A Comparative Analysis of the Impact of Barrage and Comments on Video Popularity

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ABSTRACT In recent years, watching online videos has gradually become an indispensable part of netizens' daily lives. Almost all video sites have added the barrage function. Both barrage and comments are two important ways for users to participate and play an important role in online video viewing. Based on the barrage and comments of videos uploaded by users of the bilibili website, our research explores the impact of barrage and comments with different emotional tendencies on video popularity and their differences, and explores the moderating effect of comments on the impact of the barrage. We also propose a method for calculating the emotional intensity of barrage that considers the herd effect and the emotional attenuation. The study finds that barrage has a positive impact on video popularity, while the emotional intensity of positive comments has a negative impact on video popularity, and comments play a negative role in the impact of the barrage. It explains that barrage and comments have their advantages and disadvantages. Our research has expanded the research in related fields such as user-generated content and video popularity, and the research conclusions have important management significance for video websites. In future research, we can further refine the emotional classification and consider the impact of video characteristics (video content and subtitles) on video popularity.

INDEX TERMS Barrage, comment, emotional intensity, video popularity.

I. INTRODUCTION

According to the 48th ''Statistical Report on China's Internet Development Status'' recently released by the China Internet Information Center (CNNIC), as of June 2021, the number of online video (including short video) users in China has reached 944million, an increase of 17.07 million from December 2020, accounting for 93.4% of the total netizens [1]. However, video users are often not satisfied with watching videos but pursue an active and social participation experience [2]. The most important thing in video user participation is the user's comments on the video and the barrage sent during the user's viewing process. Barrage, also known as ''bullet screen'', is a new, instantly updated interactive commenting system attached and synchronized with online videos. After being sent, it will appear from the right side of the video page and move to the left until it moves out of the video page. When the number of barrages is large, it is like bullets in a 2D shooting game [3].

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Online video comments focus more on the presentation and sharing of views on the content and plot of the video. Online video comments are less affected by prices and viewing costs, and therefore more objectively reflect users' true feelings, the interaction between users, and the expression and sharing of emotions. Video users also care more about the recognition and resonance of others rather than economic benefits.

Barrage is a special form of comment. Barrage is an instant comment overlaid on the top of a video that has appeared in recent years to express the user's evaluation or the emotional tendency of the video. Users use barrage mainly to obtain information, entertainment and seek social connections [4]. In recent years, the number of barrage users has grown rapidly. Nowadays, almost all domestic video websites support the barrage function. However, how to encourage users to participate through the barrage and promote users to watch, collect and even pay for videos is an important issue that video websites care about.

Barrage and comments, as the most important user-generated content of video websites, carry user feedback information on video resources. But there are obvious

differences between the two in many aspects. Among them, the difference in the emotion of the barrage and the comment may be the main reason for the difference in their influence. Business managers are paying more and more attention to the difference between barrage and comment. Based on this background, the core research question of this article is put forward: Do the characteristics of barrage and comments, especially emotions, have a significant impact on the popularity of online videos? As a new type of interactive mode, what is the difference between barrage and message board-style comments on the popularity of online videos? Is there an interaction? The popularity of the video can be judged by the user's barrage and comments, which allows the website administrator to accurately and quickly push the video with higher popularity to the users to obtain higher revenue. Therefore, it is of great significance to study the impact of barrage and comments on video popularity and their differences

II. RELATED RESEARCH

A. ONLINE COMMENT

Online comments refer to the evaluation and interactive content in the form of a text published by users on the Internet platform. Scholars have been more mature in the research of online comments, mainly on consumer purchasing decisions, business operations, and the perceived usefulness of online reviews. Duan W's research pointed out that the influence of online comments on consumer purchasing decisions is mainly reflected in the awareness effect and the recommendation effect [5]. Yan Qiang pointed out that the extremeness of comment emotion, comment depth, objectivity, and practical information characteristics will positively affect the perceived usefulness of online comments [6]. Regarding online videos, although scholars have done less research on online comments, comments reflect users' views on the details of the video's content, surroundings, and viewing experience. The number of comments and their emotions also affect the popularity of videos through word-of-mouth and other means.

