DYNAMIC ADVERTISING INSERTION STRATEGY WITH MOMENT-TO-MOMENT DATA USING SENTIMENT ANALYSIS: THE CASE OF DANMAKU VIDEO

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ABSTRACT

Online video platforms realize that increased user engagement increases advertising revenue. For this reason, the danmaku live chat function, which allows users to chat in real-time while watching videos, is developed. Based on Stimuli-Organisms-Response (SOR) theory, this study proposes a new approach—an effective user-targeted method for danmaku video advertising insertion strategy. Specifically, by using moment-to-moment danmaku data and listening to users' live comments, this study examines the influence of the feature variables of video advertisement groups on users' behavior and emotion. Empirical results show that the repeat times of platform advertisement, the exposure duration of a video advertisement group, the number of advertisements, and the number of brands impact users' danmaku behavior. The findings imply that enhanced content-based interactions contribute to video advertising success.

Keywords: Dynamic advertising insertion strategy; Online video; Danmaku comments; Sentiment analysis

1. Introduction

The rapid development of network and streaming media technologies make online videos indispensable. Statistics from ComScore[2] show that more than 187 million Americans watch over 48 billion online videos every month, and users willing to pay for online video services are also increasing. China has 75 million online video subscribers, and the online video market is growing at 241% a year—nine times faster than that in the USA[3]. Motivated by enormous business opportunities, the video-advertising market is booming. The Global Digital Advertising Trends 2020 Report [4] indicates that online video advertising is the fastest-growing advertising format. Online video platforms understand that increased traffic, repeat visits, and user engagement eventually increases advertising revenue (Shon et al., 2021). To this end, a live commenting function called danmaku is introduced, which enables users to chat in real-time while viewing videos. It is a form of online social media and a means of enhancing the effectiveness of interactive advertisements. Danmaku is adopted by major online video platforms in China, such as iQIYI, Tencent Video, and Mango TV.

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[2] https://www.comscore.com/
[3] https://bg.qianzhan.com/report/detail/459/170313-223982fb.html.
[4] PubMatic: "Global Digital Advertising Trends 2020 Report" www.199it.com/archives/991825.html

Figure 1: Example of Danmaku Video and Advertisements

Figure 1 illustrates the basic format of danmaku and advertisements. In the danmaku video mode, users choose different headshots to represent themselves, as well as see and reply to the previous users' danmaku comments. Compared to traditional comments, danmaku is different in terms of real timing and emotional expression. Table 1 lists danmaku's specific features. Danmaku is a dynamic comment that can participate in the user's viewing process, whereas traditional static comments occur after the viewing process. Danmaku produces a new form of moment-to-moment data, where the comments about a video are synchronized with the video content; namely, each danmaku is associated with a specific time and content in the video. Danmaku comments have the unique function of real-time communication and participation; thus, increasing user engagement and making the video format more innovative. According to the video websites' observation data, for online videos of similar types but different volumes of danmaku comments, there are significant differences in the number of video clicks and adverting insertion strategy.

Table 1: Comparison between Danmaku Comments and Traditional Comments

	Danmaku comments	Traditional comments
Features	Introduced to China by AcFun and Bilibili in 2008, developing fast	Originated in the late 20th century, more mature
	Short text, verbal expression diversity	Long text, topics focused
	Real time comments	Post-viewing comments
	Network sociality, interactivity	Opinion leader
	Emotional expression is subjective and fluctuant	Emotional expression is objective and rational
	Fragmented language	Holistic, comprehensive language

Danmaku comments convey more information about user engagement, reflecting how users interact with video content and advertisements. In the Internet marketing era, advertisers are increasingly emphasizing the effectiveness of advertising. Many online video platforms, such as Tencent Video and iQIYI, use artificial intelligence to appropriately integrate advertising brand information with plot content. "Advertising is content, and content is advertising" is achieved as brands no longer conduct one-directional communication but achieve in-depth interaction with users. By triggering danmaku interaction (see Figure 2) and viewing gift-giving and other welfare activities, users deepen impressions and approval of the brand during the interaction process. In this way, brand information and product features are unconsciously accepted and marketing efficiency is significantly improved.

Figure 2: Example of Interaction between Danmaku and Advertisement

In existing research, the insertion methods of most video advertisements are static strategies, such as fixed positioning (Li & Lo,2015), forced timing (Vermeulen et al., 2019) and quantitative (Tangmanee, 2016), ignoring the interactivity between advertisement insertion and users' engagement behavior and emotion. The users' engagement behavior and emotions while watching videos change in real time. Without considering the real-time response to user engagement, these insertion methods inevitably reduce the advertising effect because of user dissatisfaction and resistance. Posting danmaku is a real-time user engagement behavior in which users' emotions are instantly reflected, making the viewing experience more interactive and engaging, which in turn encourages people to pay more attention to advertisements (Xu & Sundar, 2016). To overcome the shortcomings of the static strategy of video advertisement insertion, this study considers users' danmaku behavior and emotions, and proposes an effective user-targeted dynamic strategy for online video advertising. This study aims to investigate the features of advertisements that attract users and the influence of posting danmaku on online video platforms' advertisement display. Through an empirical study of online video platforms in China, this study attempts to specifically answer questions at two different levels: (1) Danmaku-advertisement level: What combination characteristics of danmaku and advertisements attract users' instant attention, and (2) Video platform level: How can advertising insertion strategy be dynamically adjusted according to danmaku behavior and sentiment that reflect the real-time reaction of users? Answering these questions is not only significant for understanding the interactive behavior of danmaku and advertisement, but is also conducive to implementing a more accurate user-targeted advertisement recommendation mechanism.

The remainder of this paper is organized as follows: Section 2 presents a literature review of online video advertisements and relevant theories. Section 3 includes the research framework and hypotheses, while Section 4 describes the proposed method. Section 5 presents the empirical study and the results. Finally, Section 6 provides the conclusion and discussion, including managerial implications, limitations, and further research directions.

2. Literature Review

2.1. Insertion of Online Video Advertisements Based on User Behavior

In any advertisement scenario, the user and advertiser are the two primary participants. A paradox of interest exists between the two where users might find advertisements between videos annoying, while advertisers are expected to maximize advertisement coverage. As a result, a successful advertising insertion strategy should balance the conflicting needs of users and advertisers: increasing user engagement with advertisements while reducing the commercial disruption caused by advertisements (Boerman et al., 2017). To improve the effectiveness of online video advertisements, user engagement and interaction behaviors must be considered.

The main idea of an online video advertising insertion strategy based on users' behavior is to determine users' personal interests by analyzing their searching, browsing, clicking, and other behavioral data, so as to insert the most relevant advertising (Wang et al., 2018). Usually, establishing a personalized user portrait model is used to accurately describe the users' behavioral characteristics. Video platforms can infer user interests and preferences from their viewing history and push advertisements to users with similar preferences (Peng et al., 2020). Currently, YouTube and other streaming video platforms use advertising insertion strategies based on user behavior. The most common are in-stream advertisements, which are advertising videos inserted before the video (pre-roll), during the video (mid-roll), or at the end of the video (post-roll) with diversified duration and skipping characteristics (YouTube Help; Joa et al., 2018).

Placing advertisements based on users' behavioral history and preference can improve user experience and the effectiveness of video platform advertising (Li et al., 2020). Although several studies show that effective advertising insertion strategies should be based on user behavior, few studies focus on how to link user behavior to advertisement delivery and how to develop advertising strategies according to user response behavior (Kumar et al., 2020). Existing research on advertising insertion strategies focuses on the historical behavioral preferences of video users. However, this strategy is static and cannot reflect users' behavioral changes while watching videos in real time. Additionally, humans are driven by emotions and rational thinking; thus, emotions play an important role in influencing users' online behavior (Wani et al., 2018). Advertising insertion strategies based on user behavior are complex, and establishing a mathematical model is difficult. For the empirical analysis of user behavior, marketing and psychology studies are costly and unsuitable for large groups of individuals. In addition, user behavior may be influenced by emotions and dynamically changes over time. Therefore, traditional static video advertising strategies cannot accurately reflect dynamic changes in user behavior and emotion, resulting in biased advertisement delivery predictions. This study adopts danmaku data to effectively represent real-time changes in users' danmaku behavior and emotion toward video advertisements, and proposes a dynamic advertising insertion strategy based on users' reactions.

