingly important for celebrities and influencers to establish connections with both members in their online fan communities and the general public (Hou 2019).

A member in an online fan community is someone who nurtures a deep and positive sentimental connection with a famous person or entity, actively engaging in member-related activities (Duffett 2013). They hold significant value for celebrities and influencers, as they contribute to strengthening brand endorsements (Hung 2020), increasing purchase intentions (Lou and Yuan 2019), boosting their overall popularity (Liao 2021), as well as downplaying the impact of negative comments directed towards these public figures (Hung 2020).

General public refers to the collection of ordinary individuals who do not belong to any specific group (Boyd 2008; Brossard and Lewenstein 2009). In the context of celebrities and influencers, the general public comprises online users who are not part of or engage in online fan communities. Previous studies have indicated that celebrities and influencers can shape the public's opinions regarding their political views (Pease and Brewer 2008; Wood and Herbst 2007). However, less is known about how sentiment from the general public towards celebrities and influencers impacts their value, such as member engagement in online fan communities.

Numerous marketing studies have demonstrated how negative news about celebrities and influencers can shape customers' perceptions of associated brands. Many studies have made an underlying assumption that customers have a uniform response to such negative news. For instance, Chung et al. (2013) observed that Tiger Woods's scandal caused millions of dollar losses for the brands he endorsed. Hock and Raithel (2020) found that a firm's response to negative news can mitigate its impact. Although they acknowledged that the effectiveness varies based on the specifics of the news, they still assumed a homogeneous customer response. However, research that considers heterogeneous customer responses has found contradictory results. For instance, Till and Shimp (1998) discovered that exposure to negative magazine articles about a celebrity led to unfavorable brand perceptions, especially when subjects were unfamiliar with both the brand and celebrity, or when there is a strong collaboration between them. On the other hand, Hussain et al. (2023) examined customers' heterogenous response, suggesting that social media involvement and brand commitment did not alter the effect of negative celebrity or influencer news on attitude toward brand.

In this study, I focus on two groups of online users: members within online fan communities and the general public. Within the context of online fan communities, I explore whether members exhibit homogenous responses when confronted with public negativity. I investigate three characteristics of community members: member types, demographics, and statuses. This study provides a deeper understanding of how different segments of members react to the external impact of public negativity.

Identifying public negativity directed at online fan communities presents several challenges. Firstly, observing public negativity is challenging (Bond et al. 2012; Kuhnen and Niessen 2012). Given that all members of online fan communities favor celebrities and influencers, the general public tends to only view discussions within the communities without leaving negative comments (Brown and Billings 2013; Cialdini and Goldstein 2004; Gearhart and Zhang 2015). Even when the general public expresses negative comments about an online fan community on social media, they often use coded language outside of the community, making it difficult to identify (Miao 2020; Storm No.8 2020). Second, empirically measuring public negativity in the presence of confounding factors has been a recognized challenge (Carraro et al. 2019). In experimental studies, experimenters can measure public negativity by directly asking subjects through questionnaires (Noel et al. 1995). However, empirical researchers often face difficulties measuring public negativity from observable data. For instance, Kuhnen and Niessen (2012) used the tone of press coverage from multiple news articles as a proxy for public negativity. They also noted that such measurement of public negativity is imperfect.

In this study, I use a natural experimental design to exploit the impact of public negativity on engagement in online fan communities. To quantify this effect, I utilize a RDiT design, which helps to recover the causal effect of public negativity (Hausman and Rapson 2018). To better capture public negativity, I leverage Baidu search indexes as indicators of daily public attention toward online communities. Prior literature has suggested that online search data can represent public attention, functioning as weights for a more accurate measurement of the coefficients of interest (Gong et al. 2020; Zhang and Tang 2016). To address the potential confounding influence of internal factors on the validity of public negativity effects, I also conduct additional analyses using IVs and the Chinese RoBERTa model.

2.3 Research Context

To implement the research design and test the effect of public negativity on member engagement in online fan communities, I collect data from one of China’s most influential social media platforms. Launched by Sina in 2009, the platform heavily relies on celebrities and influencers to attract online users (Weibo 2019; Xiang 2016). As a result, numerous online fan communities dedicated to celebrities and influencers have emerged, each organized by fans.

These communities feature original posts on Fan Pages, presenting content in diverse formats, such as video, image, and text, all centered around information or activities related to particular celebrities or celebrity groups. The information includes collecting and translating texts posted by celebrities and influencers on other social media platforms, uploading videos in which the celebrities and influencers have participated (e.g., music videos, TV programs, radio shows, interviews), and sharing pictures found online of celebrities and influencers engaging in offline activities. Activities within these communities also involve group purchases of products endorsed or created by the celebrities and influencers, fundraising to support celebrities' and influencers' careers, and participating in votes for TV or online programs to help their favored celebrities win competitions (e.g., music contests). Only a few selected members who are administrators can create original posts. Other members actively engage by commenting and liking these posts. All online fan communities are accessible to the general public, allowing them to view member engagement within these communities. Figure 2 shows screenshots of an original post (Figure 2-A) and the engagement interface for commenting and liking (Figure 2-B).

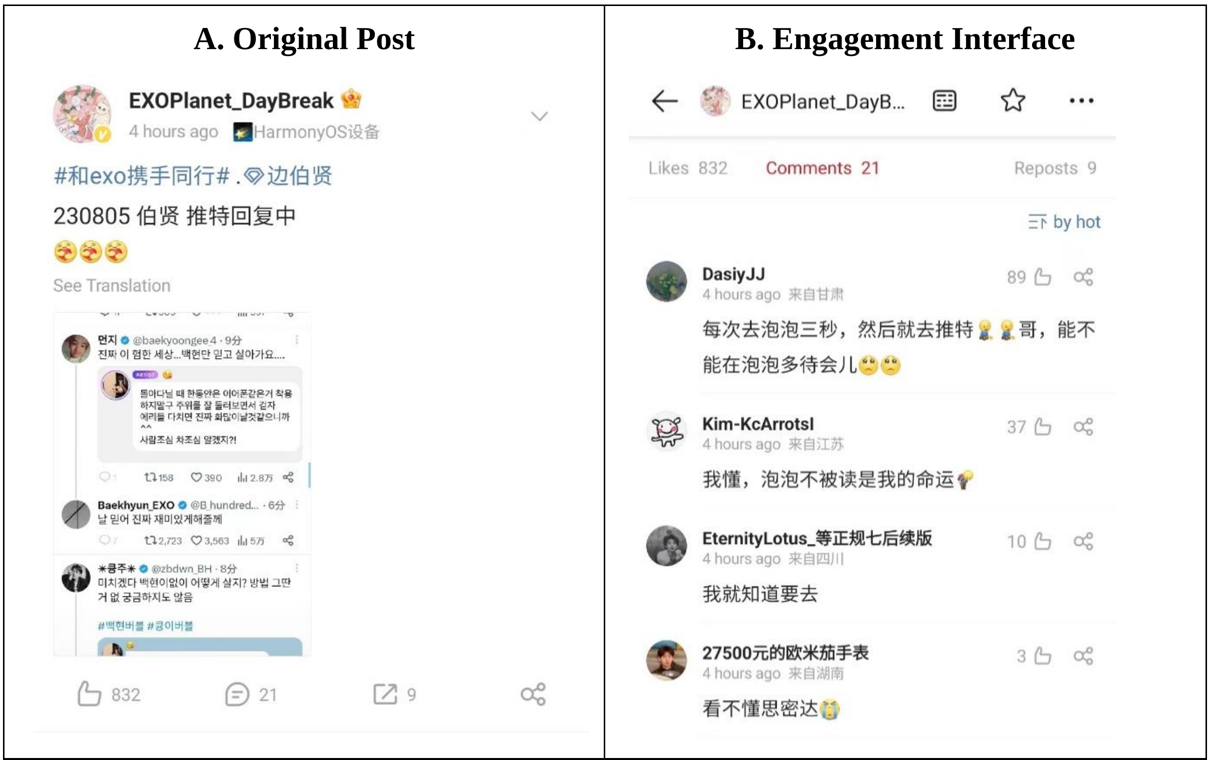


Figure 2. Screen Shots of Original Post and Engagement Interface

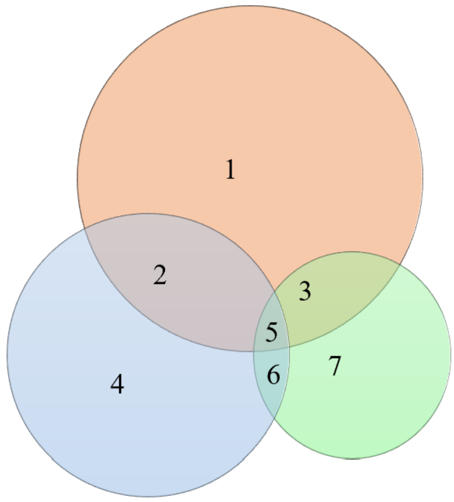
I specifically examine an event where a celebrity dropped out from a K-pop group. At the time of the event, this celebrity group was among the top performers in the music industry. Debuted in 2012 under one of the largest entertainment companies, they consistently topped major music charts with their hit songs. By the end of 2013, the celebrity group had become the first group in decades to sell over 1 million physical albums. Despite intensifying competition by 2018, they still accounted for over 30% of total revenue from all celebrities managed by their entertainment company.

The event occurred on May 15th, 2014, when a celebrity unexpectedly filed a lawsuit against his entertainment company and left the celebrity group, he was a part of before his contract had expired. The reasons cited for the lawsuit included unfair treatment, inadequate rest, and health concerns. In later interviews, the dropout celebrity suggested a significant factor reason for his leaving was the lack of artistic freedom. There was no prior indication that this event would happen. Even the remaining celebrities of the celebrity group first learned about the dropout event from online news while they were preparing for an upcoming concert.

While news reports used neutral words to describe the event, the general public formed negative opinions about the involved celebrities and the celebrity group. The public criticized the dropout celebrity for allegedly fabricating reasons for leaving the group (Dhan 2024). However, the dropout celebrity did not respond to this criticism. This negative public sentiment was reflected in the financial performance of the entertainment company. Despite being one of the dominant entertainment companies in Korea, its stock prices dropped by 5.82% following the news of the celebrity's dropout (Phillip 2014).

The selection of this event is two-fold. First, it is unlikely that the overseas company representing the celebrity group would manipulate the online fan community in mainland China, as cross-national services are challenging to obtain. Second, the celebrity dropout happened unexpectedly and without prior notice. Therefore, it is impossible for members in these online fan communities to anticipate the dropout and the public negativity afterwards.

The data sample consists of three communities: 1) dropout celebrity's community, 2) the celebrity group's community, and 3) a remaining celebrity's community. The remaining celebrity's community is selected based on two criteria: 1) the celebrity remains in the group, and 2) the celebrity shares similar activities with the dropout celebrity. I included these three communities to represent different levels of public negativity. The dropout celebrity's community has the highest public negativity, as the celebrity left the celebrity group and triggered public negativity. The celebrity group's community has moderate public negativity; although one celebrity left the group, the rest of the celebrities remained. The remaining celebrity's community has the lowest public negativity, as this celebrity is still part of the celebrity group and is less affected by the dropout. Figure 3 outlines the relationship among members in the three online fan communities. I collect data related to 4,752 original posts posted between 10th April 2014 to 19th June 2014, from the three communities. Table 10 presents the descriptive statistics for the key variables at the original post-level.



Dropout Celebrity's Community (High Public Negaitivty)
Celebrity Group's Community (Moderate Public Negativity)
Remaining Celebrity's Community (Low Public Negativity)

1 Members of the dropout celebrity's community.
2 Members of both the dropout celebrity community and the celebrity group's community.
3 Members of both the dropout celebrity community and the remaining celebrity's community.
4 Members belong to celebrity group's community.
5 Members of all three communities.
6 Members of both the celebrity group's community and the remaning celebrity's community.
7 Members of remaining celebrity's community.

Figure 3. Relationship of Members in Three Online Fan Communities

Table 10. Summary Statistics of Key Variables

	Mean	Std. Dev.	Min	p25	Median	p75	Max
Dropout Celebrity's Community (N = 2,408)							
Comments	45.533	157.795	0	9	21	44	4702
Likes	484.415	1260.885	0	214	320	529	58406
After	#N1 = 836, #N0= 1572						
Celebrity Group's Community (N = 1,284)							
Comments	55.981	148.665	0	15	30	59	3408
Likes	709.678	399.699	135	422	631	887	3304
After	#N1 = 510, #N0= 774						
Remaining Celebrity's Community (N = 1,060)							
Comments	9.721	19.837	0	2	5	10	389
Likes	106.745	85.608	0	48	88	139	1056

After	#N1 = 445, #N0= 615

2.4 Research Design and Measures

To examine the impact of public negativity on online fan communities, I leverage a natural experiment design based on regression discontinuity in time (RDiT) model, a variant of the traditional regression discontinuity (RD) approach often used in environmental economics to measure policy effects. The RDiT model focuses on observations around a specific threshold time c, treating observations before c as untreated and those after c as treated. With a relatively short observation window, the causal effect of the treatment can be recovered (Hausman and Rapson 2018). In this study, the "treatment" is a celebrity dropout event that affects all related online fan communities. It is a reasonable treatment as it is closely followed by significant public negativity, evidenced by a 5.82% decrease in the stock price of the associated entertainment company immediately after the event.

Previous researchers under the RDiT framework have developed weights to control for confounding factors along with time (Anderson 2014; Linden and Adams 2012). I use Baidu search index as a weight to gauge daily public attention (Zhang and Tang 2016). Calculated from the online search volume by the general public, this index is generated using the names of dropout celebrity, celebrity group, and remaining celebrity for their respective online fan communities. A higher search index indicates increased daily public attention to the community. Specifically, I estimate the equation:

$$y_{j(t)} = \alpha + \beta After_{j(t)} + f\big(Date_{j(t)}\big) + \boldsymbol{\sigma X_{j(t)}} + \varepsilon_{j(t)}. \tag{4}$$

In this equation $y_{j(t)}$ represents the engagement, i.e., log-transformed comments and likes original post j received. $After_{j(t)}$ is a binary variable equal to 1 after the dropout occurs and 0 otherwise. To eliminate potential endogeneity between ε_{ijt} and $Date_{j(t)}$, a flexible function f ($\cdot$) is added in the equation. Consistent with previous literature (Anderson 2014; Imbens and

Lemieux 2008), flexible function is specified as $\gamma_1\ Date_{j(t)} + \gamma_2 Date_{j(t)} \cdot After_{j(t)}$, where $Date_{j(t)}$ is normalized to be zero on the date that public negativity comes into effect. I specify a uniform kernel and use a 5-week period both before and after the dropout as the observational window.

$X_{j(t)}$ represents a set of control variables, including content, emotion, format, time characteristics, and search index (*search*). Table 11 summarizes the original post characteristic definitions. I consider four content characteristics (*content emoji, content length, mentions, purchase information*). Emotion characteristics are derived from both text and emojis, using the Ren-CECps Chinese dataset, which consists of 35,096 sentences collected from Sina blog (Cui et al. 2021; Li and Fei 2021; Quan and Ren 2010). For emotion recognition, I fine-tune a Chinese RoBERTa model, extracting 9 emotion labels for the text and emojis of each original post (*sorrow*, *anger*, *hate*, *expect*, *joy*, *love*, *anxiety*, *surprise*, and *neutral*). The intensity of each emotion is quantified on a scale from 0 to 1, with a higher value indicating stronger emotional intensity. Additionally, I consider four format characteristics (*image*, *video*, *repost*, and *link*) included in the original post. Two time characteristics (*weekday, time difference*) are also considered. Fixed effects related to posting times, including morning, afternoon, evening, and night, are taken into account. I add one to the count variables and log-transform them before analysis (e.g., ln(content length+1)).

Table 11. Definitions of Original Post Characteristics

	Content Characteristics
Content Emoji	Number of emojis in the original post.
Content Length	Number of characters in the original post (excluding web link and emoji length).
Mentions	Number of mentions (@) in the original post.
Purchase Information	Indicates if the original post is about purchasing products associated with the celebrity or celebrity group.
	Emotion Characteristics
Text Sorrow	The intensity of sorrow in text of the original post.
Text Anger	The intensity of anger in text of the original post.
Text Hate	The intensity of hate in text of the original post.

