Research on the Effect of Video Communication based on the Analysis of the Characteristics of the Bullet Screen - Take the "Eating and Broadcasting" Video as an Example

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ABSTRACT
This experiment takes the detailed possibility model as the theoretical research framework. It takes the video of the "food" section of Bilibili's bullet screen network as the research object. The researchers explore the factors that affect the playback volume of "eating and broadcasting" videos that are most closely related to the interaction of the barrage. The result of this experiment is to obtain and analyze the experimental data through data mining, sentiment analysis technology, and SPSS multiple linear regression analysis to explore the relationship between the number of likes, the number of retweets, the number of positive bullet screens, the number of negative bullet screens, and the number of author fans on the video playback volume. The effect mechanism and the adjustment effect of the video duration in this effect. Researchers explored the influencing factors of video playback by analyzing the sentiment of the bullet screen combined with video metadata. This discovery and discussion provide a reference for the research on enriching bullet screen videos. The higher the number of negative emotional bullet screens, the greater the amount of playback. The number has a driving effect on the playback volume. Analyzing the emotion of the bullet screen combined with the video metadata to explore the influencing factors of the video playback volume provides a reference for the research on enriching the bullet screen video.

Keywords
Exhaustive possibility model; eating and broadcasting; real-time comment analysis; negative preference; regression analysis

1. INTRODUCTION
With the emergence and development of real-time comment technology, real-time comment interaction, an emerging language form full of features in the new era, is applied to different types of videos. Not only "bilibili," which was initially known for its "real-time comment" videos, but also many well-known Chinese video sites such as iQiyi, Sohu, and Tencent have launched a live video comment function[1]. With the popularity of various emerging video sites, bullet screens have formed a youth subculture, reflecting young people's emotional needs and value demands [2]. Bullet screen video viewers can send their viewing experience and mood in the form of text, floating above the video to become a part of the video, reflecting significant participation and viewing pleasure.

Eat and broadcast was first born in 2014 in South Korea as a "food" program, which mainly attracted the attention of the audience by showing the audience their eating process and relying on the highly immersive "eating appearance"[3]. From the beginning, eat and broadcast video was only responsible for tasting food. Then it introduced the source of ingredients, food names, colors, tastes, and practices while eating. It further developed to eat more, eat more, and eat alternatively[4]. The video's author and the food Interaction are presented to the audience. This makes full use of the characteristics of video media and organically combines the audience's thinking, vision and hearing, giving the audience an enjoyable and satisfying psychological experience. The emergence of real-time video comments has undoubtedly injected new vitality into "Eating and Broadcasting." Viewers express their views, opinions, and ideas by watching "Eating and Broadcasting" videos and express themselves freely in real-time. At the same time, the author interacts with the food. The point of view appeal of 1 plus 1 is far more significant than two audience satisfaction. In order to better understand the influencing factors of the effect of "eating and broadcasting" real-time comment videos, This experiment takes the ELM (Elaboration Likelihood Model) as the theoretical framework. It takes the videos in the "Eat and Broadcast" section of the well-known domestic video bullet screen website "bilibili bullet screen network" as the research object.

2. REAL-TIME COMMENT RESEARCH FOR VIDEO
The bullet screen was originally a military term, referring specifically to densely packed bullets like a curtain when they attack a target—later applied to the media. Later, it is used on the medium. The first used the Danmu niconico video, the Chinese AcFun head-to-head promotion, and the subsequent Bilibili bullet screen network. Because it makes it instant, interactive, and entertaining, the user group has gained a strong identity while creating and generating real-time comments. Its information characteristics are summarized in four aspects: interactivity, visibility, entertainment, and usefulness. The traditional comments are independent of the player, and the topics are scattered, which cannot give the audience a feeling of real-time interaction. The bullet screen video can give the audience an illusion of real-time interaction when watching it. The bullet screens with different sending times appear at a particular moment in the video, and the content and themes of the comments are mostly the same to give the audience a kind of simultaneous comment and interactive feeling. Unlike general short text analysis, real-time interactivity and on-site linearity of real-time video comments allow the text analysis for real-time video comments to accurately capture the time distribution of users' interactive behavior and emotional

tendencies. Significant differences and dynamic tracking of user emotions have essential research value for users' behavioral impact and value application. Zheng uses the medium-granularity level of sentiment analysis technology to analyze the sentiment of real-time video comment comments and display it in multi-dimensional visualization[5]. Yu and Zhang explore the information participation degree of real-time comment users psychologically[6]. Ye and Zhao analyze the development of public opinion information by distinguishing the positive and negative emotions of the emotional tendencies of the real-time comment[7]. Through interviews, Rong Ting learned about users' continuous use behavior and motivation for real-time video comments[8]. Gao and Yang connected the real-time video comment information to the video recommendation algorithm, which improved the recommendation accuracy[9].