2.2. Stimuli-Organisms-Response (SOR) Theory

According to the SOR theoretical model of environmental psychology proposed by Mehrabian and Russell (1974), all aspects of the environment play a stimulating role (S), affecting the internal state of organisms (O); thus, driving their behavioral response (R). The SOR framework provides a theoretical basis for understanding consumer behavior (Bigne et al., 2020). In SOR model, "Stimulus" refers to "the influence that arouses an individual," involving social stimulus, design stimulus, and environmental stimulus (Liu et al., 2016); "Organism" refers to the emotional and cognitive state of consumers; an intervention process between the stimulus and the response to consumers. Emotional position reveals the feelings and emotions expressed by consumers after stimulation (Yin et al., 2014); "Response" indicates the interactive results of consumers' participation in the brand community on social media, which is manifested as consumers' behavior toward the brand and is an effective response of consumers to brand stimuli (Kim & Lee, 2015).

The Internet's popularity has a profound impact on consumer behavior. Existing research on the SOR theoretical framework involves consumption scenarios in the Internet. More importantly, the SOR approach can be applied to predict user behavior when using information and communication technology, such as forecasting user engagement within the online brand community (Chang et al., 2014; Islam & Rahman, 2017), co-creation in social media (Luqman et al., 2017; Kamboj et al., 2018), online shopping behavior (Peng & Kim, 2014; Huang et al., 2016), and user interactive behavior (Cambra-Fierro et al., 2017; Wu & Li, 2018). The SOR model is suitable for this study because it is widely employed in online user behavior research (Chang et al., 2014; Huang et al., 2016; Luqman et al., 2017; Li & Yuan, 2018). In the marketing context, extensive SOR-based research confirms the relationship between consumers' emotions and their behavioral responses, including their consultations, searches, purchases, and returns for the target stimuli (Knoll, 2016; Kim et al., 2018). Based on the above, SOR theory is also adopted in our study to explain users' behavioral responses to advertisements while watching danmaku videos.

In an online video environment, when users are aroused by commercials, their emotions and behaviors are dynamically altered. Danmaku, a type of online interactivity while watching videos, effectively represents users' individual reactions to video content and advertisement stimuli. In our study, stimuli are aspects of video advertisements that impact user behavior while posting danmaku (Wei et al., 2020). We consider the video advertisement features (exposure duration, number of advertisements, repeat times, and brands) as stimuli (S). We believe that these advertisement features significantly impacts users' danmaku behavior; thus, the advertisement stimuli influence the users' internal sentiment (O). This in turn leads to user response (R), which is divided into posting danmaku and danmaku sentiment change. Danmaku comments can be used to determine the placement of advertisements, which will further increase the effectiveness of the advertising insertion strategy by systematically considering the combined influence of user interactions, video plots, and commercials. This study conducts an empirical analysis to detect the effect of video advertising insertion on user behavior when posting danmaku. It uses danmaku as a new method of gauging user perceptions in response to video advertisement exposure, and establishes the relationship between advertising insertion strategy and users' danmaku behavior. This study successfully extends the SOR model to the relevant theoretical research on online video advertising strategies and danmaku comments, and ultimately improves the application framework of SOR theory.

3. Hypothesis Development

3.1 The Duration of Advertisement Exposure and Danmaku Comments

Users are exposed to thousands of advertisements on the Internet daily. Exposure to these advertisements is frequently brief, sometimes just a single glance of a few seconds or less (Elsen et al., 2016). The advertising industry is trending toward shorter advertisement units. Some studies indicate that the duration of a video advertisement affects its effectiveness, with longer advertisements presenting lower completion rates (Arantes et al., 2018). When users are exposed to longer advertisements while watching videos, they become less receptive to advertising stimuli and are more likely feel fatigued (Lu & Chen, 2020). This boredom leads users to post danmaku comments and communicate with others to pass the "boring" commercial breaks. As the volume of danmaku increases, the expression of danmaku sentiment becomes mostly negative and resistant; thus, users' emotions do not change much (Xi et al., 2021). Therefore, we propose hypothesis H1.

Hypothesis H1: The duration of advertisement exposure positively influences danmaku volume but negatively affects danmaku sentiment change.

3.2 The Number of Advertisements and Danmaku Comments

Some people are not concerned with advertisements, while others find them unnecessarily intrusive. This is due to individual differences in the standards used to determine the profit and loss associated with online advertisements, as well as differences in individual sensitivity to discomfort (Naous & Legner, 2019). According to SOR theory, users tend to watch an advertisement if it influences their internal sentiment and indicates a positive experience, especially if the conditions are favorable (the advertisement is tied to the video plot) (Frade et al., 2021). An increase in the number of advertisements means that the advertising stimuli are diverse and more attractive, which somehow increases the effectiveness of advertising communication (Zhang et al., 2017; Pelsmacker et al., 2019). This causes the user's internal sentiment towards the advertising stimuli to be positive, and the danmaku's response behavior is weakened. Therefore, we propose hypothesis H2.

Hypothesis H2: The number of advertisements negatively affects danmaku volume and danmaku sentiment change.

3.3 Platform Advertisements, Product Advertisements and Danmaku Comments

In this study, advertisements are divided into platform advertisements and product advertisements. Platform advertisements are service-based advertisements involving e-commerce platforms (Amazon, Eaby, TripAdvisor, and Trip.com) that offer online shopping or travel services. Product advertisements feature physical goods, such as food, cosmetics, apparel, and shoes. The Internet economy enhances the online advertising business in the information era. Specifically, e-commerce growth increases people's interest in service-oriented items (Belanche et al., 2020; Bellman et al., 2021), resulting to a dramatic expansion of platform advertisements compared to product advertisements in recent years (Al-Subhi, 2022). Service-based advertisements appeal to user engagement (e.g., downloading an APP), while product-based advertisements persuade users to buy. The difference is that the former promotes users' active participation, whereas the latter persuades users to passively accept the product. In contrast, users will have natural resistance to passive acceptance behavior, so they are more receptive to platform advertisements than product advertisements. On this basis, we believe that the larger the proportion of platform advertisements, the more it will positively affect the internal sentiment state of users' acceptance of advertising stimuli; thus, weakening danmaku behavioral responses in terms of danmaku volume and sentiment change. Therefore, we propose hypothesis H3.

Hypothesis H3: The ratio of platform advertisements to product advertisements negatively affects danmaku volume and danmaku sentiment change.

3.4 The Number of Platform Advertisement Repeats and Danmaku Comments

Users perceive the quality of online information as the extent to which the information meets their expectations and satisfies their requirements for the particular activity in which they are engaged (Eppler, 2006). Humans have limited time and thoughts to deal with information stimuli; poor information quality may distract individuals and make them feel useless and bored with information (Lazaroiu, 2019). In the online video industry, as advertisement repeats increase, users become less able to absorb new information and more prone to fatigue; they will more likely avoid advertisements rather than find value in them (Shon et al., 2021). McCoy (2017) investigates the impact of advertisement intrusion and repetition on the intention and attitude toward revisiting a website, demonstrating that increasing the number of advertisements repeats increases user boredom. For the reasons stated above and based on the SOR framework, the more frequent the platform advertisements are repeated, the more negative the users' internal sentiment is affected by the advertising stimuli and the more likely users are to post danmaku comments. Because the expression of danmaku sentiment is mostly negative and resistant, users' emotions do not fluctuate significantly. Therefore, we propose hypothesis H4.

Hypothesis H4: The number of platform advertisement repeats positively affects danmaku volume but negatively affects danmaku sentiment change.

3.5 The Number of Advertisement Brands and Danmaku Comments

The stimulus factors of online advertising affect consumers' emotional and cognitive status, thereby triggering consumer behavior (Sharma et al., 2021). Higher brand diversity by video advertisements triggers more online consumer behavior (Hernández-Méndez & Muñoz-Leiva, 2015). More brand advertisement appearances in a particular period lessen the users' time to focus on each online advertisement business (Zhang & Yuan, 2018). According to existing research, a shorter average brand gaze time may result to a more favorable attitude toward the online advertising business (Edlira et al., 2016). Based on the above statement, we believe that an increased number of video advertisement brands will affect the users' internal sentiment state and attract users to focus on advertisements; thus, weakening the response behavior of posting danmaku. Different users have different brand experiences, leading to diverse perceptions of brands. Moreover, users' perceived experience of different brands varies greatly, and most users' emotions are directed toward the likes or dislikes of advertisement stimuli, resulting to a large change in danmaku sentiment. Therefore, we propose hypothesis H5.