B. BARRAGE

The popularization of network technology and new media will form a culture and even create a culture [7]. Barrage is a kind of instant online comment, originally originated from ACG culture (animation, comic, and game), and is a kind of subculture [8]. Barrage users communicate and spread their views and emotions in the form of sending barrages on video websites. Users use barrage mainly to obtain information, entertainment, and seek companionship [9]. Most users who are unwilling to use the barrage think that the barrage will obscure the video content and cause visual confusion [4].

Because barrage has only emerged in recent years, there are relatively few studies on barrage by domestic and foreign scholars. In the past, scholars' research on barrage focused on the culture of barrage [10], [11], the characteristics of barrage [12], the form of video dissemination of barrage [13], and the characteristics of barrage users [14]. From the

perspective of language characteristics, Li pointed out that the barrage has the characteristics of concise expression, mixed words, humorous language, and catering to the expression and social demands of young people [15]. From the perspective of barrage users' psychology, Fan explained the psychological appeals of companionship, identity, spoiler, and emotional venting from ''otaku'' to young users when using barrage [16]. Zhou *et al.* explored whether the degree of audience interaction in the live broadcast platform will promote their rewarding behavior. Research shows that the interaction between live broadcast viewers can significantly improve their arousal behavior [17].

As a new type of comment method, the barrage has become the object of text sentiment analysis research. Existing research mainly focuses on the sentiment analysis of barrage for user classification, video recommendation, and so on. Zheng *et al.* used the barrage data from the Bilibili website to analyze the sentiment of the sentence through the sentiment dictionary and finally visualized the emotion according to the experimental results to obtain the distribution curve of the barrage emotion [18]. Deng Yang *et al.* constructed a barrage classification algorithm based on the implicit Dirichlet distribution as a recommendation basis for video clips [19]. Hong Qing *et al.* used the user as a unit to classify the sentiment of the barrage by improving the K-means algorithm and used the classification results to analyze the emotional difference of the audience of a specific work [20].

At present, domestic and foreign scholars mostly use methods such as interviews, questionnaires, and descriptive statistical analysis for barrage research, and relatively few studies have conducted an empirical analysis based on a large amount of barrage data. Scholars' research on barrage users mostly focuses on the user's motives and other psychological characteristics, while there are relatively few studies on barrage users' participation behavior.

C. THE DIFFERENCE BETWEEN BARRAGE AND COMMENT

Barrage and comments are two important ways for users to participate in video sites. However, there are obvious differences between the two in terms of time, display order, content, language, etc. (as shown in Table 1) [21].

At present, there are little researches on the difference between barrage and comment. Existing research usually describes the similarities and differences between the two from the perspective of the basic characteristics of the origin of development when studying the barrage. Relying on the video itself, the barrage is presented based on the timeline of the video, and it carries two kinds of information: rating data and interactive feedback. It is a new way to understand the audience's acceptance of the video.

Shen *et al.* compared barrage with traditional video comments and showed that the core features of a barrage are real-time synchronization and user participation [22]. Ouyang Zhao pointed out that barrage is a more unique form of comment that is different from other online comments, and it is more sticky than other flat communication that does not have

TABLE 1. Barrage and online comment features.

	Barrage	Online comment
Time	Closely integrated with the video timeline, presented when the video is playing	Combined with historical time, presented after the end of the video
Presentation order	The order of arrangement is based on the order in which the barrage appears in the video; the barrage of the same period is presented at the same time	The sort order depends on the time when the comments are posted; comments in the same period cannot be presented at the same time
Content	Related to the content of the video at this time; colloquial, exaggerated, low information value	The overall evaluation of the video; the content is more in-depth and the reading value is high.
Publisher characteristics	The publisher is anonymous, and there are no opinion leaders	The publisher's name, rank, and other information are disclosed, and there are opinion leaders.
Atmosphere	Create a strong atmosphere of companionship, dialogue, and interaction	Accompanying atmosphere, dialogue atmosphere, and interactive atmosphere are weak
Language	Mainly based on text, emoticons, and symbols, you can change the font size, position, direction, color, etc.; self-contained system, there are many code words	Mainly written, the form of the text cannot be changed, and the form of expression is single
length	Short and powerful	More words

a fixed opinion leader [21]. Wu *et al.* compared barrage and online comments, obtained comments and barrage data from the bilibili website, and explored the differences between barrage and online comments from three aspects: user participation, language style, and shared knowledge [23].