Text Expect	The intensity of expectation in text of the original post.
Text Joy	The intensity of joy in text of the original post.
Text Love	The intensity of love in text of the original post.
Text Anxiety	The intensity of anxiety in text of the original post.
Text Surprise	The intensity of surprise in text of the original post.
Text Neutral	The intensity of neutrality in text of the original post.
Emoji Sorrow	The intensity of sorrow in emojis of the original post.
Emoji Anger	The intensity of anger in emojis of the original post.
Emoji Hate	The intensity of hate in emojis of the original post.
Emoji Expect	The intensity of expect in emojis of the original post.
Emoji Joy	The intensity of joy in emojis of the original post.
Emoji Love	The intensity of love in emojis of the original post.
Emoji Anxiety	The intensity of anxiety in emojis of the original post.
Emoji Surprise	The intensity of surprise in emojis of the original post.
Emoji Neutral	The intensity of neutrality in emojis of the original post.
	Format Characteristics
Image	Indicates if the original post includes an image (binary: 1 = includes image).
Video	Indicates if the original post includes a video (binary: 1 = includes video).
Repost	Indicates if the original post reposted another post (binary: 1 = reposted).
Link	Indicates if the original post includes a link (binary: 1 = includes link).
	Time Characteristics
Weekday	Indicates if the original post was posted on a weekday (binary: 1 = weekday).
Time Difference	The time difference in minutes between the current original post and the previous original post in the community.

2.5 Main Results

Table 12 reports the results of the weighted RDiT model in Equation (4). The coefficients of estimated public negativity indicator, $After_{j(t)}$, are negative and significant for commenting in both the dropout celebrity's community (Coef. = -1.022, $p < 0.01$) and the celebrity group's community (Coef. = -0.486, $p < 0.01$). Specifically, in the celebrity group's community, which experiences a medium level of public negativity, there is a 39% decrease in comments (i.e., exp (-0.486) -1 = -0.385). However, the dropout celebrity's community, facing high public negativity, experiences a 66% greater decrease in comments relative to the celebrity group's community (i.e., (-0.640 - (-0.385))/ -0.385= 0.662). In contrast, the remaining celebrity community, which experienced low public negativity, shows no apparent impact on comments.

The results also indicate public negativity increases likes. Moreover, higher levels of public negativity lead to more likes within the community. In particular, in the dropout celebrity's community, the number of likes increase by 100% (i.e., exp(0.694)-1= 1.002) after the dropout. This increase in likes is 180% higher than that in the celebrity group's community (i.e., (1.002 - 0.358)/0.358= 1.799), and 193% higher than the increase in the remaining group's community (i.e., (1.002 - 0.342)/0.342 = 1.930).

In summary, the results reveal that public negativity leads to a decrease in comments and an increase in likes within online communities, with higher levels of public negativity resulting in more pronounced effects. This suggests that members tend to reserve their engagement when facing public negativity, adopting low involvement behavior and refraining from expressing complex emotions through comments. This change may be motivated by the desire to avoid public judgement. By engaging in low involvement behavior, members might create the illusion to the public that they do not agree with the behavior of celebrities and influencers, even if they continue to support their favorite public figures. As I controlled the emotions in post content, the results are unlikely to be affected by news information.

Table 12. Effect of Public Negativity on Online Community

	Dropout Celebrity's Community (High Public Negativity)		Celebrity Group's Community (Medium Public Negativity		Remaining Celebrity's Community (Low Public Negativity)	
	(1)	(2)	(3)	(4)	(5)	(6)
DV	log_comment	log_like	log_comment	log_like	log_comment	log_like
After	-1.022***	0.694***	-0.486***	0.306***	0.120	0.294***
	(0.294)	(0.176)	(0.138)	(0.054)	(0.122)	(0.085)
Date	-0.005	0.004	-0.009**	-0.005***	-0.002	0.013***
	(0.004)	(0.003)	(0.004)	(0.001)	(0.004)	(0.003)
*Date*After*	0.005	-0.005	0.033***	0.005*	0.002	-0.026***
	(0.007)	(0.004)	(0.007)	(0.003)	(0.006)	(0.004)
Content Characteristics						
Cotent_emoji	-2.845	-0.695	0.278	0.040	1.085***	0.555***
	(1.911)	(1.145)	(0.196)	(0.077)	(0.291)	(0.203)
Cotent_length	0.151***	0.047*	-0.040	0.006	0.061	0.006
	(0.042)	(0.025)	(0.052)	(0.021)	(0.053)	(0.037)
Mentions	-0.503***	-0.770***	-0.840***	-0.124**	0.397***	0.121
	(0.130)	(0.078)	(0.159)	(0.063)	(0.139)	(0.098)
Purchase_Information	-0.270	-1.261***	-0.131	-0.357	0.518***	-0.653***
	(0.364)	(0.218)	(0.670)	(0.264)	(0.142)	(0.100)
Emotion Characteristics						
Text_sorrow	-0.158	-0.237	-0.571	0.046	0.398	0.156
	(0.341)	(0.204)	(0.391)	(0.154)	(0.298)	(0.209)
Text_anger	1.487	0.684	2.381**	0.426	0.235	0.274
	(0.960)	(0.575)	(1.040)	(0.410)	(0.610)	(0.427)
Text_hate	2.857***	1.021*	0.906	0.686*	0.313	-0.083
	(0.979)	(0.586)	(0.900)	(0.355)	(0.512)	(0.358)
Text_expect	0.223**	-0.034	0.117	-0.057	0.066	-0.107
	(0.087)	(0.052)	(0.133)	(0.052)	(0.124)	(0.087)
Text_joy	-1.027***	-0.555***	0.244	0.074	-0.028	-0.113
	(0.124)	(0.074)	(0.155)	(0.061)	(0.135)	(0.095)

Text_love	0.345***	0.304***	0.012	0.343***	0.036	0.379***
	(0.103)	(0.062)	(0.138)	(0.054)	(0.129)	(0.090)
Text_anxiety	1.052***	0.558***	0.963**	-0.069	0.525**	-0.095
	(0.355)	(0.213)	(0.391)	(0.154)	(0.253)	(0.177)
Text_surprise	0.898	0.002	0.608	0.058	0.025	0.107
	(0.929)	(0.557)	(0.628)	(0.248)	(0.438)	(0.307)
Text_neutral	0.070	-0.031	0.115	0.144***	-0.204*	0.139*
	(0.124)	(0.074)	(0.122)	(0.048)	(0.120)	(0.084)
Emoji_sorrow	-	-	0.142	-0.306	-1.797**	-1.013**
			(0.656)	(0.259)	(0.733)	(0.513)
Emoji_anger	-3,391.406**	183.776	0.575	0.773	40.002	-3.470
	(1,625.686)	(973.532)	(1.430)	(0.564)	(25.919)	(18.146)
Emoji_hate	3,264.386*	-713.887	0.613	0.473	-2.065	
	(1,758.077)	(1,052.814)	(1.707)	(0.673)	(3.734)	
Emoji_expect	-130.929	-17.089	-1.000	-0.250	11.523**	4.651
	(400.902)	(240.078)	(1.048)	(0.413)	(5.380)	(3.766)
Emoji_joy	-	-	0.362	0.167	-1.123***	-0.336
			(0.335)	(0.132)	(0.370)	(0.259)
Emoji_love	-	-	0.320	0.123	0.180	-0.484
			(0.353)	(0.139)	(0.485)	(0.340)
Emoji_anxiety	38.585	512.396*	-0.795	0.045	-1.120	-0.341
	(484.192)	(289.956)	(0.561)	(0.221)	(0.731)	(0.512)
Emoji_surprise	-	-	2.250	-3.584	1.083	0.784
			(15.562)	(6.138)	(5.542)	(3.880)
Emoji_neutral	-	-	0.189	0.143**	-0.101	0.176
			(0.181)	(0.071)	(0.264)	(0.185)
Format Characteristics						
Image	0.780***	0.434***	0.197**	0.191***	-0.131**	-0.017
	(0.053)	(0.032)	(0.082)	(0.032)	(0.066)	(0.046)
Vedio	0.537***	0.044	0.523***	0.062	0.073	-0.083
	(0.192)	(0.115)	(0.174)	(0.069)	(0.156)	(0.109)
Repost	0.608***	-0.114**	-0.608***	-0.439***	-0.888***	-0.589***

	(0.076)	(0.046)	(0.097)	(0.038)	(0.098)	(0.069)
Link	-0.137	-0.142***	0.283***	0.005	-0.448***	-0.125*
	(0.084)	(0.050)	(0.084)	(0.033)	(0.105)	(0.074)
			Time Characteristics			
Weekday	-0.247***	-0.169***	0.308***	0.107***	0.177**	0.001
	(0.056)	(0.033)	(0.081)	(0.032)	(0.086)	(0.060)
Time_difference	0.158***	0.063***	0.035*	0.046***	0.053***	0.043***
	(0.014)	(0.008)	(0.021)	(0.008)	(0.017)	(0.012)
Search	0.900***	0.171***	0.882***	0.351***	0.886***	0.507**
	(0.102)	(0.061)	(0.158)	(0.062)	(0.303)	(0.212)
Constant	-5.827***	3.960***	-7.605***	1.699**	-5.492**	0.552
	(1.713)	(1.026)	(1.924)	(0.759)	(2.367)	(1.657)
Time FE	Included	Included	Included	Included	Included	Included
No. of Obs.	2,408	2,408	1,284	1,284	1,060	1,060
R^2	0.457	0.450	0.173	0.460	0.278	0.396
Adj R^2	0.450	0.443	0.150	0.445	0.253	0.375

*** p<0.01, ** p<0.05, * p<0.1. The dropout effect is estimated on a weighted sample. Time fixed effect is controlled in the model. All count variables are log-transformed after adding one before the analysis.

2.6 Mechanism and Additional Analyses

In this section, I conduct several robustness checks and additional analyses to validate the main findings. First, considering that the length of the observation window (i.e., bandwidth) can impact RDiT model results, with a smaller window providing greater precision, I perform a robustness check using ±25 days and ±15 days as the observation window. Second, I use instrumental variable (IV) estimation to eliminate alterative explanations for changes in members' attitudes after the dropout event caused the changes in engagement. Third, I address another alternative explanation related to internal conflict within the community after the dropout event by analyzing emotion changes using the Chinese RoBERTa model. The fourth and fifth extensions examine contingent factors that may moderate the effect of public negativity, namely member types, demographics, and statuses.

2.6.1 Alternative Model Specification

To assess the sensitivity of the results, I first conduct tests using different bandwidths. Some might argue that the choice of bandwidth, which determines the length of observation window before and after the dropout, could impact the regression results (Al Balawi et al. 2023; Lee et al. 2018b). Longer observation windows provide more data for estimation but might result in less precision compared to shorter windows. This concern is particularly relevant for the RDiT model, as it relies on discontinuity within a short time frame (Hausman and Rapson 2018; Lee and Lemieux 2010).

In addition to the initial choice of ±35 days, I also experiment with ±25 days and ±15 days as observation windows. Then, I rerun Equation 4 using these different observation windows and the results are presented in Table 13 and Table 14. Notably, the coefficients of $After_{j(t)}$ remain significant and consistent with those in the main analysis, indicating the findings are robust across various bandwidth choices. Moreover, the effect sizes of $After_{j(t)}$ are larger than those in my main analysis, suggesting the main estimations are conservative. The insignificant coefficients observed in Table 14 for the remaining celebrity's community are likely due to small sample size (N = 328).

Table 13. Robustness Check of RDiT Estimates: Bandwith [-25, 25]

	Dropout Celebrity's Community		Celebrity Group's Community		Remaining Celebrity's Community	
	(1)	(2)	(3)	(4)	(5)	(6)
DV	log_comment	log_like	log_comment	log_like	log_comment	log_like
After	-1.348***	0.720***	-0.426**	0.644***	0.244	0.504***
	(0.381)	(0.236)	(0.194)	(0.072)	(0.162)	(0.107)
Controls	Included	Included	Included	Included	Included	Included
Member FE	Included	Included	Included	Included	Included	Included
No. of Obs.	1,719	1,719	895	895	670	670
R^2	0.448	0.414	0.210	0.527	0.289	0.354
Adj R^2	0.439	0.404	0.178	0.508	0.250	0.318

*** p<0.01, ** p<0.05, * p<0.1. The dropout effect is estimated on a weighted sample. Constant and control variables align with the main model, but coefficients are omitted for display simplicity. Time fixed effects are controlled in the model.

Table 14. Robustness Check of RDiT Estimates: Bandwith [-15, 15]

	Dropout Celebrity's Community		Celebrity Group's Community		Remaining Celebrity's Community	
	(1)	(2)	(1)	(2)	(1)	(2)
DV	log_comment	log_like	log_comment	log_like	log_comment	log_like
After	-2.152***	0.818*	-1.113***	0.881***	0.171	0.325
	(0.684)	(0.448)	(0.332)	(0.114)	(0.313)	(0.233)
Controls	Included	Included	Included	Included	Included	Included
Member FE	Included	Included	Included	Included	Included	Included
No. of Obs.	1,134	1,134	672	672	328	328
R^2	0.464	0.407	0.221	0.579	0.354	0.324
Adj R^2	0.451	0.393	0.178	0.556	0.276	0.243

*** p<0.01, ** p<0.05, * p<0.1. The dropout effect is estimated on a weighted sample. Constant and control variables align with the main model, but coefficients are omitted for display simplicity. Time fixed effects are controlled in the model.

2.6.2 Is the Effect of Public Negativity Confounded with Changes in Members' Attitudes

Although online fan community members often support their favorite celebrities and groups, there is a concern that the dropout event may have altered members' attitude toward these public figures, leading to changes in their engagement within the online community. Confirmative disconfirmation theory suggests that consumer satisfaction is largely affected by the difference between their experiences and expectations (Oliver 1977; Oliver 1980). In the context of online ratings, Ho et al. (2017) found that consumers are more likely to rate when they experience a larger disconfirmation. Similarly, in the context of online fan communities, members may perceive their favored celebrity and group's behavior differently from their previous expectations, which can subsequently impact their engagement. In essence, the influence of members' changing expectations may be intertwined with the effect of public negativity.

To address this concern, I use an IV estimation. Specifically, I introduce two instrumental variables for $After_{j(t)}$ – daily stock price and stock volume of the associated entertainment company. When the market is closed, I use the stock price and volume from the previous trading day. Stock market data, influenced by the general public's investment decisions, is likely to correlate with public negativity, thus satisfying the relevance condition. Furthermore, stock market information is hypothesized to be uncorrelated with member behavior in online fan communities. This is because those members, often critical of how entertainment companies treat celebrities,[7] prefer to support celebrities directly through purchasing albums, concert tickets, and merchandise rather than by investing in stocks (Dianrama et al. 2022). While such expenditures might impact the stock price and volume in the long run, they are unlikely to cause immediate changes in the stock market. This temporal separation helps meet

[7] https://www.quora.com/Why-do-K-pop-fans-hate-the-entertainment-company-where-their-idols-belong

the exclusion criterion, suggesting that the stock market information does not directly affect the engagement in online communities or change in members' attitudes.

Table 15 displays the IV estimators using two stages least squares (2SLS) regressions. The under-identification tests (Kleibergen-Paap LM statistic) and the weak-instrument tests (Cragg-Donald Wald) suggest that the models are well identified. Sargent tests except column (6) are greater than 0.03, confirming the validity of instrumental variables. Coefficients for $After_{j(t)}$ align with the main analysis, supporting that the decreases in comments and increases in likes result from public negativity, rather than changes in members' attitudes.

Table 15. Robustness Check: Changes in Members' Attitudes

	Dropout Celebrity's Community		Celebrity Group's Community		Remaining Celebrity's Community	
	(1)	(2)	(3)	(4)	(5)	(6)
DV	Log(Comment)	Log(Like)	Log(Comment)	Log(Like)	Log(Comment)	Log(Like)
After	-1.124***	0.833***	-0.374**	0.253***	0.082	0.303***
	(0.358)	(0.214)	(0.155)	(0.061)	(0.135)	(0.095)
Controls	Included	Included	Included	Included	Included	Included
Member FE	Included	Included	Included	Included	Included	Included
No. of Obs.	2,408	2,408	1,284	1,284	1,060	1,060
R^2	0.457	0.450	0.173	0.460	0.278	0.396
Adj R^2	0.450	0.443	0.149	0.444	0.253	0.375
Kleiberg-Paap Test	Chi-sq(3)=1548.87 P-va<0.001		Chi-sq(3)=991.36 P-val<0.001		Chi-sq(3)=829.71 P-val<0.001	
Cragg-Donald Test	1070.43		1055.26		920.54	
Sargan Test	0.325	0.038	0.3176	0.1762	0.137	0.002

*** p<0.01, ** p<0.05, * p<0.1. The dropout effect is estimated on a weighted sample. Constant and control variables align with the main model, but coefficients are omitted for display simplicity. Time fixed effects are controlled in the model.