In conclusion, scholars have explored many research perspectives on the bullet screen. However, it does not consider the effect of the bullet screen user's bullet screen emotion on the video communication. It lacks the research on the mixed influencing factors of the bullet screen video metadata and the bullet screen emotion.

3. THEORETICAL BASIS AND MODEL ASSUMPTIONS

3.1 Theoretical basis

The exhaustive possibility model, proposed by scholars such as Petty, Cacioppo, and Schumann, is the most influential theoretical model in consumer information processing[10]. Suppose time does not allow or cannot understand the details of the information. In that case, the receiver of the information will tend to understand the information from the source of the information or other peripheral cues and rarely generate thoughts about the content of the information, which will reduce the possibility of a central approach, thus forming an edge path[11]. If the user generates enough trust through the main path, there is no need to use the edge paths to process information. This model can effectively explain the changes in different attitudes and behaviors of consumers and has been widely used in consumer behavior-related research[12]. From the perspective of information processing and adoption, bullet screen video playback also needs to rationally consider and compare the content and source characteristics of bullet screen videos according to personal motivation and ability[13] and choose the best information processing path. The detailed possibility model is more consistent with the research idea of this paper, so it is used as a theoretical reference when constructing the research model.

3.2 Model assumptions

Based on the exhaustive possibility model, the research summarizes the influencing factors that may affect the effect of video communication from two aspects: video information characteristics (center path) and video author characteristics (edge path). The viewers of "eat and broadcast" consider and scrutinize the video content to carefully evaluate it and make a rational choice mainly through the characteristics of the video information. Therefore, the central path includes.

- The number of video likes
- The number of retweets
- The number of positive emotional real-time comments
- The number of negative emotional real-time comments

The newly updated videos of the video author are often recommended to his fans. There is often an emotional bond between the fans and the video author. As the video author's conscious maintainer and passive recommender, "fan traffic" often unconditionally supports the author's video content. The cognitive needs and content thinking of videos are less than those of non-fan groups[14]. Therefore, the number of author followers is taken as the edge path. In addition, this study also considered the effect of video time as a moderator variable[15]. The research model framework in Figure 1 illustrates the indicators and moderator variables considered in the study of video views.