All in all, barrage and comment have their advantages, and they also have shortcomings that need to be overcome and improved. The two have realized knowledge sharing in a complementary way. Differentiating different usage scenarios, understanding the different impacts of barrage and comments on users' perception, and comparative research on emotional differences are of academic and application significance.

D. VIDEO POPULARITY
Video popularity reflects the popularity of users watching videos, and the play volume is usually used as a basic measure of video popularity [24]. A large number of scholars have shown that the distribution of video popularity is a power-law distribution, that is, the initial stage of video broadcast will attract many users to watch, but as time goes by, the play volume will become less and less [25]. With the deepening of research, many scholars have begun to try to explore the influencing factors of video popularity. The more attractive the video content, the higher the popularity of the video; user-made videos are more popular than those made by professional video producers [26]. In addition, some scholars have explored the influence of the number of barrages and the emotional intensity of barrage on video popularity and explored the moderating role of video uploader characteristics (such as the number of fans and the number of videos) [27].

Scholars' research on video popularity mostly focuses on the distribution of video popularity, the prediction of video popularity, and the factors that affect video popularity. However, there are few related types of research on user participation. We explore the impact on video popularity and its differences from two dimensions: the number of barrage and comments and the emotional intensity. A calculation

method of the emotional intensity of barrage that considers the herd effect and emotional attenuation is proposed, which enriches the research of sentiment analysis in the field of the barrage. And further study the impact of different emotional tendencies of barrage and comments on video popularity.

III. RESEARCH HYPOTHESIS
A. THE IMPACT OF BARRAGE ON VIDEO POPULARITY
Now almost all video sites have the barrage function. During the viewing process, users can directly see the barrage written by other users, and it is easy to express their feelings through the barrage, which promotes user interaction and communication, and also makes users more likely to be influenced by other users. It is a typical manifestation of the herd effect [28]. For example, when the number of barrages is large, users will be attracted to watch the video, and when they see a large number of interesting barrages, they will easily trigger their barrage.

When a video has a large number of barrages, it may attract more users to watch, and the popularity of the video may be higher. On the one hand, most video websites now display the number of barrages next to the video, and users will use the number of barrages as a signal to measure the quality of the video. On the other hand, the more barrages, the more interactive and interesting the video will be. Therefore, users are more likely to play or replay the video, and the popularity of the video will be higher.

Barrage users usually express their emotions through the barrage, and a barrage with strong emotion tends to increase the popularity of the video. The Bilibili has set up a barrage pool on the right side of the video. Users can browse the barrage situation in it before deciding whether to watch the video. When users think that the emotions expressed by the barrage are stronger, they may be infected by these barrages and send barrage with similar emotional tendencies. They may also send barrages that are opposite to their previous emotional tendencies to show how they are different from other users. Therefore, barrage with strong

emotional tendencies will attract users to play videos for interaction with the barrage, so the popularity of the video will be higher.

Based on the above, we believe that the number of barrages and emotional intensity may have a strong correlation with the popularity of videos, so the following hypotheses are proposed:

H1a. The number of barrages has a significant positive impact on video popularity.

H1b. The emotional intensity of the barrage has a significant positive impact on video popularity.

B. THE IMPACT OF COMMENT ON VIDEO POPULARITY

Similar to the number of barrages, the number of comments may also affect the popularity of the video. The more comments there are, the more people watch the video. The more intense the discussion on the video by users, the higher the popularity of the video; In terms of comment emotion, the emotion of the comment represents the comprehensive evaluation of the video after the user watches the video. When the emotion of the comment is stronger, it may attract more people's interest in the video, thereby attracting more people to watch. Therefore, the following hypotheses are proposed:

H2a. The number of comments has a significant positive impact on video popularity.