2.6.3 Is the Effect of Public Negativity Confounded with Internal Conflict?

In this section, I explore an alternative explanation by examining whether internal conflict experienced among community members influences engagement within online fan communities. Despite their shared interests and beliefs, disagreements can emerge among community members due to internal conflict rather than external negativity. This implies that the observed reserved engagement stems from community disagreement, which manifests as an increase in members expressing negative emotions following the dropout. Previous literature has indicated that conflicts within a community can lead to negative emotions toward the community and result in reduced engagement (Brewer et al. 2021; Kumar et al. 2023; Wiertz et al. 2010).

To investigate the presence of internal conflicts, I conduct a comment-level analysis by assessing emotions in text and emojis. Specifically, I utilize the Chinese RoBERTa model, fine-tuned in the main analysis, to label text and emoji into 6 categories: sorrow, anger, hate, expect, joy, love. Previous literature suggested that sorrow, angry, and hate signify negative emotions, while expect, joy, love represent positive emotions (Cui et al. 2021; Li and Fei 2021; Quan and Ren 2010). Each emotion is quantified on a scale from 0 to 1, with a higher value indicating a stronger intensity of that emotion. I retain comments only from those members who had commented at least twice in each community.

I identify 64,379 comments written by 9,360 members under 2,296 original posts in the dropout celebrity’s community, 37,309 comments written by 7,783 members under 1,248 original posts in the celebrity group’s community, and 5,726 comments written by 1,269 members under 901 original posts in the remaining group’s community. I compare the change of emotions in members’ text and emojis before and after the dropout. If there is evidence of increased negative emotions after the dropout, then it suggests the main results are confounded with the internal conflict. However, if there are no dramatic changes in emotions after the dropout, it is likely that the changes are caused by public negativity.

I estimate the following RDiT model to investigate whether members' expression of emotions becomes more negative after the dropout:

$$E_{i,j(t)} = \alpha + \beta After_{i,j(t)} + f\big(\, Date_{i,j(t)}\big) + \boldsymbol{\delta OriPost_{j(t)}} + \boldsymbol{\rho Comment_{i}} + \varepsilon_{j(t)}. \quad (5)$$

In this equation $E_{i,j(t)}$ represents the emotions in text and emoji, i.e., sorrow, anger, hate, expect, joy, love in comment i under original post j. I also include log-transformed length of comment and whether comment includes emojis as two additional dependent variables. Similar to main analysis, $After_{j(t)}$ is a binary variable equal to 1 after the dropout occurs and 0 otherwise. $f\big(\, Date_{i,j(t)}\big)$ is a flexible function which is specified as $\gamma_1\ Date_{j(t)} + \gamma_2 Date_{j(t)} \cdot After_{j(t)}$ (Anderson 2014; Imbens and Lemieux 2008). $OriPost_{j(t)}$ represents characteristics of original post, including content characteristics, emotion characteristics, and format characteristics, as controlled in the main analysis. $Comment_i$ represents comment characteristics, including time characteristics (i.e., whether the comment was posted on a weekday, afternoon, evening, or night, and time difference between original post and the comment day), member characteristics (i.e., time difference between the current comment and previous comment by the same member, the days since member’s Weibo account was created), and the search index on Baidu during the comment day. Member fixed effects are taken into account. I add one to the count variables and log-transform them before analysis.

The estimation results of dropout celebrity’s community are reported in Table 16 and Table 17. Interestingly, there is no noticeable increase in negative emotions conveyed in members’ text or their use of emojis. On the contrary, the results reveal a 43% decrease (i.e., Coef. = -0.434) in the use of sorrow-related emojis after the dropout, suggesting a more supportive atmosphere within the dropout celebrity’s community after the dropout. This indicates that internal conflicts within the dropout celebrity’s community are not evident, and the effects observed in the main analysis are likely driven by the high level of public negativity experienced by the community.

Furthermore, the results suggest that after the dropout, there is a 13% increase (i.e., Coef. = 0.130) in the probability of member using emojis in the dropout celebrity's community, while member text length decreases by 37% (i.e., exp (-0.461)-1 = -0.369). This implies that members have adopted reserved engagement, becoming less likely to express complex emotions through text and rather more inclined to convey simple emotions through emojis after the dropout.

Table 16. Emotions in Text from Dropout Celebrity's Community

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DV	Log(orilen)	sorrow	anger	hate	expect	joy	love
After	-0.461***	0.002	-0.022*	0.001	-0.005	-0.008	-0.035
	(0.068)	(0.012)	(0.012)	(0.009)	(0.025)	(0.017)	(0.026)
Controls	Included	Included	Included	Included	Included	Included	Included
Member FE	Included	Included	Included	Included	Included	Included	Included
No. of Obs.	56,604	40,109	40,109	40,109	40,109	40,109	40,109
R^2	0.618	0.401	0.490	0.450	0.405	0.346	0.483
Adj R^2	0.531	0.218	0.334	0.282	0.223	0.146	0.325

*** p<0.01, ** p<0.05, * p<0.1. The dropout effect is estimated on a weighted sample. Constant, original post characteristics, and comment characteristics are included in the model, but coefficients are omitted for display simplicity. Member fixed effects are controlled in the model.

Table 17. Emotions in Emojis from Dropout Celebrity's Community

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DV	I(emoji)	sorrow	anger	hate	expect	joy	love
After	0.130***	-0.434***	-0.043	-0.017	-0.004	-0.050	0.052
	(0.027)	(0.145)	(0.067)	(0.047)	(0.075)	(0.206)	(0.205)
Controls	Included	Included	Included	Included	Included	Included	Included
Member FE	Included	Included	Included	Included	Included	Included	Included
No. of Obs.	56,604	1,391	1,391	1,391	1,391	1,391	1,391
R^2	0.472	0.862	0.746	0.828	0.822	0.776	0.806
Adj R^2	0.352	0.573	0.216	0.469	0.449	0.308	0.402

*** p<0.01, ** p<0.05, * p<0.1. The dropout effect is estimated on a weighted sample. Constant, original post characteristics, and comment characteristics are included in the model, but coefficients are omitted for display simplicity. Member fixed effects are controlled in the model.

Next, I delve into the remaining celebrity's community, where members are exposed to a low level of public negativity. The results are presented in Table 18 and Table 19. Similarly, there is no noticeable increase in expression of negative emotions in members' text and emojis. The findings also do not show a significant change in members' texting habits or emojis usage. Moreover, the results suggest a 6% increase (i.e., Coef. = 0.062) in the use of expect-related words, indicating a rise in positivity among community members following the dropout event. This suggests that internal conflicts within the remaining celebrity community are not evident, and the effects observed in the main analysis are likely attributable to the public negativity experienced by the community.

Table 18. Emotions in Text from Remaining Celebrity's Community

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DV	Log(orilen)	sorrow	anger	hate	expect	joy	love
After	0.123*	0.003	0.016*	0.012	0.062**	-0.035	0.008
	(0.067)	(0.011)	(0.009)	(0.007)	(0.024)	(0.023)	(0.027)
Controls	Included	Included	Included	Included	Included	Included	Included
Member FE	Included	Included	Included	Included	Included	Included	Included
No. of Obs.	5,124	4,359	4,359	4,359	4,359	4,359	4,359
R^2	0.634	0.407	0.367	0.355	0.386	0.391	0.499
Adj R^2	0.462	0.098	0.038	0.019	0.067	0.075	0.238

*** p<0.01, ** p<0.05, * p<0.1. The dropout effect is estimated on a weighted sample. Constant, original post characteristics, and comment characteristics are included in the model, but coefficients are omitted for display simplicity. Member fixed effects are controlled in the model.

Table 19. Emotions in Emojis from Remaining Celebrity's Community

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DV	I(emoji)	sorrow	anger	hate	expect	joy	love
After	-0.020	-0.129	-0.073	0.00001	0.042	0.435	-0.256
	(0.035)	(0.170)	(0.064)	(0.027)	(0.066)	(0.263)	(0.243)
Controls	Included	Included	Included	Included	Included	Included	Included
Member FE	Included	Included	Included	Included	Included	Included	Included
No. of Obs.	5,124	309	309	309	309	309	309
R^2	0.499	0.862	0.763	0.797	0.784	0.830	0.818
Adj R^2	0.265	0.292	-0.219	-0.044	-0.108	0.125	0.067

*** p<0.01, ** p<0.05, * p<0.1. The dropout effect is estimated on a weighted sample. Constant, original post characteristics, and comment characteristics are included in the model, but coefficients are omitted for display simplicity. Member fixed effects are controlled in the model.

Then, I study the celebrity group's community, which experienced a moderate level of public negativity. The results are shown in Table 20 and Table 21. Surprisingly, the findings suggest a slight increase in negative expressions in text following the dropout event, albeit with relatively small effect size. Specifically, the findings reveal a 2% increase in sorrow-related words (i.e., Coef. = 0.023), a 1% increase in anger-related words (i.e., Coef. = 0.012), and a 1% increase in hate-related words within the celebrity group's community (i.e., Coef. = 0.014). Furthermore, members in this community tend to write 6% longer (i.e., exp (0.061)-1= 0.062) after the dropout occurs. However, members' emotion expression through emojis remains unchanged. In summary, these results imply the presence of internal conflicts within the celebrity group's community, with the effects observed in the main analysis likely influenced by both public negativity and internal conflicts, although internal conflicts are unlikely to be the dominant driver.

The results also show that communities exposed to moderate public negativity are more prone to internal conflicts. This aligns with finding of Chen and Berger (2013), who suggested that topics with a moderate level of controversy are more likely to be discussed by people. This finding sheds light on the entertainment companies' strategies. When facing public negativity, companies have the potential to foster unity within online fan communities by either amplifying or minimizing its negative influence.

Table 20. Emotions in Text from Celebrity Group's Community

DV	(1) Log(orilen)	(2) sorrow	(3) anger	(4) hate	(5) expect	(6) joy	(7) love
After	0.061**	0.023***	0.012***	0.014***	0.008	-0.011	-0.001
	(0.027)	(0.006)	(0.004)	(0.004)	(0.009)	(0.009)	(0.011)
Controls	Included	Included	Included	Included	Included	Included	Included
Member FE	Included	Included	Included	Included	Included	Included	Included

No. of Obs.	35,050	26,229	26,229	26,229	26,229	26,229	26,229
R^2	0.635	0.420	0.403	0.392	0.442	0.414	0.463
Adj R^2	0.473	0.100	0.074	0.057	0.134	0.090	0.167

*** p<0.01, ** p<0.05, * p<0.1. The dropout effect is estimated on a weighted sample. Constant, original post characteristics, and comment characteristics are included in the model, but the coefficients are not reported for the sake of simplicity in display. Member fixed effect is controlled in the model.

Table 21. Emotions in Emojis from Celebrity Group's Community

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DV	I(emoji)	sorrow	anger	hate	expect	joy	love
After	-0.013	0.027	-0.032	-0.002	-0.083	-0.090	-0.191*
	(0.013)	(0.092)	(0.021)	(0.025)	(0.055)	(0.139)	(0.107)
Controls	Included	Included	Included	Included	Included	Included	Included
Member FE	Included	Included	Included	Included	Included	Included	Included
No. of Obs.	35,050	1,032	1,032	1,032	1,032	1,032	1,032
R^2	0.502	0.864	0.940	0.858	0.797	0.830	0.875
Adj R^2	0.280	0.270	0.679	0.239	-0.093	0.088	0.327

*** p<0.01, ** p<0.05, * p<0.1. The dropout effect is estimated on a weighted sample. Constant, original post characteristics, and comment characteristics are included in the model, but the coefficients are not reported for the sake of simplicity in display. Member fixed effect is controlled in the model.

2.6.4 Does the Effect of Public Negativity Vary Across Member Types?

To delve deeper into the main analysis and explore whether and how the public negativity effect varies across member types, I conduct sub-group analyses. Based on the comments starting from the first original post in the community to the date just before the dropout event, I categorize members into two types: those who favor the dropout celebrity more and those who favor the dropout celebrity less. In the dropout celebrity's community, members who exclusively participated in the dropout celebrity's community are considered to favor the dropout celebrity more (i.e., area 1 in Figure 3), whereas those who participated in not only dropout community but also in other fan communities are considered to favor the dropout celebrity less (i.e., area 2, 3, and 5 in Figure 3). Conversely, in the celebrity group's community and the remaining group's community, members who participated not only in their focal community but also in the dropout celebrity's community are considered to favor the dropout celebrity more (i.e., area 2, 3, and 5 in Figure 3), while those who did not participate in the dropout celebrity's community are considered to favor the dropout celebrity less (i.e. 4, 6, and 7 in Figure 3),

For each member type, I aggregate the comments and likes from member comments under each original post and examine the effects of public negativity, respectively. Additionally, I calculate likes on the celebrity's (group's) information posted in the original post (i.e., *info like*) by measuring the difference between total likes and the number of likes from member comments I have collected. Despite potential limitations due to crawling, I believe that changes in measurement can still reflect the variations in members' favoritism toward the celebrity before and after the dropout. The subgroup analyses consist of 100,828 comments from 4,379 original posts. I rerun the model in Equation 4 using the subsample for each member type.

The results from the dropout celebrity's community are reported in Table 22. It suggests that the reduction in comments is more likely to occur among members who favor the dropout celebrity less. These members might be more inclined to withhold comments due to the fear of negative consequences for other celebrities they support within the celebrity group. In contrast, the decline in comments is smaller for the members who favor the dropout celebrity more. One possible reason is that these members have the fear that the dropout celebrity's community might be dominated by voices that are seemly unsupportive of the dropout decision, thus they attempt to keep commenting after the dropout occurs. The impact of public negativity on likes is nuanced. The results suggest a decrease in the number of likes under comments, whereas an increase in likes gathered under original posts that summarize the dropout celebrity's activities or schedules. While there is an increase in the number of likes in the main analysis, the findings indicate that the increase is primarily toward support for the dropout celebrity, rather than fostering interpersonal support among members themselves. This might be because they were facing a high level of public negativity, forcing them to reduce interpersonal support to avoid public judgment, especially as the dropout celebrity is responsible for the event.

Table 23 shows the results of the celebrity group's community. The results indicate that the reduction in commenting is also more pronounced among members who favor the dropout celebrity less, likely due to their fear of negative consequences from dropout affecting the group. As for the increases in likes, it reveals a pattern distinct from Table 22, suggesting an increase in interpersonal support among members and an increase in informational support toward the celebrity's activities and schedules. This increases in interpersonal support might be related to members' willingness to express their interpersonal support for opinions with a moderate level of controversy (Chen and Berger 2013; Zhang and Tang 2016).

Table 24 represents a subgroup analysis of the remaining celebrity's community. It does not show a decrease in commenting behaviors. However, it reveals an increase in likes, primarily aimed at supporting the remaining celebrity, while interpersonal support among members remains unaffected. One potential explanation is that the public views the remaining celebrity more favorably than the dropout celebrity, resulting in an increased support for the remaining celebrity's activities under low public negativity.

In summary, the influence of public negativity on comments is more pronounced among members who favor the dropout celebrity less. The effect of public negativity on likes is more nuanced. While there is an overall increase in the number of likes in the main analysis, this section suggests that the increases stem from different sources. In the dropout community, where facing high public negativity, members enhance their support for the celebrity's activities at the expense of reduced interpersonal support. In the celebrity group's community, where facing moderate public negativity, the increase in likes comes from both interpersonal and informational support. Meanwhile, in the remaining celebrity's community, where facing a low level of public negativity, members' interpersonal support remains unchanged, accompanied by an additional increase in informational support toward the remaining celebrity's activities and schedules.

Table 22. Subgroup Analyses – Dropout Celebrity's Community

MEMBERS	Favor Dropout Celebrity More		Favor Dropout Celebrity Less		Likes on OP
	(1)	(2)	(3)	(4)	(5)
DV	log_comment	log_like	log_comment	log_like	log_info_like
After	-0.519**	-1.167***	-0.913***	-1.442***	0.786***
	(0.241)	(0.244)	(0.225)	(0.223)	(0.171)
Controls	Included	Included	Included	Included	Included
Time FE	Included	Included	Included	Included	Included
No. of Obs.	2,153	2,153	2,155	2,155	2,267
R^2	0.375	0.283	0.381	0.297	0.461
Adj R^2	0.366	0.272	0.372	0.287	0.454

*** p<0.01, ** p<0.05, * p<0.1. The dropout effect is estimated on a weighted sample. Constant and control variables align with the main model, but coefficients are omitted for display simplicity. Time fixed effects are controlled in the model.