Hypothesis H5: The number of brands negatively affects danmaku volume but positively affects danmaku sentiment change.

3.6 Confounding Factors

This study considers three confounding factors that may affect users' danmaku behavior: video ratings, brand awareness, and number of users during advertisements. Online ratings can be regarded as a reflection of user preferences on an object dimension (online movies, videos, and music), which directly reflects users' behavioral patterns and is of the greatest concern on streaming platforms (Zhang et al., 2015). Video ratings represent users' preferences for video content that have a potential impact on user engagement behavior on online video platforms, such as posting danmaku, interactive sharing, and emotional expressions (Zhang et al., 2020). Brand awareness refers to an individual's knowledge of a particular brand, including consumer recognition, knowledge dominance, and brand attitude (Kim et al., 2008). This has a significant effect on consumer behavior and choice (Dabbous & Barakat, 2020). Some studies indicate that brand awareness is significantly correlated with purchase intention and positively influences customer preference and purchase intention (Sürücü et al., 2019). Similarly, we believe that when a user watches a video advertisement, brand awareness evokes certain memory associations and resonates with others. Therefore, brand awareness can promote users' interactive behaviors; they post danmaku to discuss familiar brands and communicate emotionally. Interaction affordance, which is based on interactive gratifications, encourages audience participation by allowing users to interact with and through the medium (Sundar & Limperos, 2013). On an online video platform, users obtain interactivity gratifications by posting danmaku (Meng & Leung, 2021). Intuitively, the larger the number of users during an advertisement, the larger the volume of danmaku, leading to a greater shift in danmaku sentiment (Wei et al., 2020).

4. Proposed Method

4.1 Data Collection

Tencent Video is a major online video platform in China, with a relatively mature pop-up system and over 1.1 billion users. We use Tencent Video's danmaku and advertisement data as the database. Python technology with a request module is applied to obtain danmaku and related advertisement data. We track two famous Chinese outdoor sports reality shows—"Running Man" season IV (2016) and "Keep Running" seasons I–III (2017-2019)—through the Tencent video platform. Each season has 12 episodes and has a different sports theme. For instance, the themes in "Keep Running" II–IV are "growth and change", "environmental protection," and "spring awakening," respectively. Artists participate in the sports reality program and compete for different teams. To solve the mystery, they follow numerous clues and the final winning team receives a prize.

While collecting advertisement data during video playback time, we find that online video advertisements are generally placed in clusters. For convenience, we define these advertisement clusters as AD groups, which contain approximately one to nine advertisements individually. On average, the time span (in seconds) of an AD group ranges from 10 s to 301 s, and the exposure duration of each advertisement unit range from 5 s to 60 s. After data preprocessing, we collect and construct a rich data set of 48 episodes of "Running Man" and "Keep Running," including 654,763 danmaku comments and 257 AD group data. Danmaku data contains the date, the time when danmaku comments appeared in the video, the content of each danmaku, and the number of users at different viewing times. The videos in the advertisement file contain dynamic information that reveals the timing and content of all advertisements. Two coders independently count and gather advertisement data, including (1) the insertion position time of AD groups; (2) the number and content of danmaku comments when an AD group was inserted; and (3) the features of video AD groups, such as the volume, exposure duration, repeat times, brands, and advertisement types.

4.2 Sentiment Analysis of Danmaku Comments

Using the text and corresponding video timestamp information, danmaku comments can effectively reflect users' immediate emotions in the current video situation. The instantaneous nature of danmaku has a more prominent influence on emotional expression and intensity. To investigate the effect of the video advertising insertion strategy on user sentiment, natural language processing technology is adopted to analyze the dynamic change in user emotion during video playing. This study applies sentiment analysis technology to analyze danmaku sentiments and evaluate emotional expressions through language. The process includes extracting emotional information, processing and analyzing data, and classifying the sentiments of danmaku comments. Based on the previous work of Li et al. (2020), a hybrid approach that combines the sentiment dictionary and naïve Bayes algorithm is used in Danmaku sentiment analysis. The sentiment dictionary method is applied to extract features from Danmaku text, and a naïve Bayesian algorithm is used to perform sentiment classification.

The danmaku sentiment dictionary study is mainly based on three dictionaries: the Chinese emotional vocabulary ontology database of the Dalian University of Technology (DUT) with 27,476 words (http://ir.dlut.edu.cn), a Catchwords dictionary with 733 network hot words, and a self-constructed danmaku emoticon set with 161 emoticons. The emotional words of the danmaku sentiment dictionary include “Like,” “Happiness,” “Surprise,” “Fear,” “Anger,” “Sadness” and “Disgust,” the seven sentiment dimensions. The sentiments “Like” and “Happiness” have positive sentiment polarity while the sentiments “Surprise,” “Fear,” “Anger,” “Sadness” and “Disgust” have negative sentiment polarity. The positive polarity intensity of the emotional vocabulary is divided into five levels: 1, 3, 5, 7, and 9. Similarly, negative polarity intensity values include -1, -3, -5, -7, and -9, indicating the degree of negative intensity of emotional words. After Chinese word segmentation, deleting stop words, and other processes, the sentimental value calculation of danmaku is implemented. A danmaku sentence may contain some sentiment words, network words, or emoticons, the first two of which can be modified by negative words and degree adverbs. Here, V is the sentimental value of a single case in a danmaku sentence, g denotes the weight of the sentiment word, h denotes the weight of the network word, θ denotes the weight of the degree adverb, and e denotes the weight of the emoticon. By analyzing emotional labels, sentiment scores for danmaku text can be a combination of “Like,” “Happiness,” “Surprise,” “Fear,” “Anger,” “Sadness,” and “Disgust” results. The following nine weight calculation cases are considered:

Case 1: When only sentiment words appear in a danmaku sentence, the formula for calculating the sentiment value is

$$V_1 = g_1 + g_2 + \cdots + g_l, \tag{1}$$

where, l represents the number of sentiment words in a danmaku sentence.

Case 2: When only emoticons appear in a danmaku sentence, the formula for calculating sentiment value is

$$V_2 = e_1 + e_2 + \cdots + e_p, \tag{2}$$

where, p represents the number of emoticons in a danmaku sentence.

Case 3: When only network words appear in a danmaku sentence, the formula for calculating the sentiment value is

$$V_3 = h_1 + h_2 + \cdots + h_z, \tag{3}$$

where, z represents the number of network words in a danmaku sentence.

Case 4: When the sentiment word is modified by negative words, the formula for calculating the sentiment value is

$$V_4 = (-1)^{r_1} g_1 + (-1)^{r_2} g_2 + \ldots + (-1)^{r_l} g_l, \tag{4}$$

where, $r_i, i = 1,2,\ldots,l$ represents the number of negative words appearing in front of the *i-th* sentiment word. Similarly, we conduct case 5 for the sentiment calculation of network words modified by negative words.

Case 5: When the network word is modified by negative words, the formula for calculating the sentiment value is

$$V_5 = (-1)^{r_1} h_1 + (-1)^{r_2} h_2 + \ldots + (-1)^{r_z} h_z, \tag{5}$$

where $r_j, j = 1,2,\ldots,z$ represents the number of negative words appearing before in front of the *j-th* network word.

Case 6: When the sentiment word is modified by degree adverbs, the formula for calculating the sentiment value is

$$V_6 = \theta_1 g_1 + \theta_2 g_2 + \cdots + \theta_l g_l, \tag{6}$$

Case 7: When the network word is modified by degree adverbs, the formula for calculating the sentiment value

$$V_7 = \theta_1 h_1 + \theta_2 h_2 + \cdots + \theta_z h_z, \tag{7}$$

Case 8: When the sentiment word is modified by both negative words and degree adverbs, the formula for calculating the sentiment value

$$V_8 = (-1)^{r_1} \prod_{u1=1}^{q_1} \theta_{u1} g_1 + (-1)^{r_2} \prod_{u2=1}^{q_2} \theta_{u2} g_2 + \ldots + (-1)^{r_l} \prod_{ul=1}^{q_l} \theta_{ul} g_l, \tag{8}$$

where $(-1)^{r_i} \prod_{ui=1}^{q_i} \theta_{ui} g_i$ implies that the *i-th* sentiment word is modified by r_i negative words and q_i degree adverbs.