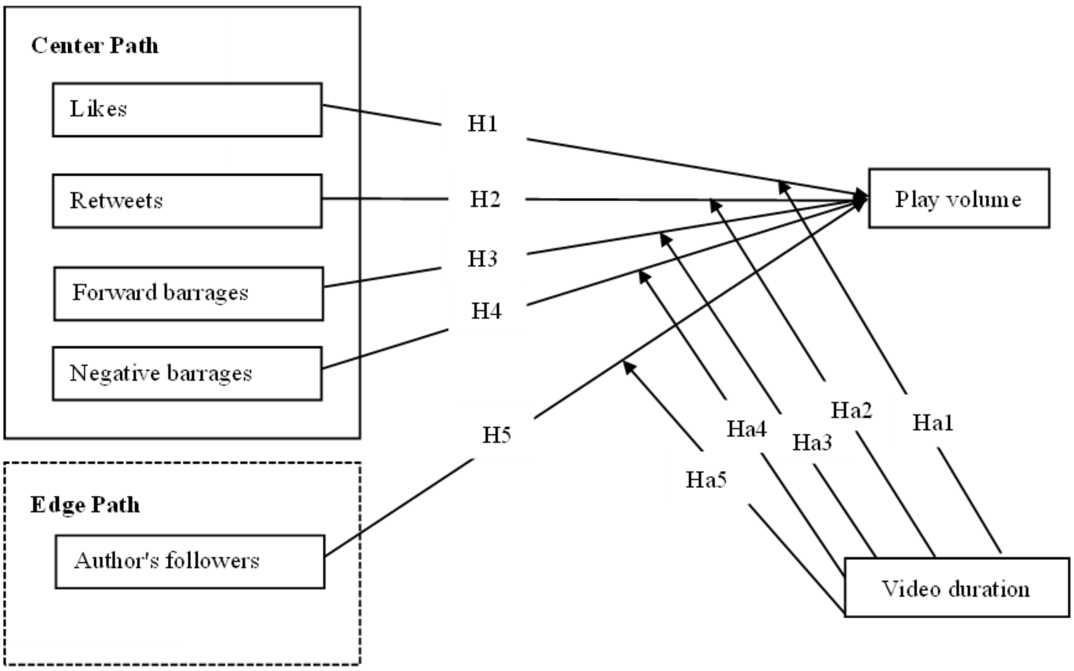

Figure 1 Theoretical research model

3.2.1 Center Path

The number of likes, reposts, and the emotional attitude of the bullet screen are closely related to the content of the bullet screen video. They are the quantitative evaluation indicators of the user's quality and value of the bullet screen video. To a certain extent, it represents the user's recognition of the bullet screen video content. 4 factors are reasonable as the central path that affects the playback of the bullet screen videos.

3.2.1.1 Video data information

Like is one of the ways to express one's attitude towards videos. In the media culture of information overload and polysemy of language symbols, multiple emotions are sometimes unable to be expressed in an appropriate language. It became an excellent way to fill the language gap and have a "silent" meaningful exchange[16]. Likes make up for the flood of information dissemination and the shortage of information processing and express a positive attitude towards high-quality content. Therefore, the number of likes provides a driving force for the number of video views.

Behind the implementation of the user's "forwarding" behavior, there is a set of psychological mechanisms for dissemination. This behavior is a behavior that transmits information and values[17].In essence, the user self-propagates the received video information about eating and broadcasting. The content of the video screen is used to satisfy the role of playing a dominant role. The generation of value recognition transforms the information into a higher-level value realization of the content in the self-propagation[18]. Forwarding is a more involved information dissemination behavior than likes and comments. People often actively forward and share information content because of self-strengthening, maintaining social relations, or altruism, which may form screen swipes and promote further in-depth use of information. Therefore, the number of video reposts is regarded as an informative feature of the main path, and it is proposed that it positively affects the playback volume.

H1: The number of real-time video comment comments significantly positively impacts the playback volume.

H2: The number of video reposts significantly positively impacts the playback volume.

3.2.1.2 User's emotional attitude

Bullet screen user interaction is more implicit in emotional expression, and the tendency of subjective emotional expression is relatively straightforward. Their emotional inclinations receive the "eating phase" stimulation of the bloggers, and their preferences for the food will affect the user's emotions to a certain extent[19]. According to modern psychological research, human beings have the natural pursuit of happiness and enjoyment. Some scholars believe that starting from theories such as emotional consistency, people are more willing to accept information that is consistent with their psychological expectations. Therefore, it is believed that the positive bullet screen positively affects the amount of video playback.

Roy Baumeister, an American psychologist, believes that bad things significantly impact people more than good things. This is a well-known psychological phenomenon called "Negativity bias" [20]. That is, people are more sensitive to negative information and events.

Compared with neutral comments, extreme and negative comments are more likely to arouse the individual's attention and interest because such information content is more likely to stimulate subsequent communication and behavior [21]. The author believes that the negative real-time comment in the video of eating and broadcasting will promote the amount of video playback.

H3: The number of positive real-time comments has a significant positive impact on the playback volume.

H4: The number of negative bullet screens significantly positively impacts playback volume.

3.2.2 Edge path

Compared with factors such as the number of main fans of UP, the author who made and uploaded the video, and the number of likes that characterize the content, users perceive it more intuitively. The level of information processing and level is higher. Low. The group of netizens assembled by eating and broadcasting is volatile. They will withdraw from the viewing area at any time that cannot meet their individual sensory needs and re-embed themselves in the new group they prefer in an accessible form. The online group is not a "live broadcast community" but a more emotional and ephemeral virtual tribe [22]. Therefore, the relevant characteristics of the content author are used as the edge path to explore how the number of fans and submissions of the video author affects the number of video views.

H5: The number of author followers significantly positively impacts the number of views.