Table 23. Subgroup Analyses – Celebrity Group's Community

MEMBERS	Favor Dropout Celebrity More		Favor Dropout Celebrity Less		Likes on OP
	(1)	(2)	(3)	(4)	(5)
DV	log_comment	log_like	log_comment	log_like	log_info_like
After	-0.093	0.297***	-0.359***	0.388***	0.260***
	(0.107)	(0.088)	(0.112)	(0.113)	(0.056)
Controls	Included	Included	Included	Included	Included
Time FE	Included	Included	Included	Included	Included
No. of Obs.	1,076	1,076	1,238	1,238	1,242
R^2	0.248	0.121	0.236	0.185	0.448
Adj R^2	0.223	0.0919	0.214	0.161	0.432

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. The dropout effect is estimated on a weighted sample. Constant and control variables align with the main model, but coefficients are omitted for display simplicity. Time fixed effects are controlled in the model.

Table 24. Subgroup Analyses – Remaining Celebrity's Community

MEMBERS	Favor Dropout Celebrity More		Favor Dropout Celebrity Less		Likes on OP
	(1)	(2)	(3)	(4)	(5)
DV	log_comment	log_like	log_comment	log_like	log_info_like
After	0.028	0.051	-0.080	-0.004	0.328***
	(0.093)	(0.044)	(0.103)	(0.049)	(0.096)
Controls	Included	Included	Included	Included	Included
Time FE	Included	Included	Included	Included	Included
No. of Obs.	533	533	801	801	870
R^2	0.267	0.203	0.301	0.203	0.384
Adj R^2	0.215	0.147	0.269	0.167	0.358

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. The dropout effect is estimated on a weighted sample. Constant and control variables align with the main model, but coefficients are omitted for display simplicity. Time fixed effects are controlled in the model.

2.6.5 Does the Effect of Public Negativity Vary Across Demographics and Statuses?

In this section, I investigate whether the effect of public negativity varies across socio-demographic factors. Prior literature has indicated that users' engagement levels may diverge depending on their demographic and status characteristics (Atasoy et al. 2021; Bardina et al. 2020). To explore this, I employ an RDiT model using comment-level data to assess the moderating effects of socio-demographic factors ($ScioDemo_i$):

$$D_{i,j(t)} = \alpha + \beta After_{i,j(t)} + \gamma After_{i,j(t)} \times \boldsymbol{ScioDemo_i} + f\big(\,Date_{i,j(t)}\big) + \boldsymbol{\delta OriPost_{j(t)}} + \boldsymbol{\rho Comment_i} + \varepsilon_{j(t)}. \tag{6}$$

I use the variable $D_{i,j(t)}$ to represent the time difference in minutes between the current comment and the previous comment by the same member within the community (*PostDiff*). The larger the difference, the slower comment frequency, indicating reserved engagement in comments. I consider the time difference between adjacent comments instead of number of comments for the following reasons. Firstly, aggregating comments under an original post by members is challenging, as it is not common for one member to repeatedly participate under one original post. Secondly, if comments are aggregated by members across different original posts, it is difficult to control the characteristics of different original posts. I don't consider liking behavior, as individual information of those who like a comment is untraceable.

I take into account two demographic characteristics of the members including gender (*Female*) and age (*Age*). To address potential issues with age data such as non-authentic entries (e.g., birth year was 1900), I apply a winsorization technique to the age variable at 10% and 95% percentiles. Regarding status characteristics, I examine whether a member is a verified online user (*Verified*), the duration since the Weibo account was created (*AccountDay*), as well as total number of posts (*Posts*), followers (*Followers*), and friends (*Friends*) as of the data collection date (April 21st, 2023). The controls and data sample remain consistent with those in Section 2.6.3.

The results of examining the moderating effects of socio-demographic characteristics within the dropout celebrity's community, celebrity group's community, and remaining celebrity's community are presented in Table 25, 26, and 27, respectively. The coefficients of interest $After_{j(t)}$, remain positive and significant in the dropout celebrity's community and remaining group's community, indicating reserved engagement as frequency of comments decreases. Moreover, the higher the public negativity, the stronger the effect, which is consistent with the findings in the main analysis. Similarly, I do not observe an effect of public negativity on comments in the remaining celebrity's community, which is experiencing low public negativity.

Across all communities, the moderating effects of demographic and status factors are found to be statistically insignificant. This suggests that members within the same community have homogenous responses to public negativity. In other words, regardless of variations in factors such as gender, age, and online social status among members, their reactions to public negativity are primarily influenced by their member types within the online community.

Table 25. Effect of Public Negativity Across Member's Demographics and Statuses – Dropout Celebrity's Community

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DV	Log(PostDiff)	Log(PostDiff)	Log(PostDiff)	Log(PostDiff)	Log(PostDiff)	Log(PostDiff)	Log(PostDiff)
After	2.245***	2.090***	2.062***	2.088***	2.180***	2.028***	2.297***
	(0.295)	(0.401)	(0.219)	(0.403)	(0.278)	(0.300)	(0.341)
*After*Female*	-0.206						
	(0.213)						
*After*Age*		-0.028					
		(0.204)					
*After*Verified*			-0.223				
			(0.245)				
*After*AccountDay*				-0.006			
				(0.056)			
*After*Posts*					-0.017		
					(0.022)		
*After*Followers*						0.004	
						(0.036)	
*After*Friends*							-0.045
							(0.048)
Controls	Included	Included	Included	Included	Included	Included	Included
Member FE	Included	Included	Included	Included	Included	Included	Included
No. of Obs.	56,604	33,031	56,604	56,604	56,604	56,604	56,604
R^2	0.522	0.529	0.522	0.522	0.522	0.522	0.522
Adj R^2	0.413	0.420	0.413	0.413	0.413	0.413	0.413

*** p<0.01, ** p<0.05, * p<0.1. The dropout effect is estimated on a weighted sample. Constant, original post characteristics, and comment characteristics are included in the model, but the coefficients are not reported for the sake of simplicity in display. Member fixed effect is controlled in the model. The dependent variable is the log-transformed time difference in minutes between the current comment and previous comment posted by the same member.

Table 26. Effect of Public Negativity Across Member's Demographics and Statuses – Celebrity Group's Community

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DV	Log(PostDiff)	Log(PostDiff)	Log(PostDiff)	Log(PostDiff)	Log(PostDiff)	Log(PostDiff)	Log(PostDiff)
After	0.237	0.656*	0.329***	0.857**	0.555***	0.551**	0.628**
	(0.221)	(0.348)	(0.104)	(0.382)	(0.185)	(0.233)	(0.290)
*After*Female*	0.088						
	(0.209)						
*After*Age*		-0.012					
		(0.017)					
*After*Verified*			-0.181				
			(0.210)				
*After*AccountDay*				-0.087			
				(0.060)			
*After*TotalPosts*					-0.033		
					(0.022)		
*After*Followers*						-0.042	
						(0.038)	
*After*Friends*							-0.057
							(0.050)
Controls	Included	Included	Included	Included	Included	Included	Included
Member FE	Included	Included	Included	Included	Included	Included	Included
No. of Obs.	35,050	21,403	35,050	35,050	35,050	35,050	35,050
R^2	0.560	0.564	0.560	0.560	0.560	0.560	0.560
Adj R^2	0.364	0.368	0.364	0.364	0.364	0.364	0.364

*** p<0.01, ** p<0.05, * p<0.1. The dropout effect is estimated on a weighted sample Constant, original post characteristics, and comment characteristics are included in the model, but the coefficients are not reported for the sake of simplicity in display. Member fixed effect is controlled in the modell. The dependent variable is the log-transformed time difference in minutes between the current comment and previous comment posted by the same member.

Table 27. Effect of Public Negativity Across Member's Demographics and Statuses – Remaining Celebrity's Community

DV	(1) Log(PostDiff)	(2) Log(PostDiff)	(3) Log(PostDiff)	(4) Log(PostDiff)	(5) Log(PostDiff)	(6) Log(PostDiff)	(7) Log(PostDiff)
After	-0.890	0.947	-0.232	0.800	-0.036	-0.630	-0.378
	(0.566)	(1.083)	(0.268)	(1.015)	(0.515)	(0.590)	(0.702)
*After*Female*	0.683						
	(0.524)						
*After*Age*		-0.072					
		(0.055)					
*After*Verified*			-0.170				
			(0.573)				
*After*AccountDay*				-0.172			
				(0.163)			
*After*TotalPosts*					-0.030		
					(0.064)		
*After*Followers*						0.068	
						(0.092)	
*After*Friends*							0.026
							(0.123)
Controls	Included	Included	Included	Included	Included	Included	Included
Member FE	Included	Included	Included	Included	Included	Included	Included
No. of Obs.	5,124	2,933	5,124	5,124	5,124	5,124	5,124
R^2	0.562	0.535	0.562	0.562	0.562	0.562	0.562
Adj R^2	0.356	0.295	0.356	0.356	0.356	0.356	0.356

*** p<0.01, ** p<0.05, * p<0.1. The dropout effect is estimated on a weighted sample. Constant, original post characteristics, and comment characteristics are included in the model, but the coefficients are not reported for the sake of simplicity in display. Member fixed effect is controlled in the model. The dependent variable is the log-transformed time difference in minutes between the current comment and previous comment posted by the same member.

2.7 Discussion

2.7.1 Summary of Results

Figure 4 summarizes the findings of the analyses. In this chapter, I examine public negativity on engagement within online communities, using data from a popular social media platform in China. To do this, I leverage an event where a celebrity dropped out from a celebrity group, allowing me to design a natural experiment using the RDiT model. The findings reveal that public negativity decreases comments and increases likes within the online fan community. It suggests a reserved engagement when facing public negativity, as members engaged in lower involvement behaviors and express themselves through a less complex format.

I examine alternative explanations that could impact engagement after the dropout event. Findings from the IV analysis, which is designed to separate public negativity from changes in members' attitudes, align consistently with the main analysis. Additionally, an analysis utilizing the RoBERTa model supports that public negativity is the primary driver of the reserved engagement, albeit with a subtle impact on the celebrity group's community resulting from internal conflicts.

I investigate heterogeneity based on members' characteristics. I find that the effect of public negativity on comments is more pronounced among members who favor the dropout celebrity less. However, the effect of public negativity on likes shows less variability across different member types but varies more among the sources of likes across communities. I also explore heterogeneous effects by members' demographic and status characteristics. Surprisingly, I find that the effect does not vary across demographics and statuses. These results suggest that member responses are homogenous across characteristics outside online fan communities, such as demographics and status on social media; however, heterogenous across member types within online fan communities.

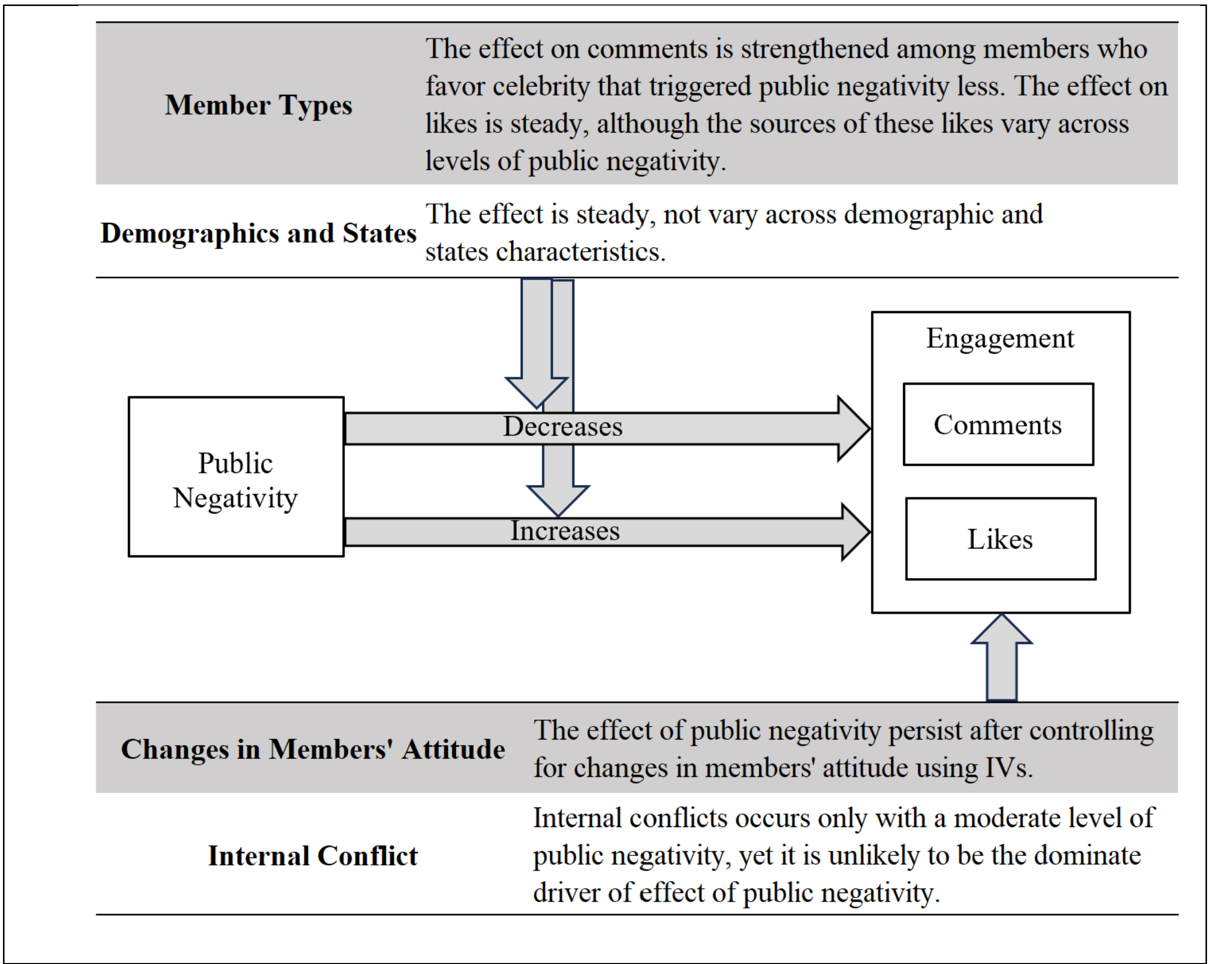


Figure 4. Summary of Chapter 2's Findings

2.7.2 Theoretical Contribution

The results offer several theoretical contributions. Firstly, this study differs from and contributes to previous research on online communities. Unlike previous studies that primarily delved into how internal factors affect engagement (Dewan et al. 2017; Tsai and Bagozzi 2014; Wang et al. 2018a), this research investigates the impact of an external factor on engagement in online fan communities. Given the public nature of online communities, members' engagement might be influenced by users outside the community. The mechanisms driving these engagement change and their effects may differ substantially.

Secondly, this study contributes to celebrity and influencer literature by quantifying negative impact of public negativity on online fan communities. Unlike previous studies that focused on the effect of negative news on celebrities and influencers (Chung et al. 2013; Hock and Raithel 2020), I argue that public judgement could also affect engagement in an online community. Although observing and measuring public negativity is typically challenging, I quantify its effects through a natural experiment design and RDiT model. The quantification method can be easily adopted by other researchers studying celebrities and influencers.

Furthermore, this study adds to celebrity and influencer literature by exploring the heterogenous effect of public negativity. Previous work on how customers respond to negative news often assumed a homogenous response (Halonen - Knight and Hurmerinta 2010; Till and Shimp 1998). This study moves forward by investigating whether and how members' responses to public negativity vary across different member characteristics.

2.7.3 Practical Implication

The results carry significant implications to celebrities, influencers, entertainment companies, and platform designers.

Firstly, celebrities and influencers can utilize these results to connect with their online fans. For instance, when a celebrity or influencer is viewed negatively by the public, and they have substantial members in the online fan community, they can strategically address the situation to either enhance or de-escalate it, thereby preserving unity within their online fan community and gaining support from them. Furthermore, it is worth noting that public negativity does not necessarily lead to a reduction in revenue for celebrities and influencers, even if they are held responsible for the negative public impression.

Secondly, for entertainment companies, especially those employing group strategies, this study quantifies the potential negative impact of grouping celebrities (influencers) together. The results suggest that the effect of public negativity on engagement within online fan communities is primarily influenced by their member types, regardless of their gender, age, popularity, or online experience. Therefore, it is crucial for entertainment companies to foster a sense of belonging within the online fan community. Furthermore, since the results demonstrate that members' behavior can be affected by the general public, creating a private online fan community becomes essential, especially if celebrities are frequently involved in negative events.