Case 9: When the network word is modified by both negative words and degree adverbs, the formula for calculating the sentiment value

$$V_9 = (-1)^{r_1} \prod_{u1=1}^{p_1} \theta_{u1} h_1 + (-1)^{r_2} \prod_{u2=1}^{p_2} \theta_{u2} h_2 + \ldots + (-1)^{r_z} \prod_{uz=1}^{p_z} \theta_{uz} h_z, \tag{9}$$

where, $(-1)^{r_j} \prod_{uj=1}^{p_j} \theta_{uj} h_j$ implies that the *j-th* network word is modified by r_j negative words and p_j degree adverbs.

Consequently, considering the case where a danmaku sentence contains the above cases, the formula for calculating the sentiment value is expressed as

$$V = V_1 + V_2 + ... + V_9 . \tag{10}$$

Based on the constructed danmaku sentiment dictionary, the general rules of the sentence and weight calculation of sentiment words or emoticons, sentiment value calculation and classification of danmaku comments are implemented.

4.3 Extracting Feature Variables of Danmaku Video Advertisement Groups

Video advertisements often include contexts, characters, objects, and backgrounds. As mentioned in Section 4.1, we obtain 257 video advertisement (AD) groups with an average time span (in seconds) of 10–301s for each AD group and an exposure time of 5-60s for each advertisement unit. Through statistical data analysis, we find that advertisements for “Running Man” IV and “Keep Running” I-III primarily contain product and platform advertisements (e-commerce platform promotion). Following the literature on online advertisements, we identify the major dimensions of video advertisements. Elsen et al. (2016) demonstrate that advertisement evaluation strongly depends on the duration of advertisement exposure and the brand that advertisement promotes. Additionally, advertisement exposure time and the display frequency of product brands are the main drivers of advertising effectiveness (Michel & Pieters, 2015; Bruce et al., 2020). Guided by Elsen et al. (2016) and Bruce et al. (2020), we extract the two most important properties of AD groups: exposure duration and number of brands. According to some schools of thought, different advertising brands and categories can affect users’ visual attention (Bellman et al., 2017; Costa et al., 2019). Intuitively, while watching videos, users tend to be more attracted to the advertisement for the brands they buy (Simmonds et al., 2020). However, users become more distracted as more advertisements are inserted (Bendak & Al-Saleh, 2010). Thus, the number and categories of advertisements are considered as the other properties of the AD groups.

Existing research shows that increasing the amount of advertisement exposure can improve users’ purchase intention and satisfaction (Meenakshi & Ajeet, 2015; Eun & Chan, 2015). We calculate the repeat times of advertisements in each AD group to evaluate advertisement effectiveness. Moreover, Zhang et al. (2020) share that video ratings reflect users’ preferences for video content and potentially influence user participation behavior (interactive sharing and emotional expression) on online video platforms. Some studies indicate that brand awareness significantly affects consumer behavior and choices (Sundar & Limperos, 2013; Dabbous & Barakat, 2020), which can promote users’ interactive behaviors such as posting danmaku to discuss familiar brands. The number of users during the advertisement period also affects danmaku volume and sentiment change (Wei et al., 2020).

Consequently, in our research models, we consider the feature variables of video AD groups: exposure duration (ED), number of advertisements (NUMA), repeat times of platform advertisements (RTP), ratio of platform advertisements to product advertisements (QR), and number of brands (NUMB) as the independent variables; and video ratings (VR), brand awareness (BA), and number of users (MUMU) (per AD group) as the confounding variables. We also consider the characteristics of the AD group related to danmaku information: danmaku volume (DV) (per AD group) and sentiment value difference of danmaku (SDD) (measured 2 minutes before and after an AD group) as the dependent variables. Table 2 presents the variables.

Table 2: Descriptive Statistics of AD Group Characteristics (N = 257)

	Mean	Std. Deviation	Minimum	Maximum	Median
Danmaku volume (DV)	259.265	220.467	2	1664	174
Sentiment value difference of danmaku (SDD)	-0.003	0.588	-1.59	2.50	-0.014
Exposure duration (ED)	65.957	50.870	10	301	47
Number of advertisements (NUMA)	5.782	3.902	1	27	5
Repeat times of platform advertisements (RTP)	1.568	1.810	0	12	1
Ratio of platform advertisements to product advertisements (QR)	0.767	0.928	0	4	0.5
Number of brands (NUMB)	3.342	1.228	1	7	3
Video ratings (VR)	4.231	1.251	1	5	3
Number of users (MUMU)	30482.153	1508.298	563	123986	29358
Brand awareness (BA)	33.259	12.108	0	65	32

5. Experimental Results and Analysis

We perform sentiment analysis of danmaku and correlation of AD groups and danmaku sentiments. Furthermore, by combining the data of 654,763 danmaku and 257 AD groups, we conduct a regression analysis to explore how video advertisement characteristics affect users' real-time danmaku responses.

5.1 Sentiment Analysis of Danmaku

Figure 3 shows the results of the sentiment analysis of danmaku comments for "Running Man" IV and "Keep Running" I-III based on the seven-dimensional danmaku dictionary. Considering "Like," "Happiness," "Surprise", "Fear", "Anger", "Sadness" and "Disgust", Figure 3 reflects the statistical results of the DV sent by users in each dimension of sentiment. Variables "Like," "Happiness," and "Disgust" have higher average numbers of users, whereas "Surprise," "Fear," and "Anger" have lower average numbers of users. Because the selected sample data came from various entertainment shows, most user experiences are enjoyable rather than painful. This may result in the uneven distribution of the seven dimensions of sentiment.