3.2.3 Regulated variable

In ELM, the paths users choose are directly related to their motivations and abilities and are also affected by moderator variables. This study uses video time as a moderator variable.

The video length is the entire playback time from the beginning to the end of the video. When uploading the video to the content server, it is often saved on the server as metadata describing the video. According to research, when the video time is longer than 10 minutes, users will be more attracted to watch the entire video[23]. However, if the video is too long, it will bring more useless information. In today's fast-paced life and increasingly fragmented environment, most "eat and broadcast" viewers will not finish watching a video, a short video perhaps more attractive [24]. For users who communicate with each other for the second time, the longer the video, the easier it is to attract viewers.

Ha1: The video time negatively adjusts the impact of the number of video likes on the playback volume.

Ha2: Video time positively adjusts the effect of forwarding number on playback volume.

Ha3: The video time positively adjusts the impact of the number of positive real-time comments on the playback volume.

Ha4: The video time positively adjusts the influence of the number of negative real-time comments on the playback volume.

Ha5: The length of the video positively adjusts the influence of the author's number of followers on the playback volume.

4. DATA ACQUISITION AND PROCESSING

4.1 Data sources

Use python crawler to crawl the video data of the "food section" of the largest domestic bullet screen video website, "Bilibili video bullet screen network," and select the most popular eating and broadcasting videos from January 12th to January 19th. A total of 30 videos were collected, including video playback, likes, reposts, real-time video comment, video time, and author followers. Among them, there are a total of 89,337 bullet screens.

4.2 Real-time comment sentiment analysis

This research uses Baidu's open sentiment classification project Senta (Sentiment Classification) to judge the sentimental tendency of crawled real-time video comments. Senta is widely used in emotion polarity category classification, which can help enterprises understand users' consumption habits, analyze hot topics and monitor crisis public opinion, and provide powerful decision support for enterprises. The real-time comment acquisition and sentiment analysis process is shown in Figure 2.

4.2.1 The principle of the BiLSTM model

Because LSTM only considers the previous content, for example: "I like a cat," LSTM only considers the previous participle "I," which is not enough. The subsequent participle "cat" also has a significant meaning. The bi-directional LSTM is thus born. BiLSTM reads the text from the front and back simultaneously so that all the contextual information of the data at the current moment can be fully utilized.

BiLSTM (Bidirectional Long Short-Term Memory Network) is a combination of forwarding LSTM (Long Short-Term Memory) and backward LSTM. The two reverse LSTMs provide additional contextual information for the model. The forward LSTM hidden vector and the backward obtained hidden vector are spliced to obtain a new vector. The sentiment classification is performed on it in Figure 3.

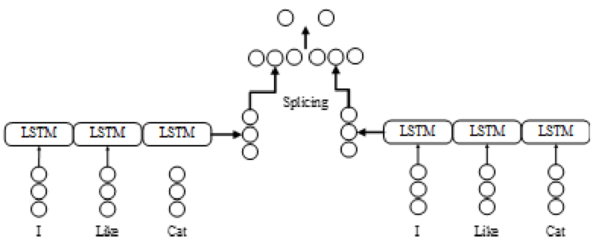

Figure 3 Schematic diagram of BiLSTM

4.2.2 BiLSTM model training

Use the BiLSTM model to train and predict 10,000 data sets that have been segmented. The first field of the training data is the sentimental tendency, which takes a value of 0 or 1, representing negative and positive emotional tendencies, respectively; the second field is the text Content. The test data is separated similarly but with some differences from the training data in terms of sentiment class labels. There are 200 test data, of which there are three types of emotional tendencies. The values are 0, 1, and 2, representing negative, neutral, and positive, respectively. The data set is shown in Table 1.

Table 1 Training and testing datasets

Dataset type	Positive (bar)	Negative (bar)	Neutral (bar)	Total (bar)
Training	4996	5004	0	10000
Test	49	31	120	200

5. DESIGN EXPERIMENT

5.1 Multiple regression analysis

After testing the collinearity and model fit of each independent variable in this model, the results show that the VIF values of all independent variables are all less than 5, there is no multicollinearity among the variables, and the fitting is good.