Thirdly, this study offers valuable insights to platform designers who prioritize sustained online engagement. These findings can help improve platform design, particularly for those heavily reliant on celebrities' and influencers' influence. For instance, implementing features like filter bubbles to reduce the exposure of one community's members to posts from other online users may mitigate the reserved engagement result caused by the public negativity effect. Alternatively, introducing functions that support private group discussions could enhance platforms, potentially increasing revenues and engagement levels.

2.7.4 Limitations and Future Research

This chapter acknowledges certain caveats and limitations of this study. These challenges also open up promising avenues for future research. First, while I observe the effect of public negativity on online fan communities, it is unclear whether and how this effect influences other online communities, such as customer support communities and brand communities. Future research can make valuable contributions by generalizing the impact of public negativity to other online communities.

Second, while this study provides valuable insights based on a significant event, it is worth noting that the dataset used in this study is relatively dated. Additionally, the study predominantly concentrates on online communities in Chinese social media platforms. Future research could enhance the current understanding by corroborating these findings with more recent data sourced from international social media platforms.

Third, although I have observed changes in members' engagement within the community due to public negativity, it remains uncertain whether their behaviour outside the community, while still on the platform, is affected. Unfortunately, due to data limitations, I cannot provide a comprehensive understanding of how public negativity impacts the overall engagement on the platform. However, this presents an opportunity for future research in this area.

Chapter 3

Examining Relationship Between Previews and Ratings: Evidence from Digital Serial Publication

3.1 Introduction

With the rise of the digital market, various forms of media, including music, movies, news, manga, and even education, have transitioned from physical to digital formats. This shift has granted consumers the convenience of shopping from the comfort of their own homes, in contrast to the traditional market. However, this digital landscape also presents consumers with increased uncertainty in evaluating digital products, especially those they have not previously encountered before (Chen et al. 2021; Wang and Zhang 2009). To reduce uncertainty, digital products must provide information to potential consumers before they make a purchase. *Ratings* serve as indirect indicators of product quality, providing insights based on the experiences of others. Conversely, *previews* offer direct product experiences, allowing potential consumers to evaluate how well a product aligns with their own preferences. Both ratings and previews are prevalent in the digital market.

Digital serial publications represent a burgeoning business in digital content marketing. Although serial publications can be traced back before the Victorian era, they have gained significant popularity in the digital age (Bernstein and Derose 2012; Choi et al. 2022). This unique business model involves publishers releasing creators' content gradually, over months or even years, rather than all at once (Li et al. 2023). In this model, potential consumers have the flexibility to add new ratings with each update. Consequently, maintaining a high rating is crucial for the survival and prosperity of digital serial contents.

On the survival side, given the cost-effectiveness of online publishing and timely feedback from the audience, publishers are inclined to discontinue serial content with low ratings, regardless of its initial success. For example, Shueisha, one of Japan's leading comic publishers, cancels its online and offline comics based on readers' timely survey results (Sherman 2017). On the prosperity side, with numerous writers publishing content daily or weekly, there is an ever-increasing pool of content competing for the limited attention of potential consumers. The higher the ranking of serial content, the more visible it becomes, enhancing its likelihood of outperforming competitors and maintaining its consumer base. Moreover, the target audience for digital serial content is typically young adults, who are often drawn to popular content (Finkelstein et al. 2017; Gitnux 2023). Nearly all platforms showcase serial content based on these ratings. Therefore, it is urgent for content publishers to understand which strategies can enhance ratings in this landscape.

Providing previews is a common strategy in the world of digital serials. Publishers often provide portions of published serial content to potential consumers for free, helping them in making purchase decisions about subsequent content. Preview and rating are often seen as *complementary*. These digital serials are akin to experience goods, making it challenging for consumers to evaluate them before consumption. Without a preview, consumers might end up purchasing an episode or chapter of digital serial content that doesn't align with their interests, potentially resulting in low ratings if they are not satisfied with their purchase. Allowing consumers to view a portion of currently published content before purchase enables them to form more accurate expectations. Even if they don't end up liking the content, they are less likely to leave low ratings due to the reciprocity effect of receiving the preview (Lin et al. 2019). However, preview and rating can also act as *substitutes*. As previews become more extensive with increasing content, consumers who have already purchased the serial content may become dissatisfied with what follows. Moreover, with more potential consumers attracted to the preview content, there is a higher chance of frustration and disappointment if they suddenly encounter paid content which they might not afford. In essence, while previews and ratings are common components of digital serial content, less is known about their exact relationship.

In this chapter, I aim to uncover the relationship between previews and ratings in the context of digital serial content. I also explore how two important factors, namely rating value and market scale, impact the choice of optimal preview strategy with respect to ratings. First, ratings with substantial value, such as those on platforms recognized for their credibility and helpfulness, can assist consumers in identifying products that align more closely with their preferences compared to ratings with lower information value (Chen et al. 2018). For example, prior research suggested that consumers might view excessively high ratings as less trustworthy, especially when rating manipulation is possible (Luca and Zervas 2016; Mayzlin et al. 2014). Second, Zhu and Zhang (2010) have emphasized that the impact of ratings varies with market scale, with greater importance observed in niche markets. They argued that since niche products are mainly sold through online channels and tend to have a limited number of reviews, even a single negative review could be detrimental to the business. Sun (2012) further suggested that a high variance in rating is more likely to happen in niche markets, where consumers' preferences are more diverse, and reaching a consensus on ratings is harder to achieve. This diversity in ratings can assist consumers in making more informed evaluations of niche products and setting appropriate expectations.

This study asks the following research questions:

1) What is the relationship between the proportion of content included in preview and equilibrium of user rating?

2) What is the optimal preview strategy with respect to the equilibrium of user rating? And how does the optimal preview strategy vary with the rating value and the market scale?

To achieve this, I have developed an analytical model that reflects real-world consumer decision-making regarding the rating of digital serial publications. I account for consumers' diverse selection biases on expected utility, which can lean towards favoring preview content and average rating. Drawing upon the expectation disconfirmation theory, I delve into how proportion of content included in a preview for digital serials impact the equilibrium of user rating through rating process. Noted that, in this study, I do not consider trade-off between profit and cost; it is primarily look at the relationship between preview and ratings when the market reaches a static state.

The analytical model yields two key findings. *First*, it uncovers a U-shaped relationship between previews and equilibrium of user rating. Specifically, as the proportion of content in preview increases, the equilibrium of user rating first decreases and then increases. *Second*, it suggests that the optimal strategy hinges on the rating value and market scale. In the mass market, if rating value is low, the optimal strategies are either offering little content or abundant content in the preview; if rating value is moderate, the optimal strategy is providing abundant content in the preview; if the rating value is high, the optimal strategy is providing all content for free. On the other hand, in the niche market, if rating value is low, the optimal strategies are either offering little content or abundant content in the preview; if rating value is moderate, the optimal strategy is providing little content in the preview; if the rating value is high, the optimal strategy is to not provide any preview content.

This research offers several theoretical contributions. First, it expands upon the existing preview literature by examining the proportion of content included in previews, moving beyond the binary choice of providing or not providing previews research (Choi et al. 2019; Zhang et al. 2022). Second, it diverges from the prevalent research focused on the impact of previews on sales (Choi et al. 2023; Hoang and Kauffman 2018; Zhang et al. 2022), by investigating the relationship between preview proportions and long-term goodwill, specifically, the equilibrium of user ratings. Third, it adds to the digital serial publication literature by shedding light on how publishers could employ preview strategies to sustain long-term good will, and how the optimal strategy varies with rating value and market scale. Finally, while previous literature primarily focused on cases where consumers provide a single rating, this study delves into the scenario where consumers can rate a digital serial multiple times, thus extending our understanding of rating literature. This study uncovers valuable implications for publishers of digital serial publications, particularly concerning effective preview strategies that can bolster business survival and prosperity.

I organize the rest of this study as follows: First, I discuss the relevant literature. Next, I present an analytical model that captures consumer's decision-making processes when it comes to rating serial digital content. Following this, I explain the analytical findings. Finally, I draw conclusions from this study and offer insights into future implications.

3.2 Related Literature

3.2.1 Sample and Trial

In the traditional markets, sellers utilize samples to promote their products and alleviate uncertainty (Heiman et al. 2001; Jain et al. 1995; Lehmann and Esteban-Bravo 2006). While providing physical product samples can be costly (McGuinness et al. 1992), previous research has demonstrated that this strategy is effective not only in boosting immediate sales but also in facilitating the adoption of new products (Jain et al. 1995), increasing brand sales (Bawa and Shoemaker 2004) and building long-term goodwill (Heiman et al. 2001).

In the digital marketplace, online sampling has become increasingly popular, primarily because the cost of providing free digital samples is significantly lower compared to traditional physical samples. Many studies have investigated the optimal sampling strategies for sales, answering when to offer free samples (Lambrecht and Misra 2017; Shi et al. 2019; Wang and Zhang 2009). Findings suggest that providing online samples is beneficial for publishers with higher sample search cost (Wang and Zhang 2009), improved advertising effectiveness (Halbheer et al. 2014), and when there are asymmetric network externalities (Shi et al. 2019). It is also advantageous during high demand season (Lambrecht and Misra 2017). However, most of the strategies discussed in these studies are limited to binary decisions (to provide sample or not). One exception is the work of Li et al. (2019), where they considered variations in the quality of samples. Based on data from a website offering an online version of the entire physical book as a sample, their results indicated that the higher the quality of an online sample, the greater its impact on the sales of the corresponding physical book.

Similarly, extensive research has examined optimal trail strategies for increasing sales. Although trails are acknowledged as an effective sales tactic, the optimal trail varies depending on software category (Faugère and Tayi 2007), consumers' initial beliefs (Niculescu and Wu 2014), usage and learning cost (Cheng and Liu 2012), network effects (Cheng and Tang 2010), and word-of-mouth influences (Zhou and Duan 2012). Furthermore, targeting current consumers for future consumption has proven to be a beneficial strategy (Reza et al. 2021).

Online preview differs substantially from online samples and trials in several ways. *Firstly*, unlike samples and trials, online previews are less susceptible to cannibalization. Samples or trials are often viewed as a substitute for the final product. For example, publishers might offer an online version of a book while charging for the print copy (Li et al. 2019). Similarly, software sellers might offer a basic version for free and charge for a more advanced one (Niculescu and Wu 2014). However, consumers might find free online samples or basic service functions satisfactory, giving them little incentive to make further purchases. In essence, consumers can have a complete user experience through samples or trials. In contrast, consuming the first chapter by viewing a preview does not provide access to the entire content.

Therefore, preview strategy may need to be distinct from that of samples and trials. *Secondly*, online previews are less likely to suffer from quality differentiation. When consumers cannot replicate their sample usage experience with a purchased product, such as when sample quality deviates from product quality, it might hinder future sales (Heiman et al. 2001). Such deviations also exist in online trials, as sellers often provide limited features or functionality (Faugère and Tayi 2007; Li et al. 2019). However, online previews do not encounter such deviation, as they are directly extracted from the content. Instead, they face a different challenge aside from designing signals to indicate content quality and avoiding taste mismatches: the more content included in a preview, the less exclusive it becomes for purchase. Therefore, determining the optimal proportion of content to include in a preview is an important question.

3.2.2 Online Preview in Digital Serial Publication

An online preview is a portion of published content offered to potential consumers for free to assist them in making purchase decisions. Although there are limited studies on this topic, researchers have been exploring the impact of online preview on sales. For instance, Choi et al. (2019) discovered that previews positively affect purchase decisions in the context of e-book purchases. Similarly, the results from Zhang et al. (2022) indicated that preview contributes to immediate sales of online video courses.

Recent research has turned its attention to a new area concerning online preview: digital serial publications. The industry is marked by the unique feature of serial publication, where publishers release content episode by episode, or chapter by chapter, typically on a weekly and monthly basis (Li et al. 2023). From the consumers’ perspective, this means that potential consumers must make their rating decisions with each new update. Given the repetitive nature of these decisions and the increasing competition among serials, maintaining a high rating is of utmost importance.

However, researchers have predominantly focused on examining the impact of online preview on sales, leaving the relationship between previews and ratings of digital serial content underexplored. For example, in the context of video-on-demand viewing records, Hoang and Kauffman (2018) found that the more previews a family watched, the more series dramas they end up purchasing. In the realm of web comics, Choi et al. (2023) also discovered that online previews facilitate the sales of digital serial content. They suggested a curvilinear relationship between online previews and the likelihood of purchase, where including a higher percentage of content (i.e., more episodes) in the preview initially increases willingness to purchase but decreases after reaching a certain preview threshold. In another study, Choi et al. (2022) examined the heterogeneity promotion effects of comics to maximize viewership. In this study, our focus shifts to understanding how ratings change over the course of content included in preview.

3.2.3 Online Ratings

Prior research has identified several factors influencing subsequent ratings. Firstly, existing ratings have a significant impact on subsequent rating decisions. This phenomenon was first observed by Schlosser (2005) in a controlled lab experiment setting, where individuals posting rating tend to express opinions different from those already present online. This observation was further supported by Wu and Huberman (2008), who, using data from an online forum, found that users often shared distinct opinions from previous ones, often expressing more extreme opinions. Secondly, empirical evidence has suggested that the rating value affects the consumers' evaluations of products, which, in turn, can influence their rating incentives. For instance, Chen et al. (2018) showed that high-information-value ratings help consumers better evaluate products compared to low-information-value ratings. Luca and Zervas (2016) highlighted that the information value of ratings decreases if businesses engage in fraud rating practices. Additionally, Guo and Zhou (2016) found that the credibility of the rater, such as the rater’s expertise, might affect subsequent ratings. Thirdly, previous literature has indicated the importance of market scale in relation to ratings. For example, Zhu and Zhang (2010) emphasized that the impact of ratings varies with market scale, and it holds greater importance in niche markets. They argued in niche markets, where the majority of products are sold online and have received only few ratings from previous consumers, even a single negative review can severely harm a business. Sun (2012) further suggested that rating information, such as the variance of ratings, is particularly valuable in niche markets. This suggests that in the market where consumer preferences are more diverse and reaching a consensus on reviews is challenging, diverse ratings can aid consumers in evaluating niche products effectively. This, in turn, has the potential to increase ratings. In this study, I examine an interactive rating process, and explore how the rating value and market scales influence the selection of optimal preview strategies with respect to ratings.

In marketing and information system literature, there has been a growing focus on understanding the individual rating process. In the empirical literature, Godes and Silva (2012) developed a model for the generation of five-star ratings. They found that ratings are determined by the comparisons between latent expectations and cutoff points. Similarly, Moe and Schweidel (2012) estimated the rating probability of a five-star rating based on comparisons between latent experience and log difference of adjacent cutoffs. More recently, Ho et al. (2017) empirically studied how disconfirmation affects the online rating process. They have found that consumers are more likely to rate when they experience larger disconfirmation.

While abundant empirical research has examined the rating process, most studies have made an underlying assumption: people have a complete product experience before posting a rating (Moe and Schweidel 2012). A recent paper has challenged this assumption, suggesting that people do not necessarily complete consumption before rating, with some even rating before initiating consumption (Lee et al. 2021). This phenomenon is particularly relevant in the context of digital serial publications, where consumers can leave a rating before a purchase, based on the preview content. In my analytical model, I allow all potential customers to leave a rating, even without purchasing the subsequent content, with a focus on examining the relationship between previews and ratings.

My rating decision model is based on expectation disconfirmation theory (EDT) (Oliver 1977; Oliver 1980). Oliver (1977, 1980) famously articulated the EDT theory in the context of consumer satisfaction. Their model results suggest that consumer satisfaction is largely influenced by disconfirmation (i.e., the difference between experience and expectation). Specifically, a consumer is satisfied (i.e., positively disconfirmed) if a product exceeds their expectation and dissatisfied (i.e., negatively disconfirmed) if it falls short of their expectation.

Previous studies have applied EDT to describe the rating formation process in e-commerce (Ho et al. 2017). Given empirical evidence that consumers tend to differentiate their own rating from the existing rating, a consumer's rating decision is made based on a comparison between others' existing rating and his disconfirmation. In other words, a consumer only rates if their satisfaction or dissatisfaction cannot be represented by the existing rating. Further details on the rating model are discussed in the following section.

A study similar to mine is that of Lin et al. (2019). Although focusing on providing free physical samples in e-commerce, they examined the effect of free sampling and found that engaging in free sampling significantly increases product ratings. However, this study differentiates itself in several ways. *Firstly*, it goes beyond the traditional approach of comparing the effects of providing preview versus not providing it. Instead, it focuses on the proportion of content provided in preview. *Moreover*, this study delves into the relationship between previews and ratings, and shows how the optimal preview strategies vary across rating value and market scale. Thirdly, it focuses on digital serial publications, where providing content in previews directly competes with paid content, and maintaining a high rating is of paramount importance for long-term well-being. *Finally*, my model considers a more practical rating process, allowing consumers to add new ratings per content update, instead of making just a one-time rating decision.