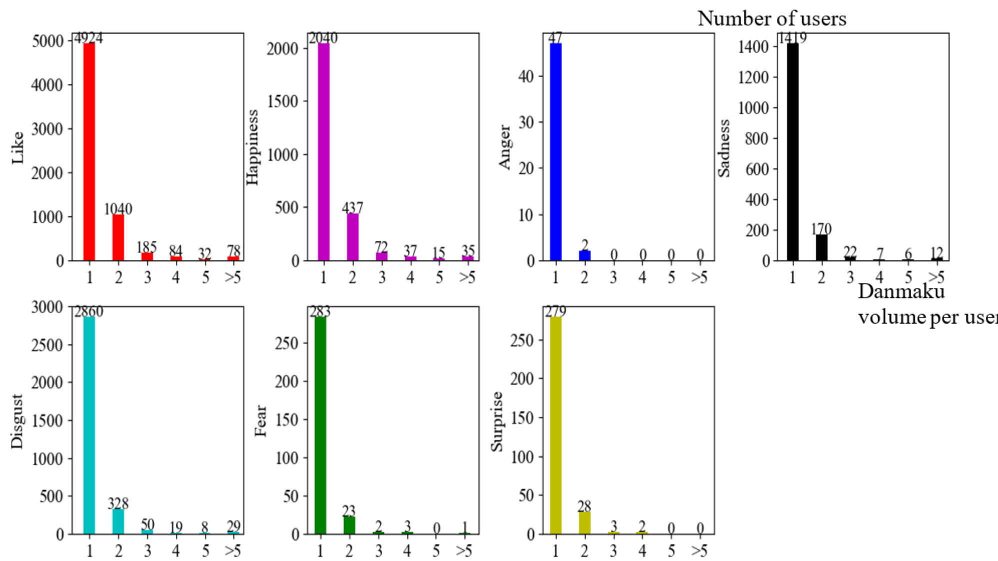


Figure 3: Danmaku Volume – User with Seven Dimensions Sentiment

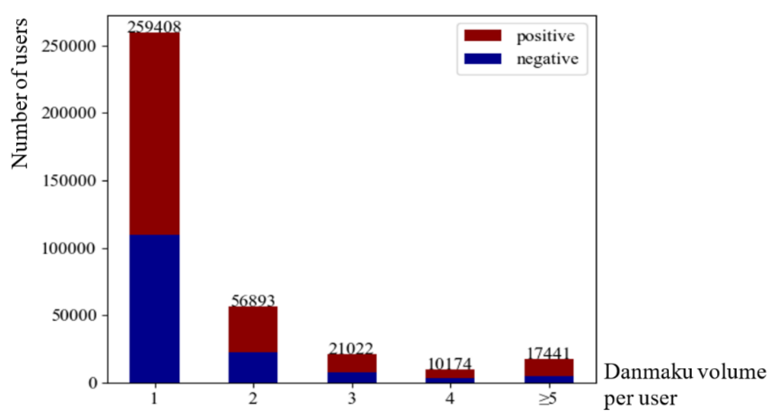


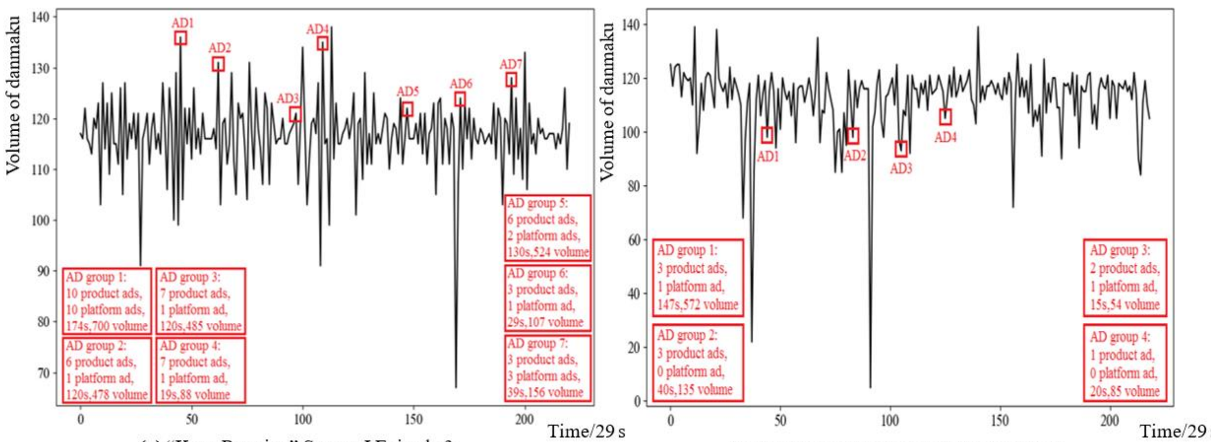
Figure 4: Danmaku Volume – User with Two Dimensions of Sentiment

According to the sentiment analysis results, the seven dimensions of sentiment danmaku can be divided into positive and negative sentiment polarities. Figure 4 shows a bar diagram with two sentiment dimensions describing the distribution of DV per user, which further estimates the sentiment polarity of users when posting danmaku comments. Users who posted only one danmaku comment account for 71.1% of the total comments. In addition, 15.6% are users who posted two danmaku comments and 13.3% are those who posted three or more danmaku comments.

While watching a variety of entertainment programs, users are more willing to post positive danmaku comments than negative ones. Over a short viewing time span, users are more likely to post 1–2 danmaku comments.

5.2 Correlation between Video Advertisement and Danmaku

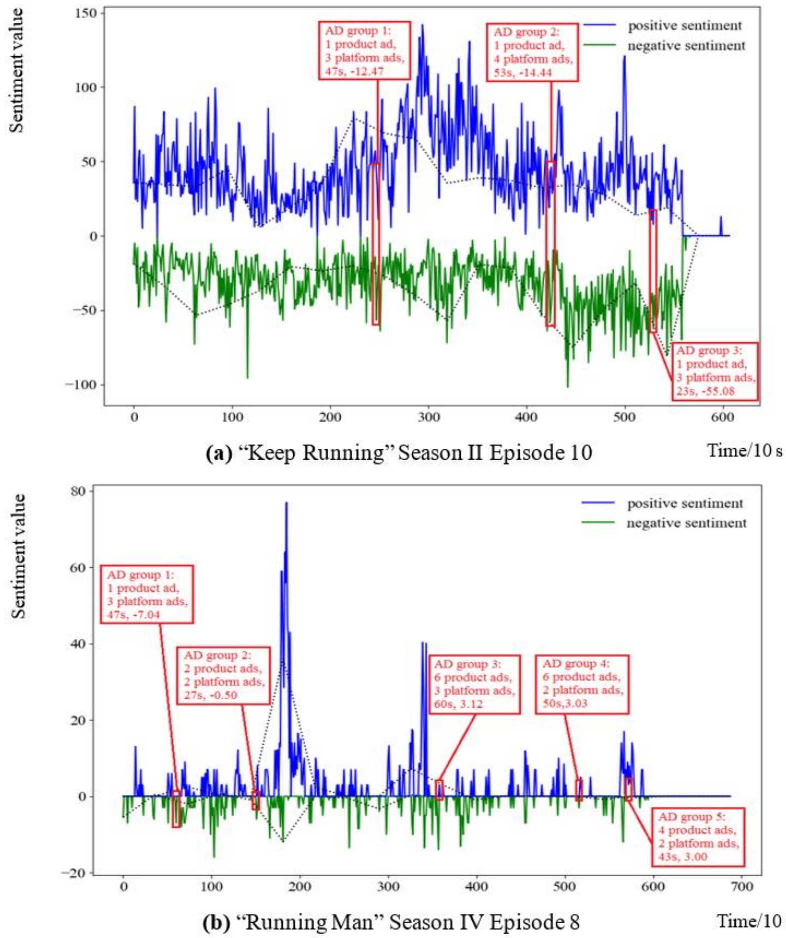
To explore a possible connection between danmaku and video advertising insertion strategy, we evaluated the variation trend in the distribution of DV with regard to playback time, where the insertion locations of the video advertisements are marked. Figure 5 (a) and (b) show the experimental results, in which the peak-valley intervals appear, forming pulse graphs. The bold line represents the barrage every 29s, and the red box shows the inserted AD groups. The AD groups are on the crests (Figure 5 (a)) or troughs (Figure 5 (b)). Generally, the number of product advertisements is greater than the number of platform advertisements. Moreover, the longer an AD group exists in a particular period, the more danmaku comments users post. For instance, the ED of AD group 1 in Figure 5(a) is 174s, with 700 danmaku comments; and the ED of AD group 3 in Figure 5(b) is 15s, with 54 danmaku comments. This is because of their real-time nature, and danmaku comments and video advertisements are two types of moment-to-moment data in video consumption. Figure 5 (a) and (b) reflect the synchronicity between temporal variations in AD groups and user reactions (in the form of danmaku) to these variations.



(a) "Keep Running" Season I Episode 3 **(b)** "Keep Running" Season III Episode 9

Figure 5: Distribution of Danmaku Volume and Time with Advertisements

This type of synchronicity is also reflected in the correlation between the sentiment of danmaku comments and AD group variations at a moment-to-moment level. Figure 6 (a) and (b) show two-way positive and negative emotion line graphs representing the distributions of danmaku sentiments and inserted AD groups. When the inserted AD group corresponds to a negative composite sentiment value (see Figure 6 (a); for AD groups 1, 2, and 3, the sentiment values are -12.47, -14.44, and -55.08, respectively), the number of platform advertisements is greater than the number of product advertisements. However, for the AD groups with positive composite sentiment values (see Figure 6 (b); AD groups 3, 4, and 5 have sentiment values of 3.12, 3.03, and 3.00, respectively), product advertisements have an advantage in quantity. Figures 5 and 6 also indicate that the higher the correlation between inserted advertisements and danmaku comments, the more effective the advertisement is. As a stimulus, the insertion of advertisements impacts users' viewing experiences, which is reflected in DV and sentiment. Danmaku interactive advertisements improve the quality of users' experiences and guarantee the highest click-through rate.



(a) "Keep Running" Season II Episode 10

(b) "Running Man" Season IV Episode 8

Figure 6: Time Distribution of Two Polarity Sentiment of Danmaku with Advertisements

5.3 Regression Analysis

We use R software to analyze the influence of advertisement features on moment-to-moment user responses in two aspects: the effect of AD group features on danmaku volume and danmaku sentiment, which are expressed by regression Models 1 and 2, respectively. The ordinary least squares (OLS) method is used for the sample.

Model 1*: *Effect of AD group features on danmaku volume

To empirically capture the relationship between user moment-to-moment commenting behaviors and video advertisements, the following regression model is used to construct the influence of AD group features on DV:

$$DV = Constant + C_1 \cdot ED + C_2 \cdot NUMA + C_3 \cdot RTP + C_4 \cdot QR + C_5 \cdot NUMB + \lambda_1 \cdot VR + \lambda_2 \cdot NUMU + \lambda_3 \cdot BA.$$

Tables 3 and 4 show the correlation and regression results for Model 1, respectively. The results show that the F-statistic is significant, reflecting that Model 1 has been tested (F-statistic= 137.6, p-value < 2.8e-11). In addition, Model 1's overall degree of explanation is relatively good (R^2= 0.6841), indicating that the influence of AD group variables on danmaku volume can be roughly regarded as a multivariate linear trend. However, the *t* test of NUMA was not passed, indicating that NUMA has no significant influence on danmaku volume. In Model 1, key variables such as ED, RTP, QR, and NUMB are very significant, indicating that they matter for users' danmaku reaction. Analyzing the multicollinearity test based on the procedure applied by Li et al. (2006), there should be no multicollinearity problem if the variance inflation factor (VIF) is less than 10. Table 4 shows that VIF ranged from 1.638 to 4.521, indicating no multicollinearity issues in Model 1.