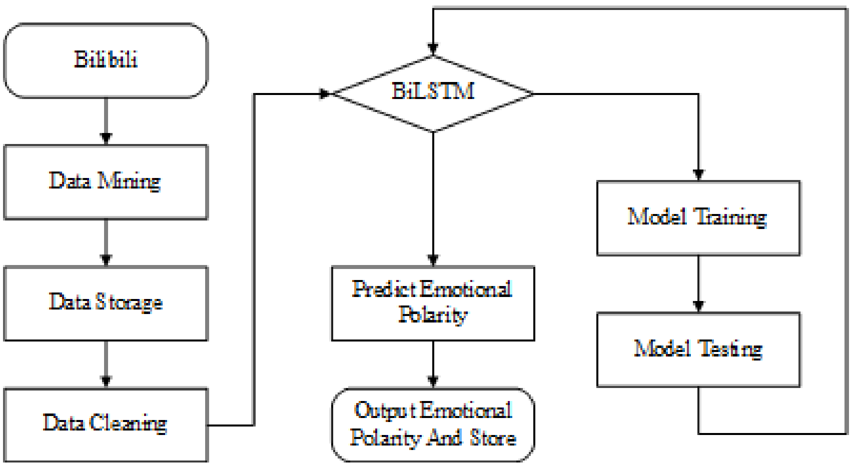

Figure 2 Flowchart of sentiment analysis of real-time comment

Table 2 Regression analysis results

	Beta	t	p	VIF	R^2	AdjustR^2	F
Constant	-	0.342	0.736	-			
Likes	0.732	10.167	0.000***	3.514			
Retweets	0.209	3.077	0.005***	3.113			
Positive real-time comments	0.018	0.277	0.784	2.967	0.965	0.957	F=130.64 P=1.3544498434920992e-16
Negative real-time comments	0.197	3.292	0.003***	2.415			
Followers	-0.129	-2.103	0.046**	2.567			
Dependent variable: total number of plays							

Remarks：***represents the 1% significance level、** represents the 5% significance level

According to the results of multiple regression analysis, it was found that the Beta values of the independent variables of the number of likes, shares, negative real-time comments, and author fans were 0.732 (p<0.01), 0.209 (p<0.01), and 0.197 (p<0.01), respectively. , -0.129 (p<0.05), the significance meets the requirements. It shows that the above four variables significantly impact the playback volume of eating and broadcasting videos. The normalization coefficient Beta value of the number of positive real-time comments is 0.018 (p>0.05). The sign does not meet the requirements, indicating that the number of positive real-time comments has no significant effect on the playback volume. That is, it is assumed that H1, H2, H4, and H5 are verified, and assumption H3 is not established.

5.2 Moderating effect analysis

Consider the video time as a moderating variable to participate in the number of likes, shares, positive real-time comments, negative real-time comments, and the number of author fans on the dependent variable video playback volume.

According to Table 3, it can be seen that the video time is significantly related to the interaction items of the number of likes, the number of retweets, and the number of negative bullet screens, which means that the number of likes, the number of retweets, and the number of negative bullet screens affect the total playback volume when the moderating variable (time) is at different levels, the influence magnitude is significantly different. The influence of the author's number of followers as an edge path on the total playback volume is not affected by different video times, assuming that Ha1, Ha2, and Ha4 are verified. The interaction between the number of likes, the number of retweets, the number of negative real-time comments, and the video time is plotted separately, and how the video time adjusts the influence of the interaction item is further explored.

Table 3 The variable relationship when the video time is used as the adjustment variable

	p	R^2	F
Likes*Time	0.0022***	0.023	11.5771
Retweets *Time	0.0000***	0.1131	23.8248
Positivereal-time comments* Time	0.3803	0.0236	0.7965
Negative real-time comments*Time	0.0434**	0.0768	4.5085
Followers *Time	0.432	0.0178	0.637
Dependent variable: total number of plays Moderator variable: video time			

** $p<0.05$ *** $p<0.01$

According to Figure 4, it is found that the interaction slope between the number of likes and the playback volume is positive no matter under the high video time or low video time. However, the slope of the high video time is slight, indicating that the longer video time will weaken the impact of the number of likes on the playback volume. Positive effect.