3.3 Model

In this section, I study a monopoly publisher and consumers with differentiated selection biases. Without loss of generality, I treat publisher and creator as equivalent entities. I assume that the publisher provides previews of content at no cost. The extent to which content is included in the preview affects how well consumers can evaluate digital content. While consumers might benefit from a higher proportion of content revealed in the preview, there is a delicate balance, as excessive content may result in a drop in interest, which decreases the consumer utility (Choi et al. 2023). Examples of previews in digital serial publications are abundant. Manga publishers often offer some episodes for free. Podcasters provide free listening materials. TV series provide the first few episodes for viewing.

In addition to previews, publishers frequently display the current rating of the digital serial publication. A higher rating indicates greater popularity, making it more likely that potential consumers will engage with the content (Finkelstein et al. 2017). For example, nearly every platform, such as Spotify, Audible, Naver Comic, and Netflix, ranks their product based on ratings. The higher the ranking, the more visible the content is to potential consumers, the higher utility consumers gain from consuming.

Consumers often have distinct preferences when selecting content. The model considers two types of biases among consumers – those biased toward crowd and those biased toward content. Consumers biased toward crowd tend to follow the collective wisdom; they are more likely to consume with higher rating, driven by the desire to conform. On the other hand, consumers biased toward content are more interested in the actual substance of the content; they prefer to evaluate the content by themselves.

Formally, consider that at the beginning of each update (such as the release of a new episode), a unit of consumers arrives. These consumers are distributed uniformly along a line based on their selection bias. If a consumer has a selection bias of γ, her utility can be expressed as:

$$u = W_{Pre}\gamma + W_R(1 - \gamma). \tag{7}$$

Here, W_{Pre} is a concave function with respect to a, representing the proportion of content included in the preview. It varies from 0 to 1, denoted as $a \in [0,1]$. In extreme cases, publishers may choose not to provide any content in the preview (i.e., $a = 0$) or reveal everything for free (i.e., $a = 1$). Previous literature has indicated a concave relationship between the proportion of preview content and the preview utility in digital serial context (Choi et al. 2019; Choi et al. 2023). Specifically, I assume that $W_{Pre} = v - \frac{1}{2}(a - a_0)^2$, where $a_0 \in (0,1)$ is the market scale indicator . A small value of a_0 implies a mass market, where it is easy for consumers to understand and enjoy the product. Therefore, a small proportion of content is enough for consumers to grasp the whole story. Conversely, a large value of a_0 suggests a niche market, where content is less common and only consumers whose tastes align well with the content find it enjoyable. Therefore, it requires a lot of preview content to make people fully understand the story. The parameter $v > 0$ represents the value of the digital serial content.

$\gamma \sim U[0,1]$, representing consumers' selection bias. A higher value of γ indicates that a consumer is more biased toward content relative to the crowd, and vice versa. W_R represents the average rating observed by consumers at the beginning of each update. It is defined as $W_R = \sum R_j N_j$, where R_j represents the value of rating j and N_j represents the proportion of consumers given rating j. I assume $R_j \geq 0$, suggesting that digital serial content with posted ratings is not less helpful for consumers to further consume than content without ratings. For simplicity, $j \in \{H, L, NR\}$, meaning that consumer can choose to rate high (H), rate low (L), or not to rate (NR). This assumption is supported by previous empirical research, which suggests that consumers tend to post extreme ratings when evaluating content online (Dellarocas and Narayan 2006). Then, R_L, and R_H are rating values for given low and high ratings, respectively. The rating value is predefined by the market. A higher rating value indicates the rating on the platform is more credible and helpful for further consuming the digital serial content. Specifically, the more credible and helpful the low rating on the platform, the less likely a consumer is to further consume the content, leading to a lower R_L. Conversely, the more credible and helpful the high rating on the platform, the more likely a consumer is to further consume the content, leading to a higher R_H. For example, a scenario with a high R_H and low R_L might involve an environment with minimal rating manipulation. Naturally, $R_H > R_L$. A consumer will decide to purchase subsequent episodes if and only if her utility u is greater than or equal to price p. However, it is worth noting that rating decisions are independent from purchase decisions. This means that all consumers have the option to provide a rating, regardless of whether they made a purchase (Lin et al. 2019).

Consumer satisfaction, as per the expectation disconfirmation model (Oliver 1980), is greatly influenced by the gap between expectations and experiences. Hence, I assume that consumers are more inclined to rate when this discrepancy is greater. Additionally, empirical research has indicated that consumers tend to express opinions that differ from existing ones (Schlosser 2005). Therefore, I assume that a consumer is not motivated to rate if her opinion is similar to the existing opinions. Mathematically, the consumer i's rating decision j is given by:

$$j = \begin{cases} L & if\ \Delta U \le -W_R \\ H & if\ \Delta U \ge W_R, \\ NR & if\ -W_R < \Delta U < W_R \end{cases} \tag{8}$$

where $\Delta U = s - u$ represents the extent of disconfirmation. Specifically, $s > 0$ characterizes the consumer's experience with the paid digital content. Within Equation (8), W_R serves as a cut-off point. Essentially, if a consumer's experience aligns closely with her expectations (i.e., within the range of $-W_R < \Delta U < W_R$), she refrains from providing a rating.

In contrast, if the disparity between her experience and expectation is no smaller than W_R, she gives a high rating. On the other hand, if the difference is no greater than $-W_R$, she leaves a low rating. For each updated digital serial publication, consumers must reevaluate and make rating decisions. As this process repeats multiple times, average rating eventually reaches equilibrium at time t. In this equilibrium, the rating W_R consumers see at the beginning of the t^{th} update is equivalent to the updated rating after the t^{th} rating decision.

The consumer rating process is described in Figure 5. In these studies, I primarily focus on consumers' rating decisions and the equilibrium of user rating when the market reaches a static state. Understanding equilibrium of user rating is crucial, particularly for digital serial publications that require consistently attracting consumer attention for repeated consumption on a daily or weekly basis. Unlike traditional publications, where consumption is typically a one-time event, digital serial publications require a highly repetitive consumption process. Additionally, digital serial content is highly replaceable. If the average rating declines, consumers can easily switch to other digital serials. Consequently, digital serial publishers prioritize long-term goodwill more than traditional publishers, aiming to maintain consumer engagement over time. While this study does not delve into purchase decisions, determining the equilibrium of user rating is a critical first step towards calculating an equilibrium price for publishers that considers long-term revenues—a topic reserved for future research.

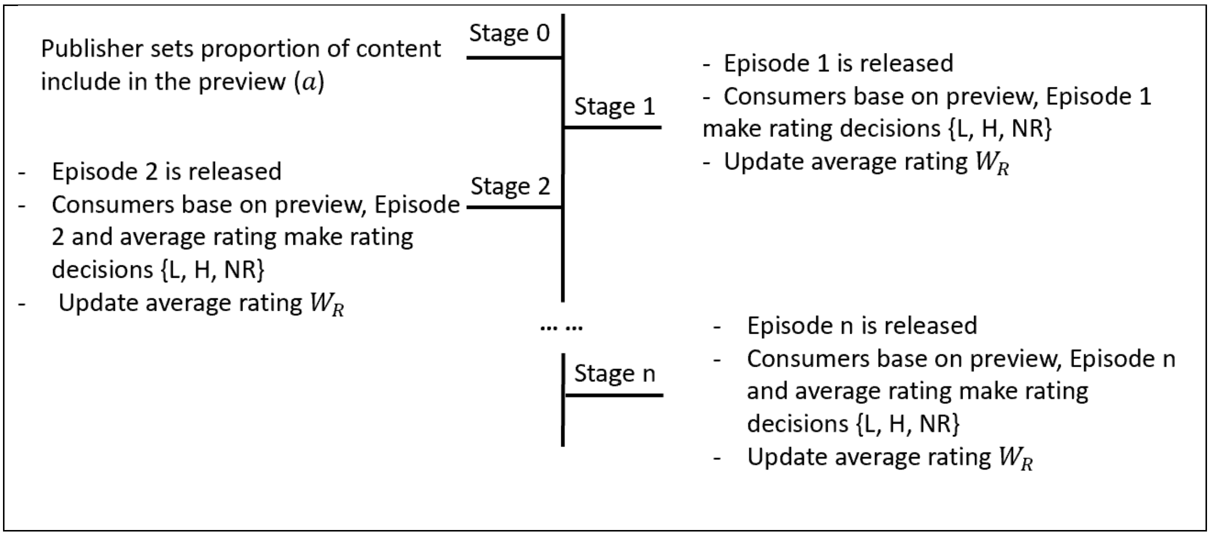


Figure 5. Timeline of Consumer Rating Process

3.4 Equilibrium Average Rating and Optimal Preview Design

Substituting Equation (7) into Equation (8) yields the average rating of digital serial content. When applying rational expectation equilibrium, the equilibrium average rating of the digital serial content can be found by equating the previous average rating W_R and the new rating generated after new content is released. Although calculating the equilibrium average rating is difficult, I have proved that the equilibrium average rating exists under most scenarios, as summarized in the following lemma:

Lemma 1. The existence of equilibrium average rating $\mathrm{W}_{\mathrm{R}}^{*}$ *are*:

	$(a-a_0)^2 < 2\mathbb{E}(v) - \mathbb{E}(s)$	$(a-a_0)^2 = 2\mathbb{E}(v) - \mathbb{E}(s)$	$(a-a_0)^2 > 2\mathbb{E}(v) - \mathbb{E}(s)$
$\mathrm{W}_{\mathrm{R}}^{*}$	Unique and exist.	$if\ 0 < R_H \leq \frac{\mathbb{E}(s)}{2}$: Unique and exist. $if\ R_H > \frac{\mathbb{E}(s)}{2}$: Not exist.	Unique and exist.

Lemma 1 illustrates the existence of equilibrium average ratings under conditions related to the proportion of preview content a. It shows that the equilibrium average ratings always exist when consumers are either highly satisfied ($\mathbb{E}(s) > 2\mathbb{E}(v)$) or dissatisfied ($0 < \mathbb{E}(s) < \min\{2\mathbb{E}(v) - 1, 0\}$). In the case of moderate satisfaction, equilibrium average ratings persist unless (i) the information gained from reading preview ($\mathbb{E}(v) - \frac{1}{2}(a-a_0)^2$) is equal to half of the satisfaction derived from paid content ($\frac{1}{2}\mathbb{E}(s)$) and (ii) rating value is higher than half of the satisfaction derived from paid content ($R_H > \frac{\mathbb{E}(s)}{2}$). Thus, when giving a high rating significantly encourages further consumption, and the preview content is very predictable from satisfaction, the overall rating tends to fluctuate over time. This phenomenon arises when paid content fails to surprise consumers and giving a high rating significantly influences future sales, since consumers might feel unsure about adding new ratings with just okay content.

To simplify the calculations, I further assume that R_L = 0, suggesting that giving a low rating will not contribute to an increase in further consumption. Without loss of generality, I normalize the value of v and s to 1. In other words, I assume that the expected value of digital serials equals the expected satisfaction with paid content. Proposition 1 describes the equilibrium average rating of the digital serial content given preview strategy under these conditions.

Proposition 1. If R_L = 0 and $\mathbb{E}(v) = \mathbb{E}(s) = 1.$ The equilibrium average rating is

$$\mathrm{W}_{\mathrm{R}}^{*} = \begin{cases} R_H & \text{if } 0 \leq a < \max\{0, a_0 - \sqrt{2R_H}\} \\ R_H + \frac{1}{2} - \frac{1}{4}(a-a_0)^2 - \sqrt{\frac{\left(1-\frac{1}{2}(a-a_0)^2 + 2R_H\right)^2}{4} - R_H} & \text{if } \max\{0, a_0 - \sqrt{2R_H}\} \leq a \leq \min\{1, a_0 + \sqrt{2R_H}\} \\ R_H & \text{if } \min\{1, a_0 + \sqrt{2R_H}\} < a \leq 1 \end{cases}.$$

In summary, Proposition 1 reveals a U-shaped relationship between the proportion of content included in the preview and the long-term goodwill building. For all $\mathrm{W}_{\mathrm{R}}^{*}$, the equilibrium average rating first decreases then increases as preview percentage increases around a_0 ($\max\{0, a_0 - \sqrt{2R_H}\} \leq a \leq \min\{1, a_0 + \sqrt{2R_H}\}$). It indicates that providing a proportion of preview content to ensure consumers fully understand the digital serials is not the preferred strategy. For example, in the mass market where most consumers can easily grasp the story (small a_0), providing a low preview percentage (small a) will lead to a low rating. On the other hand, for serial content in the niche market where stories only appeal to consumers with specific tastes (large a_0), providing a large preview percentage (small a) will result in a low rating.

When a is low ($0 \leq a \leq a_0 - \sqrt{2R_H}$), the equilibrium average rating remains as R_H only if R_H is low ($0 < R_H \leq \frac{a_0^2}{2}$). Similarly, when a is high ($a_0 + \sqrt{2R_H} \leq a \leq 1$), the equilibrium average rating remains as R_H only if R_H is low ($0 < R_H \leq \frac{(1-a_0)^2}{2}$). It indicates that equilibrium $\mathrm{W}_{\mathrm{R}}^{*} = R_H$ can be reached if R_H is low. Note that $\mathrm{W}_{\mathrm{R}}^{*} = R_H$ means that all consumers rate high. In other words, one of the scenarios that all consumers give high ratings is when giving high ratings is not very helpful and credible, such as on an online platform full of rating manipulation.

The optimal preview strategies for maintaining a high rating depend on the market scale a_0 and rating value R_H. Specifically, proposition 2a summarizes the optimal preview strategies in a mass market (low a_0).

Proposition 2a. Given R_L = 0 and $\mathbb{E}(v) = \mathbb{E}(s) = 1$, when a_0 <0.5, the optimal preview strategy depends on R_H as follows:

$$a^* = \begin{cases} \left[0, a_0 - \sqrt{2R_H}\right] \; or \; \left[a_0 + \sqrt{2R_H}, 1\right] & if \; 0 \leq R_H < \frac{\mathrm{a}_0^2}{2} \\ \left[a_0 + \sqrt{2R_H}, 1\right] & if \; \frac{\mathrm{a}_0^2}{2} \leq R_H < \frac{(1-\mathrm{a}_0)^2}{2} \\ 1 & if \; R_H \geq \frac{(1-\mathrm{a}_0)^2}{2} \end{cases}$$

Figure 6 shows how the optimal preview strategy varies by rating value in the mass market intuitively. When the rating value is low (Figure 6-A), such as ratings on platforms full of manipulations, the optimal preview strategy is either provide little content in the preview ($0 < \mathrm{a} \leq \mathrm{a}_0 - \sqrt{2\mathrm{R}_\mathrm{H}}$) or provide the majority of the content for free ($\mathrm{a}_0 + \sqrt{2\mathrm{R}_\mathrm{H}} \leq \mathrm{a} \leq 1$). That is, when ratings are not helpful and credible, the rating tends to remain high if the preview percentage is relatively low or high. There is no difference between them. However, when ratings have no value ($\mathrm{R}_\mathrm{H} \rightarrow 0$), such as when all ratings are manipulated, optimal average rating will be reached regardless of preview strategies.

When the rating value is moderate in the mass market (Figure 6-B), such as ratings on platforms that contain both fake ratings and authentic ratings, the optimal preview strategy is to provide most of the content for free ($\mathrm{a}_0 + \sqrt{2\mathrm{R}_\mathrm{H}} \leq \mathrm{a} \leq 1$). In this scenario, when consumers find part of the ratings helpful, the publisher of serial content should offer more preview for free in the mass market. As the rating value increases, the minimum preview percentages resulting in the high average rating also increase, suggesting that consumers prefer more preview content if the platform becomes more trustworthy. Moreover, the range of optimal preview percentage varies with a_0. If the content is favored by every consumer ($a_0 \rightarrow 0$), there is less necessary to set the preview strategies as optimal average rating is easily achievable.

When the rating value is high in the mass market (Figure 6-C), such as ratings on platforms that contain only authentic ratings, the optimal preview strategy is to provide all content for free. Although seemly counterintuitive, this approach is commonly observed in the news industry, exemplified by BBC News, which offers free access to online news while funded by annual television licensing fees. It suggests that when ratings on the platform are helpful and credible, content in preview becomes more crucial to attract consumers' attention and satisfaction in the mass market. As providing all previews for free means no profit can be generated from selling content, it also helps to explain why some platforms are not incentivized to eliminate fake ratings.