Table 3: Correlations of Model 1

	Danmaku volume (DV)	Exposure duration (ED)	Number of advertisements (NUMA)	Repeat times of platform advertisements (RTP)	Ratio of platform advertisements to product advertisements (QR)	Number of brands (NUMB)	Video ratings (VR)	Number of users (NUMU)	Brand awareness (BA)
Danmaku volume (DV)	1.000	0.793	0.531	0.408	0.092	0.070	0.236	0.478	0.173
Exposure duration (ED)	0.793	1.000	0.681	0.480	0.221	0.192	0.074	-0.055	0.229
Number of advertisements (NUMA)	0.531	0.681	1.000	0.676	0.011	0.580	0.127	0.088	0.190
Repeat times of platform advertisements (RTP)	0.408	0.480	0.676	1.000	0.473	0.223	0.098	0.041	0.157
Ratio of platform advertisements to product advertisements (QR)	0.092	0.221	0.011	0.473	1.000	-0.257	-0.101	0.008	0.115
Number of brands (NUMB)	0.070	0.192	0.580	0.223	-0.257	1.000	0.339	-0.028	0.166
Video ratings (VR)	0.236	0.074	0.127	0.098	-0.101	0.339	1.000	0.303	-0.018
Number of users (NUMU)	0.478	-0.055	0.088	0.041	0.008	-0.028	0.303	1.000	0.255
Advertisement brand awareness (BA)	0.173	0.229	0.190	0.157	0.115	0.166	-0.018	0.255	1.000

Table 4: Regression Results of Model 1

	Estimate	Std. Error	t value	Pr (>|t|)	VIF
Constant	0.108	0.014	5.927	0.000	
Exposure duration (ED)	0.548	0.066	10.638	0.000	2.329
Number of advertisements (NUMA)	-0.072	0.065	-1.119	0.264	4.521
Repeat times of platform advertisements (RTP)	0.192	0.059	3.685	0.000	3.307
Ratio of platform advertisements to product advertisements (QR)	-0.052	0.016	-4.538	0.000	1.915
Number of brands (NUMB)	-0.134	0.081	-2.923	0.000	1.876
Video ratings (VR)	0.138	0.085	2.089	0.027	1.638
Number of users (NUMU)	0.305	0.104	4.897	0.000	3.574
Brand awareness (BA)	0.092	0.078	1.335	0.139	2.187

Model summary of model 1: R^2= 0.6841; adjusted R^2= 0.6692; F-statistic= 137.6 for 8 and 251 DF; p-value < 2.8e-11, respectively.

Model 2: Effect of AD group features on danmaku sentiment

We also construct the effect of AD group features on danmaku sentiment and obtain the following regression model equation:

$$SSD = Constant + C_6 \cdot ED + C_7 \cdot NUMA + C_8 \cdot RTP + C_9 \cdot QR + C_{10} \cdot NUMB + \mu_1 \cdot VR + \mu_2 \cdot NUMU + \mu_3 \cdot BA.$$

Tables 5 and 6 present the correlation and regression results, respectively. The results indicate that Model 2 passed the test (F-statistic= 36.5, p-value < 1.9e-8), with a total variance of 59.22%. Namely, SDD is significantly influenced by AD group features. According to the results, inserted advertisements can affect users' emotions during the viewing process. To capture the moment-to-moment reaction of users to inserted advertisements, users' instant emotions can be expressed by danmaku sentiments. Table 6 shows that all VIFs in Model 2 are less than the threshold value of 10 (Li et al., 2006). Hence, multicollinearity is not present in our formative scale.

Table 5: Correlations of Model 2

	Sentiment value difference of danmaku (SDD)	Exposure duration (ED)	Number of advertisements (NUMA)	Repeat times of platform advertisements (RTP)	Ratio of platform advertisements to product advertisements (QR)	Number of brands (NUMB)	Video ratings (VR)	Number of users (NUMU)	Brand awareness (BA)
Sentiment value difference of danmaku (SDD)	1.000	-0.251	-0.273	-0.270	-0.439	0.087	0.248	-0.031	0.138
Exposure duration (ED)	-0.251	1.000	0.681	0.480	0.221	0.192	0.023	0.098	0.242
Number of advertisements (NUMA)	-0.273	0.481	1.000	0.676	0.011	0.580	-0.018	0.027	0.009
Repeat times of platform advertisements (RTP)	-0.270	0.480	0.476	1.000	0.473	0.223	0.086	0.101	0.117
Ratio of platform advertisements to product advertisements (QR)	-0.439	0.221	0.011	0.473	1.000	-0.257	0.132	-0.065	0.306
Number of brands (NUMB)	0.087	0.192	0.380	0.223	-0.257	1.000	0.066	0.122	0.411
Video ratings (VR)	0.248	0.023	-0.018	0.086	0.132	0.066	1.000	0.298	-0.037
Number of users (NUMU)	-0.031	0.098	0.027	0.101	-0.065	0.122	0.298	1.000	0.172
Brand awareness (BA)	0.138	0.242	0.009	0.117	0.306	0.411	-0.037	0.172	1.000

Table 6: Regression Results of Model 2

	Estimate	Std. Error	t value	Pr(>|t|)	VIF
Constant	0.331	0.064	12.557	0.000	
Exposure duration (ED)	0.153	0.037	3.289	0.000	2.329
Number of advertisements (NUMA)	-0.562	0.137	-5.332	0.000	4.946
Repeat times of platform advertisements (RTP)	0.268	0.092	4.528	0.000	3.697
Ratio of platform advertisements to product advertisements (QR)	-0.133	0.044	-6.596	0.000	1.907
Number of brands (NUMB)	0.266	0.060	4.525	0.000	1.871
Video ratings (VR)	0.088	0.057	1.267	0.143	1.378
Number of users (NUMU)	0.144	0.062	2.357	0.022	2.468
Brand awareness (BA)	-0.026	0.013	-1.041	0.207	1.493

Model summary of Model 2: R^2= 0.5922; adjusted R^2= 0.5431; F-statistic= 36.5 for 8 and 251 DF; p-value < 1.9e-8, respectively.

The relationship between the three possible confounding factors VR, MUMU, and BA on the dependent variables of Models 1 and 2 is also analyzed. In Model 1, the results indicate that VR (coeff. = 0.138, t = 2.089, p = 0.027) and NUMU (coeff. = 0.305, t = 4.897, p = 0.000) have a significant positive effect on danmaku volume (DV), whereas BA (coeff. = 0.092, t = 1.335, p = 0.139) does not significantly affect DV. In Model 2, the findings show that NUMU (coeff. = 0.144, t = 2.357, p = 0.022) has a positive effect on SDD, whereas VR and BA have no significant effect on SDD. Furthermore, the confounding factors VR, MUMU, and BA are included in Models 1 and 2 to examine the effect of advertisement variables on DV and SDD.

In summary, ED has a positive impact on DV (coeff. =0.548) and SDD (coeff. =0.153). The results indicate that, as advertisement time increases, users become bored and tend to post danmaku comments to communicate with others. As the volume of danmaku increases, the expression of danmaku sentiment becomes mostly negative, and users' emotions hardly change. Thus, H1 is supported. In addition, NUMA is not significant in Model 1, which means that users' danmaku responses are insensitive to NUMA in the AD group. However, the regression results of Model 2 show that SDD is negatively influenced by NUMA (coeff. = -0.562, t = -5.332, p = 0.000). This means that NUMA causes a slight fluctuation in individual emotions, but this effect does not change the user's behavior of posting danmaku comments. In fact, while watching videos, diversified advertisement information makes users empathize with advertisements (e.g., evoking memories), which has as no significant impact on danmaku posting behavior. Therefore, H2 is partially supported.