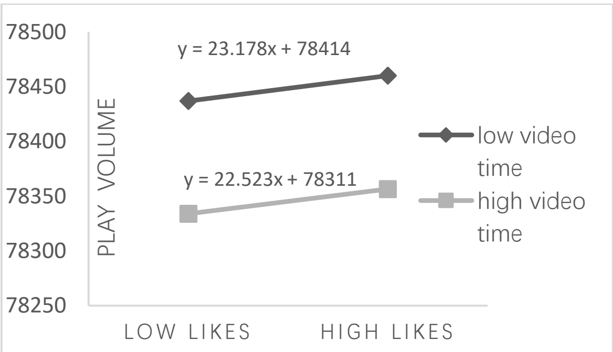

Figure 4 Like number map

According to Figure 5, it is found that the interaction slope of the number of negative bullet screens and the playback volume is positive regardless of the high video time or the low video time. However, the high video time slope is more prominent, indicating that a longer video time will promote the negative bullet screen.

Figure 5 Number of negative bullet screens

According to Figure 6, it is found that under low video time, the interaction slope of the number of retweets and playback volume is negative. In contrast, at high video time, the interaction slope of the number of forwarding and playback volume is positive. In the process of "forwarding" the secondary communication, longer videos are more likely to attract the attention of the secondary communication audience. A longer video time will promote the positive effect of the number of retweets on the playback volume.

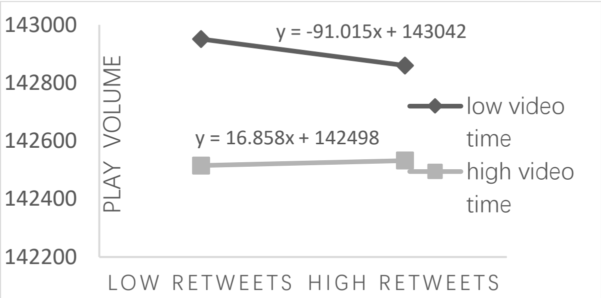

Figure 6 Forwarding number map

6. CONCLUSION AND DISCUSSION

6.1 Analysis conclusion

This study examines the influence of the number of likes, forwards, positive real-time comments, negative real-time comments, and author fans on the number of "eat broadcast" real-time comment videos and explores the influencing factors of the propagation effect of real-time comment videos. ; At the same time, it explores the influence and difference of the number of likes, reposts, and negative real-time comments on the communication effect when the video time is used as a moderating variable factor. According to the regression analysis results of the dependent variables of the center path and the edge path on the video playback volume of "eat and broadcast," the study found that the number of likes, the number of retweets, and the number of negative real-time comments as the center path all have a significant positive impact on the spread of the video. The author's number of followers as an edge path has a significant negative impact on the spread of the video. The video time is used as an adjustment variable. When the video time is too long, it will weaken the promotion effect of the number of likes on the playback volume. It will enhance the promotion effect of the number of retweets and negative real-time comments on the playback volume.

The results indicate the importance of the video length, engagement metrics (likes, retweets, and negative comments), and content creators' popularity in determining video playback volume. It suggests that for video creators on platforms like Bilibili, creating longer videos might lead to more engagement and retweets. They should also pay attention to the kind of feedback they receive, as even negative comments can increase viewership. However, overly positive feedback might not be as influential. This research can guide content creators in tailoring their videos to optimize engagement and reach on the platform.

6.2 Research discussion

The bullet screens, once a military term, has transformed how audiences interact with video content, offering a novel blend of real-time feedback and engagement. Unlike the conventional comment section, the bullet screen creates a dynamic atmosphere of interaction, mak ing viewers feel more involved with the content they're consuming.

While this research focused primarily on the "eating and broadcasting" genre on Bilibili, similar studies can be replicated for other genres and platforms. Investigating how bullet screen sentiments impact other genres might reveal distinct patterns of user engagement.

There's potential for more nuanced sentiment analysis that goes beyond just "positive" and "negative." Different emotional categories, like humor, sarcasm, or surprise, can be analyzed for a deeper understanding of how specific emotions relate to playback volume .

A deeper dive into the content of the "eating and broadcasting" videos could reveal correlations between specific types of food, presentation methods, or cultural nuances and audience engagement metrics.

A behavioral study could be conducted to understand why users are more driven to watch videos with higher negative bullet screen interactions. Are they driven by curiosity, schadenfreude, or a desire for balanced views?

In essence, the research has opened up avenues to explore the intricate dynamics of real-time commenting and its impact on video consumption. As platforms evolve and user behavior shifts, understanding these nuances will remain crucial for the creators, marketers, and platform developers alike .

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