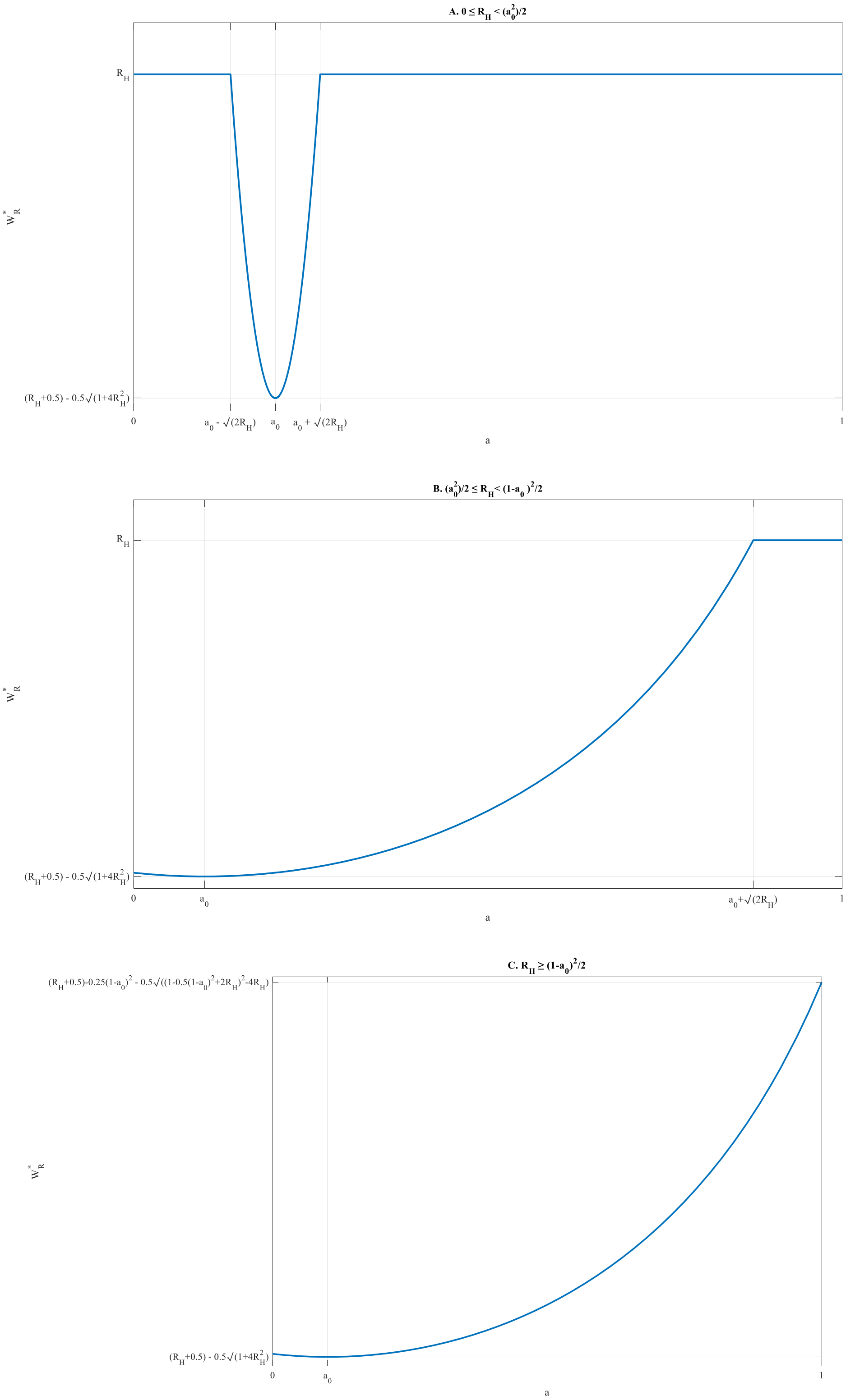


Figure 6. Equilibrium Average Rating in Mass Market (a0 < 0.5)

Proposition 2b. Given R_L = 0 and $\mathbb{E}(v) = \mathbb{E}(s) = 1$, when $a_0 \geq$ 0.5, the optimal preview strategy depends on R_H as follows:

$$a^* = \begin{cases} [0, a_0 - \sqrt{2R_H}] \text{ or } [a_0 + \sqrt{2R_H}, 1] & \text{if } 0 \leq R_H < \frac{(1-a_o)^2}{2} \\ [0, a_0 - \sqrt{2R_H}] & \text{if } \frac{(1-a_o)^2}{2} \leq R_H < \frac{a_0^2}{2} \\ 0 & \text{if } R_H \geq \frac{a_0^2}{2} \end{cases}$$

Figure 7 illustrates how the optimal preview strategy varies by rating value in the niche market intuitively. Similar to the mass market scenario, when the rating value is low (Figure 7-A), the optimal preview strategy is either to provide little content in the preview ($0 < a \leq a_0 - \sqrt{2R_H}$) or to provide the majority of the content for free ($a_0 + \sqrt{2R_H} \leq a \leq 1$). It indicates that when ratings are less helpful and credible, the optimal preview strategy is less important, as a high rating can be achieved by either providing the majority of the content or offering only a little content in preview. When the rating value becomes negligible ($R_H \rightarrow 0$), such as where all ratings are manipulated, optimal ratings will be reached regardless of the chosen proportion of content in the preview.

When the rating value is moderate in the niche market (Figure 7-B), such as ratings on platforms that contain both fake ratings and authentic ratings, the optimal preview strategy is to provide little content for free ($0 \leq a \leq a_0 - \sqrt{2R_H}$). This result is opposite to that in the mass market, indicating that content consumers in the niche market prefer to buy and explore the content themselves even when they only find part of the ratings helpful and credible. This strategy is frequently used in industries like animation and manga, particularly in countries with a smaller consumer base, such as China. For example, Kuaikan Manhua, one of the leading comic platforms in China, often offers fewer than 5% episodes for serial content spanning approximately 500 episodes. [8]

[8] https://www.kuaikanmanhua.com/web/topic/3615/.

As the rating value increases in Figure 7-B, the maximum proportion of content resulting in the optimal average rating decreases, indicating that consumers prefer less preview content if the platform becomes more trustworthy. The range of optimal preview percentage also varies with a_0, with higher a_0 leading to a wider range of optimal preview percentages. When the content is only favored by very few consumers ($a_0 \rightarrow 1$), it is less necessary to set the preview, as an optimal average rating is easily achievable. However, as differences in consumer taste decrease, the range of optimal proportion of preview content also decreases.

When the rating value is high in the niche market (Figure 7-C), such as ratings on platforms that contain only authentic ratings, the optimal preview strategy depends on the a_0. If $a_0 > 0.5$, in niche market with greater differentiation in tastes, the optimal preview strategy is to not provide a preview. This suggests that although ratings on the platform are helpful and credible, as consumers' tastes differ a lot in the niche market, revealing content in the preview can lead to lower ratings, as consumers who read the preview might find it hard to satisfy their expectations. Not offering content means that consumers who paid have more tolerance for the content, even if the content deviates from their expectations. However, if $a_0 = 0.5$, for content that is indifferent to being considered niche or mass, the optimal preview strategy can be either not to provide a preview or provide all content for free.

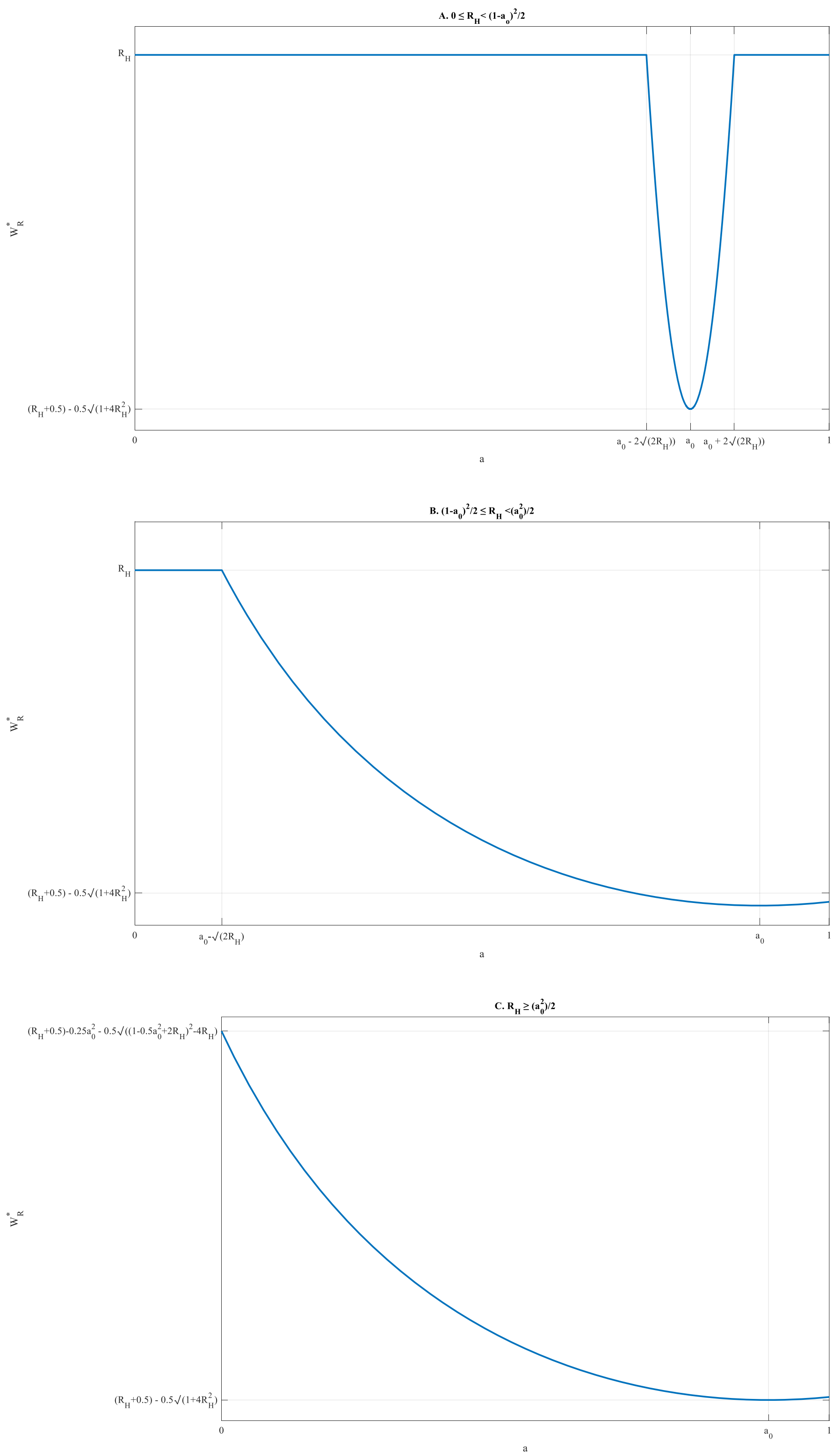


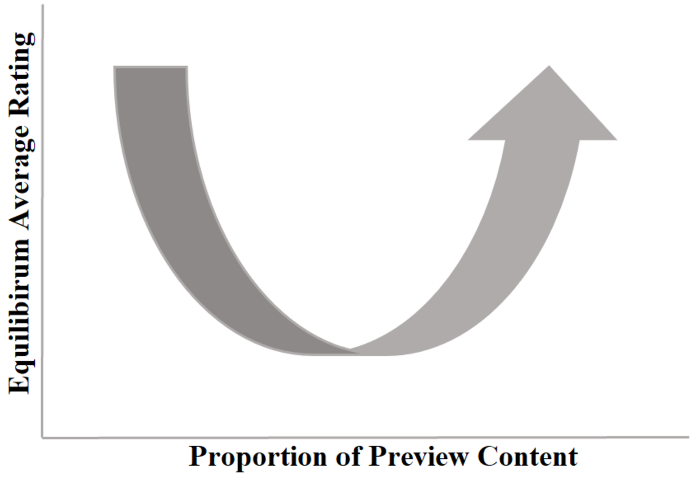
Figure 7. Equilibrium Average Rating in Niche Market (a0 ⩾ 0.5)

3.5 Discussion

3.5.1 Summary of Results

In this chapter, I delve into the impact of preview design on building goodwill for digital serial publication, with a focus on the optimal proportion of content to include in the preview. After assuming value of low rating is zero and normalizing content value and reading satisfaction with paid content, theoretical analysis reveals that the relationship between preview and equilibrium average rating is not a simple matter of complementarity or substitution; instead, it follows a *U-shaped pattern*, meaning that the equilibrium average rating first decreases and then increases as the proportion content included in preview grows.

I find that the optimal preview strategies depend on *rating value* and *market scale*. In the mass market, when the rating value is low, the optimal preview strategies could be either offering little content in the preview or offering most content in the preview; when the rating value is moderate, the optimal preview strategy is offering most content in the preview; when the rating value is high, the optimal preview strategy is providing all content for free in the preview. On the other hand, in the niche market, when the rating value is low, the optimal preview strategies could be either offering little content in the preview or offering most content in the preview; when the rating value is moderate, the optimal preview strategy is providing little content in the preview; when the rating value is high, the optimal preview strategy is not providing preview content. However, if the content can fit into both the niche market and mass market when rating value is high, the optimal preview strategies are either not providing a preview or providing the entire content for free.



Optimal Preview Strategy	**Mass Market**	If rating value is **low**:	Either offer **little** content in the preview or offer **most** content in the preview.
		If rating value is **moderate**:	Offer **most** content in the preview.
		If rating value is **high**:	Offer **all** content for free in the preview.
	Niche Market	If rating value is **low**:	Either offer **little** content in the preview or offer **most** content in the preview.
		If rating value is **moderate**:	Offer little content in the preview.
		If rating value is **high**:	If content can fit into both niche and mass markets, either **not** providing preview or offering **all** content free. If content can only fit into niche market, **not** providing preview.

Figure 8. Summary of Chapter 3's Findings

3.5.2 Theoretical Contribution

This study makes several theoretical contributions. Firstly, it extends the preview literature. Unlike previous studies that mainly focused on the binary decision of having a preview or not (Choi et al. 2019), this research considers the proportion of preview content in the model. The findings also suggest that providing preview may not always be the optimal strategy for digital serial publications, challenging the conventional wisdom found in previous research (Choi et al. 2019; Zhang et al. 2022).

Secondly, instead of focusing on the effect of purchase on sales (Choi et al. 2023; Hoang and Kauffman 2018; Zhang et al. 2022), this study builds an analytical model to demonstrate how preview strategy impacts long-term well-being. Consequently, this study deepens understanding of how the percentage of content included in the preview influences the equilibrium average rating.

Thirdly, this study contributes to the emerging digital serial publication literature. Few studies have delved into this unique yet important market. Li et al. (2023) addressed this topic by modelling content creators' decisions, with a particular focus on incentive plans to manage content creators. Choi et al. (2023) examined the effect of pricing schemes on monetization of digital serial content, particularly the impact of the "wait for free" scheme. Similarly, Choi et al. (2022) also examined "wait for free" scheme, but explore its heterogeneous effects on the platform's viewership. This study, on the other hand, addresses a different practical problem within the context of digital serial publication: how to employ preview strategies to maintain the long-term goodwill of content and keep it constantly favored by the audience, and how these strategies vary with value of rating and market scale.

Lastly, this study expands the online rating literature. Previous research, although also based on expectation disconfirmation theory, largely focused on describing the one-time rating decisions in e-commerce (Ho et al. 2017; Lin et al. 2019). In contrast, this study considers a more practical scenario for digital serial publications by allowing consumers to post new ratings after each content update.

3.5.3 Practical Implication

The findings of this study hold significant implications for digital serial publishers. Firstly, it highlights the nuanced nature of preview strategies in the digital serial publications market, suggesting that offering preview is not always the best approach, which sets it apart from traditional markets. Additionally, it underscores the importance of proportion of content in preview, suggesting that publishers should avoid providing a preview that ensures consumers fully understand the digital serials, as this could negatively impact its average rating.

Secondly, this study emphasizes the importance of considering rating value and market scale when formulating preview strategies for long-term goodwill. The results show that in the mass market, publishers often achieve higher average ratings by providing abundant preview content. With increasing rating helpfulness and credibility, such as when rating manipulation decreases, the minimum proportion of preview needed to achieve a high rating increases, indicating consumers prefer viewing more preview content when the platform becomes more trustworthy. On the other hand, in the niche market, publishers often have a high rating when maintaining an air of mystery. With increasing rating helpfulness and credibility, such as when rating manipulation decreases, the maximum proportion of preview needed to attain a high rating decreases, suggesting consumers' growing willingness to explore the content by themselves after purchase rather than from preview content if the platform becomes more trustworthy.