RTP and QR directly influence users' danmaku behavior in both Models 1 and 2, but the effect of RTP is positive (coeff. =0.192, 0.268) and the influence of QR is negative (coeff. = -0.052, -0.133). Currently, the rise in platform advertisements is popular in the video advertisement field. An increase in the proportion of platform advertisements affects the internal emotional state of users' acceptance of advertising stimuli and weakens danmaku behavioral responses in terms of danmaku volume and sentiment change. Thus, hypotheses H3 and H4 are supported. The coefficient of NUMB on DV is negative (coeff. = -0.134), whereas that on SDD is positive (coeff. = 0.266). Owing to the obvious increase in the number of brands, users receive more advertising information, which affects their internal sentiment state. Diversified advertising stimuli cause emotional fluctuations in users and further weaken danmaku posting behavior. Thus, H5 is supported.

Based on the empirical results, we examine dynamic advertising insertion strategies. This study suggests that appropriately increasing RTP enhances the level of danmaku interaction. At the same time, QR should not be too high, as this may reduce danmaku interaction. More importantly, the results indicate that increasing the proportion of platform advertisements improves advertisement delivery effectiveness. Advertisements can be inserted during periods when users post many danmaku comments or when their emotions fluctuate greatly. In these periods, the AD group's ED, RTP, and NUMB can be increased to promote advertisement effectiveness.

6. Conclusion and Discussion

6.1 Main Findings and Contributions

This study adopts a hybrid approach that combines the sentiment dictionary and naïve Bayes algorithm. Based on the results of sentiment analysis, the study further investigates users' emotional responses to online video advertisements. Specifically, it aims to capture user engagement during the online content consumption process and empirically examine how advertising insertion strategies affect user sentiment changes. Our findings indicate that RTP and ED of an AD group are positive critical influencing factors for both DV and user sentiment. Among advertisement features, NUMA has a negative impact on user sentiment but has no significant impact on DV. NUMB has a negative impact on DV but a positive impact on user sentiment.

The study contributes to the existing research in three ways. First, it elucidates the underlying mechanism and characteristic variables of users' danmaku behavior toward advertisements in online video platforms. As the main marketing tool of social commerce, danmaku-responded advertisement in online video platforms are extremely pervasive. However, compared to fruitful findings on TV, websites, and mobile phones, research on danmaku-responded advertisement in online video platforms is relatively rare (Wei et al., 2020). The study provides insights on danmaku-responded advertisement in online video platforms, thus enriching understanding in the advertising field. Second, existing research recognizes that video advertisements should be more personalized and targeted. They mostly consider static information such as personal characteristics (age, gender, and preferences), while ignoring individual communication, where advertisers can iterate messages based on user behavior and needs. Our study focuses on users' danmaku behavior, which is a new important way to reach target users. Based on this, we propose a dynamic advertising insertion strategy to achieve more precise targeting. Third, although some studies have investigated the effectiveness of video advertisements (Cooper et al., 2016; Teona et al., 2020), few examine the users' instantaneous reactions when they are exposed to these advertisements (Yang et al., 2017; Joa, 2018). We consider both users' danmaku behavior and sentiment change as factors in the users' real-time response to the advertisements, study the impact of video advertisement features on users' danmaku responses, and then systematically evaluate the effectiveness of dynamic advertising insertion strategies.

6.2 Managerial Implications

The results of this study provide some management insights for the online video advertising industry. For video platforms, it is a great challenge to balance the interests of advertisers and user experiences. Therefore, video platforms should not only select advertising insertion strategies according to the characteristics of advertisements, but also dynamically adjust strategies with users' real-time reactions when they watch videos. In addition, as the response of users to advertising insertion strategy presents a double-dimensional performance of danmaku sentiment and posting behavior, video platforms should consider advertisers' delivery demands (such as arousing users' emotional resonance or increasing the interactive behavior) and reasonably place advertisements. For advertisers, high-intensity advertisement exposure does not always maximize the effectiveness of advertisement campaign. This is because users who are constantly interrupted by advertainments while watching videos will not have an exposure effect. In contrast, repeated advertisement stimulation will degrade users' viewing experience, causing them to develop negative attitude and boredom. Therefore, advertisers should adjust the information characteristics of advertisements, such as the exposure duration and number of advertisements, in a timely manner according to users' reactions so as to reasonably control investment costs and maximize advertising effects.

6.3 Limitations and Future Research Directions

Although our results are consistent with practical evidence, there are several limitations and opportunities for future research. In terms of data sources, this study only targets one video platform in China, the Tencent video platform, and the empirical results may not be applicable to every online video platform. As users have a variety of emotional and behavioral preferences for different video platforms, advertising insertion strategies need to vary depending on the user and the video platform. In the future, it will be necessary to study and compare the advertising insertion strategies of multiple platforms, such as iQIYI and Youku. As mentioned earlier, regarding the theoretical framework, we mainly considered the main impact of the characteristic of advertisement groups on users' danmaku behavior and sentiment change. However, the findings do not address the interference resulting from video program quality and plot. Therefore, future research could consider the interactive effects of video plot clips and advertisement features on users' danmaku behavior.

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REFERENCES

Al-Subhi, A. S. (2022). Metadiscourse in online advertising: Exploring linguistic and visual meta discourse in social media advertisements. *Journal of Pragmatics, 187*, 24-40.

Arantes, M., Figueiredo, F., Almeida, J. M., & Prates, R. O. (2018). An investigation of user actions and experiences when exposed to YouTube video ads. In *Proceedings of the 24th Brazilian symposium on multimedia and the web* (pp. 283-290).

Belanche, D., Flavián, C., & Pérez-Rueda, A. (2020). Consumer empowerment in interactive advertising and eWOM consequences: The PITRE model. *Journal of Marketing Communications, 26*(1), 1-20.

Bellman, S., Nenycz-Thiel, M., Kennedy, R., Larguinat, L. , McColl, B., & Varan, D. (2017). What makes a television commercial sell? Using biometrics to identify successful ads. *Journal of Advertising Research, 56*(4), 53-66.

Bellman, S., Potter, R. F., Robinson, J. A., & Varan, D. (2021). The effectiveness of various video ad-choice formats. *Journal of Marketing Communications, 27*(6), 631-650.

Bendak, S., & Al-Saleh, K., (2010). The role of roadside advertising signs in distracting drivers. *International Journal of Industrial Ergonomics, 40*(3)*,* 233-236.

Bigne, E., Chatzipanagiotou K., & Ruiz, C. (2020). Pictorial content, sequence of conflicting online reviews and consumer decision-making: The stimulus-organism-response model revisited. *Journal of Business Research, 115,* 403-416.

Boerman, S.C., Kruikemeier, S., & Borgesius, F. J.Z. (2017). Online behavioral advertising: A literature review and research agenda. *Journal of Advertising, 46*(3), 363-376.

Bruce, N I., Becker, M., & Reinartz, W. (2020). Communicating brands in television advertising. *Journal of Marketing Research, 57*(2)*,* 236-256.

Chang, S. H., Chih, W. H., Liou, D. K., & Wang, L.R. (2014). The influence of web aesthetics on customers' PAD. *Computers in Human Behavior, 36,* 168-178.

Cambra-Fierro, J., Melero, I., & Sese, F. J. (2017). Online customer-initiated contacts and the development of profitable relationships. *Electronic Commerce Research and Applications, 26,* 13-22.

Costa, M., Bonetti, L., Vignali, V., Bichicchi, A., Lantieri, C., & Simone, A. (2019). Driver's visual attention to different categories of roadside advertising signs. *Applied Ergonomics, 78,* 127-136.

Cooper, C. P., Gelb, C. A., & Chu, J. (2016). Gynecologic cancer information on YouTube: Will women watch advertisements to learn more? *Journal of Cancer Education*, *31*(3), 602-604.

Edlira, S., Bijmolt, T.H.A., & Clement, M. (2016). Effects of likeability dynamics on consumers' intention to share online video advertisements. *Journal of Interactive Marketing, 35,* 27-43.

Elsen, M., Pieters, R, & Wedel, M. (2016). Thin slice impressions: How advertising evaluation depends on exposure duration. *Journal of Marketing Research, 53*(4), 563-579.

Eppler, M. J. (2006). *Managing information quality: Increasing the value of information in knowledge-intensive products and processes.* Springer Science & Business Media.

Eun, L., & Chan, P. (2015). Does advertising exposure prior to customer satisfaction survey enhance customer satisfaction ratings. *Marketing Letters, 26*(4), 513-523.

Frade, J. L. H., Oliveira, J. H. C., & Giraldi, J. M. E. (2021). Advertising in streaming video: An integrative literature review and research agenda. *Telecommunications Policy, 45*(9), 102186.

Hernández-Méndez, J., & Muñoz-Leiva, F. (2015). What type of online advertising is most effective for eTourism 2.0? An eye tracking study based on the characteristics of tourists. *Computer of Human Behavior, 50*, 618-625.

Huang, L.T. (2016). Flow and social capital theory in online impulse buying. *Journal of Business Research, 69*(6),

2277-2283.
Islam, J., & Rahman, Z. (2017). The impact of online brand community characteristics on customer engagement: An application of stimulus-organism-response paradigm. *Telematics and Informatics, 34*(4), 96-109.
Joa, C. Y., Kim, K., & Ha, L. (2018). What makes people watch online in-stream video advertisements? *Journal of Interactive Advertising*, *18*(1), 1-14.
Kamboj, S., Sarmah, B., Gupta, S., & Dwivedi, Y. (2018). Examining branding co-creation in brand communities on social media: Applying the paradigm of stimulus-srganism-response. *International Journal of Information Management, 39,*169-185.
Kim, E., & Lee, C. (2015). How do consumers process online hotel reviews? The effects of eWOM consensus and sequence. *Journal of Hospitality and Tourism Technology*, *6*(2),113-126.
Kim, M. J., Lee, C-K., & Jung, T. (2018). Exploring consumer behavior in virtual reality tourism using an extended stimulus-organism-response model. *Journal of Travel Research, 59*(1), 69-89.
Knoll, J. (2016). Advertising in social media: A review of empirical evidence. *International Journal of Advertising*, *35*(2), 266-300.
Kumar, S, Tan, Y.L., & Wei, L. (2020). When to play your advertisement? Optimal insertion policy of behavioral advertisement. *Information Systems Research, 9,* 1-18.
Lazaroiu, G. (2019). The attention economy of docial media: Networked publics, the performance of self, and digital leisure. *International Conference on Economic Sciences and Business Administration, 5*(1)*,* 95-101.
Li, D., Browne, G.J., & Wetherbe, J.C. (2006). Why do internet users stick with a specific web site? A relationship perspective. *International Journal of Electronic Commerce*, *10*(4), 105-141.
Li, H., & Lo, H. Y. (2015). Do you recognize its brand? The effectiveness of online in-stream video advertisements. *Journal of Advertising*, *44*(3), 208-218.
Li, W., & Yuan, Y. (2018). Purchase experience and involvement for risk perception in online group buying. *Nankai Business Review International, 9,* 587-607.
Li, Z., Li, R., & Jin, G. (2020). Sentiment analysis of danmaku videos based on naïve bayes and sentiment dictionary. *IEEE Access, 5*, 1-12.
Liu, H., Chu, H., Huang, Q., & Chen, X. (2016). Enhancing the flow experience of consumers in China through interpersonal interaction in social commerce. *Computers in Human Behavior, 58,* 306-314.
Lu, X., & Chen, Y. (2020). Situations matter: Understanding how individual browsing situation routines impacts online users' advertisement clicks behavior. *Journal of Electronic Commerce Research*, *21*(2), 113-129.
Luqman, A., Cao, X., Ali, A., Masood, A., & Yu, L. (2017). Empirical investigation of Facebook discontinues usage intentions based on SOR paradigm. *Computers in Human Behavior, 70*, 544-555.
McCoy, S., Everard, A., Galletta, D. F., & Moody, G.D. (2017). Here we go again! The impact of website ad repetition on recall, intrusiveness, attitudes, and site revisit intentions. *Information & Management,54*,14-24.
Meenakshi, H., & Ajeet, S. (2015). Attitude towards the brand: Does advertising exposure matter. *Journal of Management Research,15*(3)*,* 139-155.
Mehrabian, A., & Russell, J. A. (1974). *An approach to environmental psychology.* The MIT Press.
Meng, K. S., & Leung, L. (2021). Factors influencing TikTok engagement behaviors in China: An examination of gratifications sought, narcissism, and the big five personality traits. *Telecommunications Policy, 45*(7)*,* 102172.
Michel, W., & Pieters, R. (2015). The buffer effect: The role of color when advertising exposures are brief and blurred. *Marketing Science, 34*(1), 134-143.
Naous, D., & Legner, C. (2019). Understanding users' preferences for privacy and security features–A conjoint analysis of cloud storage services. *International conference on business information system* (pp. 352-365).
Peng, C., & Kim, Y. G. (2014). Application of the stimuli-organism-response (S-O-R) framework to online shopping behavior. *Journal of Internet Commerce, 13,* 159-176.
Peng, D., Tian, W., Zhu, M., Ren, Y.K., Lin, X.J., & Li, M. Z. (2020). TargetingVis: Visual exploration and analysis of targeted advertising data. *Journal of Visualization,23*(6), 1113-1127.
Pelsmacker, P.D., Nathalie D., & Verberckmoes S. (2019). How ad congruity and interactivity affect fantasy game. *Journal of Electronic Commerce Research*, *20*(1), 55-74.
Shon, M., Shin, J., Hwang, J., & Lee, D. (2021). Free contents vs. inconvenience costs: Two faces of online video advertising. *Telematics and Informatics*, *56,* 101476.
Simmonds, L., Bellman, S., Kennedy, R., Nenycz-Thiel, M., & Bogomolova, S. (2020). Moderating effects of prior brand usage on visual attention to video advertising and recall: An eye-tracking investigation. *Journal of Business Research, 111*, 241-248.
Sundar, S. S., & Limperos, A. M. (2013). Uses and grats 2.0: New gratifications for new media. *Journal of Broadcasting & Electronic Media, 57*(4), 504-525.

Sürücü, Ö., Öztürk, Y., Okumus, F., & Bilgihan, A. (2019). Brand awareness, image, physical quality and employee behavior as building blocks of customer-based brand equity: Consequences in the hotel context. *Journal of Hospitality and Tourism Management, 40*, 114-124.

Tangmanee, C. (2016). Fixation and recall of YouTube ad banners: An eye-tracking study. *International Journal of Electronic Commerce Studies*, *7*(1), 49-76.

Teona, G, Ko, E., & Kim, S.J. (2020). Environmental claims in online video advertising: Effects for fast-fashion and luxury brands. *International Journal of Advertising*, *39*(6), 858-887.

Vermeulen, I., Droog, E., & Burgers, C. (2019). Overlay ads in humorous online videos: It's a matter of timing. *International Journal of Advertising*, *38*(7), 1046-1066.

Wani, M. A., Agarwal, N., Jabin, S., & Hussain, S. Z. (2018). User emotion analysis in conflicting verses non-conflicting regions using online social networks. *Telematics and Informatics, 35,* 2326-2336.

Wang, G., Zhou, L., Li J., Ren, D.Y., & Zhang, J. (2018). An efficient method of content-targeted online video advertising. *Journal of Visual Communication and Image Representation, 50,* 40-48.

Wei, L., Sun T., & Liu, B. (2020). Exploring the effect of incorporating danmaku into advertising. *Journal of Interactive Advertising, 20*(1), 31-46.

Wu, Y. L., & Li, E. Y. (2018). Marketing mix, customer value and customer loyalty in social commerce. *Internet Research, 28*(1), 74-104.

Xi, D., Xu W., Chen, R., Zhou, Y., & Yang, Z. (2021). Sending or not? A multimodal framework for danmaku comment prediction. *Information Processing and Management, 58*(6)*,* 102687.

Xu, Q., & Sundar, S. S. (2016). Interactivity and memory: Information processing of interactive versus non-interactive content. *Computers in Human Behavior, 63*, 620-29.

Yin, D., Bond, S., & Zhang, H. (2014). Anxious or angry? Effects of discrete emotions on the perceived helpfulness of online reviews. *MIS Quarterly*, *38*(2), 539-560.

Zhang, H., Cao, X., Ho, J.K., & Chow, T.W. (2017). Object-level video advertising: An optimization framework. *IEEE Transactions on Industrial Informatics, 13*(2), 520-531.

Zhang, Q., Wang, W.B., & Chen, Y.X. (2020). Frontiers: In-consumption social listening with moment-to-moment unstructured data: The case of movie appreciation and live comments. *Marketing Science, 39*(2), 285-295.

Zhang, X.B., & Yuan, S-M. (2018). An eye tracking analysis for video advertising: Relationship between advertisement elements and effectiveness. *IEEE Access, 3,*10699-10707.

Zhang, Y-L, Guo, Q., Ni, J., & Liu, J-G. (2015). Memory effect of the online rating for movies. *Physica A: Statistical Mechanics and its Applications, 417,* 261-266.