3.5.4 Limitation and Future Research

This chapter has limitations, yet these challenges present promising opportunities for future research. Firstly, it is important to note that the discussion of the preview strategy primarily takes place within a monopoly setting. However, the applicability of this strategy in a competitive market with multiple publishers remains uncertain. While the results within a monopoly setting provide a solid baseline, digital serial publication is inherently competitive. Future research could offer valuable insights by comparing the findings from this study in a monopoly setting to scenarios with multiple publishers, such as in a duopoly setting.

Secondly, the focus in this study is examining optimal preview strategy with respect to ratings. However, the influence of the percentage of content included in preview on the pricing and purchase of digital serial publications remains unexplored. While existing serial publication literature has examined previews' effects on price and purchase (Choi et al. 2023), future researchers could make meaningful contributions by investigating the dynamic interplay between short-term revenue (sales) and long-term revenue (ratings).

Thirdly, this study takes place within a relatively relaxed rating environment, where consumers are allowed to rate irrespective of whether they have purchased the serial content or not. The effect of preview strategies in a more restricted rating environment, where only buyers can rate, requires further investigation. Exploring diverse rating environments in future research could provide a more comprehensive understanding of the impact of preview strategies on ratings.

Moreover, I have set the value of low rating to 0 and normalized satisfaction and value of content to simplify the analysis. Further research could enhance the model by including factors such as considering the cases where low rating might also facilitate sales, and variation in content value and satisfaction.

Lastly, beyond modelling ratings, future researchers might explore coarser-grained characteristics related to the review. Previous empirical research has revealed that factors such as product-related meta-information, comparative information, and richness of topics in review influence the review helpfulness (Li and Choi 2017). It would be worthwhile to incorporate these factors into the model as well.

Conclusion

This dissertation aims to explore sentiment within the evolving landscape of UGC through three studies. Each study examines a distinct aspect of UGC sentiment: the influence of dynamic sentiment patterns arising from discussions on subsequent discussions, the impact of external sentiment factor on online community engagement, and the use of preview strategies to foster positive sentiment for digital serials.

In the first study, I investigate the impact of sentiment congruency on subsequent discussions drawing on priming theory. Utilizing observational data from online discussion forums and employing a dynamic panel model, my empirical results suggest that higher sentiment congruency decreases subsequent response interval and increases response valence and volume, aligning with my hypotheses. Furthermore, the effect of sentiment congruency is more pronounced with a higher proportion of inquiries raised during a discussion and varies across different discussion phases. These findings contribute to the literature on dynamic online discussions and priming by investigating sentiment congruency patterns, empirically studying the priming effect on subsequent discussions, and exploring the underlying mechanisms.

In the second study, I empirically examine how public negativity influences member engagement within online fan communities. Utilizing a natural experimental design and a weighted RDiT model, I find a decrease in communities' comments and an increase in likes within communities in response to public negativity, suggesting a reserved engagement. The effect is more pronounced with higher levels of public negativity. I further explore how the effect of public negativity varies among member types, demographic characteristics, and status characteristics. This study contributes to the literature on online communities by examining external rather than internal factors as antecedents of online community engagement. Moreover, it contributes to celebrity and influencer literature by quantifying public negativity and examining the common assumption about fans' homogenous response.

In the third study, I construct analytical models to explore how publishers can utilize preview strategies to maintain a high average rating. The results suggest that the relationship between preview and rating is neither complementary nor substitutable; instead, it follows a U-shaped pattern. I further demonstrate that the optimal strategies depend on rating value and market scale. When the rating value is low, there is no difference between including little or extensive content in previews. However, as the rating value increases, maintaining an air of mystery is more effective in the niche market, and revealing most content is more effective in the mass market. This study contributes to the preview literature by extending binary preview decisions to the proportion of content in the preview and focusing on goodwill rather than sales. It also adds to digital serial publication literature by studying the impact of preview strategies on average ratings while considering the rating value and market scale, and online rating literature by incorporating the iterative rating process.

While researchers have highlighted the role of sentiment in information systems and marketing studies (Derks et al. 2008; O'Brien and Toms 2008; Oh et al. 2022; Vosoughi et al. 2018), this dissertation delves into UGC sentiment in the modern digital era, contributing to both theoretical understanding and practical applications. Future research could further explore dynamic sentiment patterns in video-based online engagement, such as in livestreaming and short-form videos. Additionally, more studies are needed to examine the duration of these effects over time and their corresponding economic impacts.

Appendix

Lemma 1. The existence of equilibrium average rating W_R^* *are*:

	$(a-a_0)^2 < 2\mathbb{E}(v)-\mathbb{E}(s)$	$(a-a_0)^2 = 2\mathbb{E}(v)-\mathbb{E}(s)$	$(a-a_0)^2 > 2\mathbb{E}(v)-\mathbb{E}(s)$
W_R^*	Unique and exist.	$if\ 0 < R_H \le \frac{\mathbb{E}(s)}{2}$: Unique and exist. $if\ R_H > \frac{\mathbb{E}(s)}{2}$: Not exist.	Unique and exist.

Proof. Substituting Equation (7) into Equation (8) yields the average rating of digital content as:

$$W_R = \begin{cases} \left(\left(1-\frac{\mathbb{E}(s)}{W_{Pre}-W_R}\right)R_L I_{0<\mathbb{E}(s)<2W_R} + \left(\frac{\mathbb{E}(s)-2W_R}{W_{Pre}-W_R}R_H + \left(1-\frac{\mathbb{E}(s)}{W_{Pre}-W_R}\right)R_L\right) I_{2W_R\le\mathbb{E}(s)\le W_{Pre}-W_R} + \frac{\mathbb{E}(s)-2W_R}{W_{Pre}-W_R}R_H I_{W_{Pre}-W_R<\mathbb{E}(s)\le W_{Pre}+W_R} + R_H I_{\mathbb{E}(s)>W_{Pre}+W_R}, & 0 \le W_R \le \frac{1}{3}W_{\mathrm{Pre}} \\ \left(1-\frac{\mathbb{E}(s)}{W_{pre}-W_R}\right)R_L I_{0<\mathbb{E}(s)\le W_{Pre}-W_R} + \frac{\mathbb{E}(s)-2W_R}{W_{Pre}-W_R}R_H I_{2W_R\le\mathbb{E}(s)\le W_{Pre}+W_R} + R_H I_{\mathbb{E}(s)>W_{Pre}+W_R}, & \frac{1}{3}W_{\mathrm{Pre}} < W_R \le W_{\mathrm{Pre}} \\ R_H I_{\mathbb{E}(s)\ge 2W_R}, & W_R = W_{\mathrm{Pre}} \\ \left(1-\frac{2W_R-\mathbb{E}(s)}{W_R-W_{\mathrm{Pre}}}\right)R_H I_{W_{pre}+W_R\le\mathbb{E}(s)<2W_R} + R_H I_{\mathbb{E}(s)\ge 2W_R}, & W_R > 2W_{\mathrm{Pre}} \end{cases}. \qquad (9)$$

To solve the equation, W_R must be removed from the "if" conditions. Transforming the Equation (9) as follows:

$$W_R = \begin{cases} \left(\left(1-\frac{\mathbb{E}(s)}{W_{\text{Pre}}-W_R}\right)R_L + \frac{\mathbb{E}(s)-2W_R}{W_{Pre}-W_R}R_H\right)I_{0\le W_R\le\frac{\mathbb{E}(s)}{2}} + \left(1-\frac{\mathbb{E}(s)}{W_{\text{Pre}}-W_R}\right)R_L I_{\frac{\mathbb{E}(s)}{2}<W_R\le W_{\text{Pre}}-\mathbb{E}(s)}, & 0<\mathbb{E}(s)\le\frac{2}{3}W_{\text{Pre}} \\ \left(\left(1-\frac{\mathbb{E}(s)}{W_{Pre}-W_R}\right)R_L + \frac{\mathbb{E}(s)-2W_R}{W_{\text{Pre}}-W_R}R_H\right)I_{0\le W_R\le W_{\text{Pre}}-\mathbb{E}(s)} + \frac{\mathbb{E}(s)-2W_R}{W_{\text{Pre}}-W_R}R_H I_{W_{\text{Pre}}-\mathbb{E}(s)<W_R\le\frac{\mathbb{E}(s)}{2}}, & \frac{2}{3}W_{\text{Pre}}<\mathbb{E}(s)\le W_{\text{Pre}} \\ R_H I_{0\le W_R<\mathbb{E}(s)-W_{\text{Pre}}} + \frac{\mathbb{E}(s)-2W_R}{W_{\text{Pre}}-W_R}R_H I_{\mathbb{E}(s)-W_{\text{Pre}}\le W_R\le\frac{\mathbb{E}(s)}{2}}, & W_{\text{Pre}}<\mathbb{E}(s)<2W_{\text{Pre}} \\ R_H I_{0\le W_R\le\frac{\mathbb{E}(s)}{2}}, & \mathbb{E}(s)=2W_{\text{Pre}} \\ R_H I_{0\le W_R\le\frac{\mathbb{E}(s)}{2}} + \left(1-\frac{2W_R-\mathbb{E}(s)}{W_R-W_{\text{Pre}}}\right)R_H I_{\frac{\mathbb{E}(s)}{2}<W_R\le\mathbb{E}(s)-W_{Pre}}, & \mathbb{E}(s)>2W_{\text{Pre}} \end{cases}. \tag{10}$$

The existence of equilibrium average rating W_R^* is solved as the following:

1. Condition $\mathbb{E}(s)=2W_{\text{Pre}}$:
   - It is equivalent to $(a-a_o)^2 = 2\mathbb{E}(v)-\mathbb{E}(s)$. Consider the left- and right-hand side of Equation (10) as regressions $y_1 = W_R$ and $y_2 = R_H I_{0\le W_R\le\frac{\mathbb{E}(s)}{2}}$, respectively.

     The existence of equilibrium average rating is then equivalent to proving that y_1 and y_2 intersect, with the number of intersection points indicating the number of solutions.

     Case 1.1: If $0<R_H\le\frac{\mathbb{E}(s)}{2}$, y_1 and y_2 have a unique intersection point at (R_H, R_H), hence $W_R^*=R_H$.

     Case 1.2: If $R_H>\frac{\mathbb{E}(s)}{2}$, for $0\le W_R\le\frac{\mathbb{E}(s)}{2}$, $y_1=W_R<y_2=R_H$. Thus, there is no intersection point and W_R^* does not exist if $R_H>\frac{\mathbb{E}(s)}{2}$.

2. Condition $0<\mathbb{E}(s)\le\frac{2}{3}W_{\text{Pre}}$:
   - It is equivalent to $(a-a_o)^2\le 2\mathbb{E}(v)-3\mathbb{E}(s)$.

     Case 2.1: When $0\le W_R\le\frac{\mathbb{E}(s)}{2}$, consider $y_1 = W_R$ and $y_{21} = \left(1-\frac{\mathbb{E}(s)}{W_{\text{Pre}}-W_R}\right)R_L + \frac{\mathbb{E}(s)-2W_R}{W_{Pre}-W_R}R_H$. The derivation of y_{21} with respect to W_R can be calculated as follows:

$$\frac{dy_{21}}{dW_R} = \frac{d}{dW_R}\left(\left(1-\frac{\mathbb{E}(s)}{W_{\text{Pre}}-W_R}\right)R_L + \frac{\mathbb{E}(s)-2W_R}{W_{Pre}-W_R}R_H\right)$$
$$= \frac{d}{dW_R}\left(\left(1-\frac{\mathbb{E}(s)}{W_{\text{Pre}}-W_R}\right)R_L\right) + \frac{d}{dW_R}\left(\frac{\mathbb{E}(s)-2W_R}{W_{Pre}-W_R}R_H\right)$$

$$= -\frac{\mathbb{E}(s)}{(W_{\text{Pre}} - W_R)^2} R_L + \frac{-2(W_{Pre} - W_R) + (\mathbb{E}(s) - 2W_R)}{(W_{\text{Pre}} - W_R)^2} R_H$$
$$= \frac{-R_H\big(2W_{Pre} - \mathbb{E}(s)\big) - sR_L}{(W_{\text{Pre}} - W_R)^2}$$

Given that $0 < \mathbb{E}(s) \leq \frac{2}{3} W_{\text{Pre}}$ and $R_H > R_L \geq 0$, $\frac{dy_{21}}{dW_R}$ <0. This implies that during the interval $0 \leq W_R \leq \frac{\mathbb{E}(s)}{2}$, y_{21} continuously decreases as W_R increases. Simultaneously, $y_1 = W_R$ indicates that y_1 continuously increases as W_R increases.

Case 2.2: When $\frac{\mathbb{E}(s)}{2} < W_R \leq W_{\text{Pre}} - \mathbb{E}(s)$, consider $y_1 = W_R$ and $y_{22} = \left(1 - \frac{\mathbb{E}(s)}{W_{\text{Pre}} - W_R}\right) R_L$. The derivation of y_{22} with respect to W_R can be calculated as follows:

$$\frac{dy_{22}}{dW_R} = \frac{d}{dW_R}\left(\left(1 - \frac{\mathbb{E}(s)}{W_{\text{Pre}} - W_R}\right) R_L\right)$$
$$= -\frac{\mathbb{E}(s)}{(W_{\text{Pre}} - W_R)^2} R_L$$

Given that $0 < \mathbb{E}(s) \leq \frac{2}{3} W_{\text{Pre}}$ and $R_H > R_L \geq 0$, $\frac{dy_{22}}{dW_R} \leq 0$. This suggests that during the interval $\frac{s}{2} < W_R \leq W_{\text{Pre}} - \mathbb{E}(s)$, y_{22} continuously decreases as W_R increases. Simultaneously, $y_1 = W_R$ indicates that y_1 continuously increases as W_R increases.

Combining 2.1 and 2.2, when $0 \leq W_R \leq W_{\text{Pre}} - \mathbb{E}(s)$, functions y_1 and y_2 are defined as follows:

$$y_1 = W_R$$
$$y_2 = \begin{cases} y_{21} = \left(1 - \frac{\mathbb{E}(s)}{W_{\text{Pre}} - W_R}\right) R_L + \frac{\mathbb{E}(s) - 2W_R}{W_{Pre} - W_R} R_H, & 0 \leq W_R \leq \frac{\mathbb{E}(s)}{2} \\ y_{22} = \left(1 - \frac{\mathbb{E}(s)}{W_{\text{Pre}} - W_R}\right) R_L, & \frac{\mathbb{E}(s)}{2} < W_R \leq W_{\text{Pre}} - \mathbb{E}(s) \end{cases}$$

In this interval, y_1 continuously increases as W_R increases. y_2 is a pairwise function, particularly notable at $W_R = \frac{\mathbb{E}(s)}{2}$, where $y_{21} = y_{22} = \left(1 - \frac{\mathbb{E}(s)}{W_{\text{Pre}} - W_R}\right) R_L$. Given that $\frac{dy_{21}}{dW_R} < 0, \frac{dy_{22}}{dW_R} \leq 0$, y_2 continuously decreases as W_R increases. Thus, f y_1 and y_2 intersect, there will be a unique intersection point, establishing the existence of a unique equilibrium average rating W_R^* within this range.

Now, let's verify the presence of this intersection point. When $W_R = 0, y_1 = 0, y_2 = \left(1 - \frac{s}{W_{\text{Pre}}}\right) R_L + \frac{\mathbb{E}(s)}{W_{Pre}} R_H$ >0, thus $y_1 < y_2$. When $W_R = W_{\text{Pre}} - \mathbb{E}(s)$, $y_1 = W_{\text{Pre}} - \mathbb{E}(s)$, $y_2 = 0$, thus $y_1 > y_2$. Since $\frac{dy_1}{dW_R}$>0 while $\frac{dy_2}{dW_R} < 0$, there exist a unique intersection point between y_1 and y_2. Thus, the equilibrium average rating W_R^* exists is confirmed to exists when $(a - a_o)^2 \leq 2\mathbb{E}(v) - 3\mathbb{E}(s)$.

By analyzing all conditions, I have established the existence of a unique equilibrium average rating W_R^*, except for when $(a - a_0)^2 = 2\mathbb{E}(v) - \mathbb{E}(s)$ and $R_H > \frac{\mathbb{E}(s)}{2}$. In this case, equilibrium average rating does not exist. ☐

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