H2b. Comment sentiment intensity has a significant positive impact on video popularity.

C. DIFFERENCES IN THE IMPACT OF BARRAGE AND COMMENTS ON VIDEO POPULARITY

Barrage and comments are two important ways for users to participate in video sites. Barrage is the discussion and emotional expression of a certain segment of the video while the user is watching the video. The emotional tendency of the barrage cannot express the user's emotional tendency towards the entire video. But the comments are the user's evaluation and feelings after watching the entire video and express the user's emotions about the entire video and the uploader. Therefore, there is a certain difference between the impact of barrage and comment on video popularity. However, they all have a certain degree of influence on the popularity of the video and affect the popularity of the video together. Based on the above, the following hypotheses are proposed:

H3a. The number of barrages has a higher impact on video popularity than the number of comments.

H3b. The emotional intensity of the barrage has a lower impact on video popularity than the emotional intensity of comments.

H4. Comments will negatively adjust the impact of barrage on video popularity.

H4a. The number of comments will negatively adjust the impact of the number of barrages on video popularity.

H4b. The emotional intensity of comments will negatively adjust the impact of the emotional intensity of the barrage on video popularity.

IV. DATA AND VARIABLES
A. SAMPLE SELECTION AND DATA SOURCES

Bilibili is a comprehensive video community with a high degree of aggregation for the young generation in China. Bilibili has built an ecosystem covering thousands of categories such as life, games, fashion, knowledge, music, etc. Users attract other users' attention by reposting videos and original videos. Our research uses the barrage and comment data of videos uploaded by users of the Bilibili website to analyze the impact and difference of the barrage and comments on video popularity.

In terms of user types, on the one hand, we selected individual users authenticated by the Bilibili website, and screened out users with high influence (such as corporate users, celebrity artists, official accounts, etc.); On the other hand, we choose the account category as life, which has a large number of users and rich video content.

We use crawler technology to crawl the basic information of individual users. We crawled 236 individual users whose account category is life and crawled the basic information of videos uploaded by individual users (3,180 in total), as well as barrage and comment data (4,358,490 barrages, 1,708,888 comments). (the website of the dataset: https://gitee.com/fusummer/bilibili_barrage_comment).

B. VARIABLE DEFINITIONS

The number of barrages: Refers to the number of effective barrages in each video. We process all the barrage of each video crawled, and the number of barrages obtained after removing empty content, invisible characters, garbled characters, etc.

The number of comments: Refers to the number of valid comments in each video, including comments, replies, reposts, etc. under the video. At the same time, after removing some empty content, invisible characters, and garbled characters in the comments, the number of valid video comments is finally obtained.

Video popularity: We use the play volume of the video on www.bilibili.com to measure the popularity of the video.

The emotional intensity of barrage: Refers to the average value of all barrage emotions in the video. We propose a method of calculating the emotional intensity of barrage that considers the herd effect and the sentiment attenuation model to calculate the emotional intensity of video barrage.

The emotional intensity of comment: Refers to the average of the sentiment of all comments in the video. We build a sentiment dictionary and used the method based on the sentiment dictionary to calculate the sentiment intensity of video comments.

V. BARRAGE EMOTIONAL INTENSITY CALCULATION METHOD CONSIDERING THE HERD EFFECT AND THE SENTIMENT ATTENUATION

In the video barrage, many users will follow the previous users to send barrage, forming a large number of repetitive and similar barrage in a short period, which is a typical

manifestation of the herd effect. This phenomenon will lead to an increase in the emotion of the barrage during this period. At the same time, the barrage has the time attribute. Since the barrage appears directly on the video content, the semantic and emotional information contained in the text will also be received by the user and then spread downward. Therefore, when analyzing the overall sentiment of the barrage text, not only the sentiment of the text itself must be analyzed, but also the impact of sentiment attenuation in the last period must be considered. Based on the above, we propose a method for calculating the emotional intensity of barrage that considers herding effect and sentiment attenuation.

A. BARRAGE EMOTIONAL DICTIONARY CONSTRUCTION

We segment the crawled barrage data, manually annotate the sentiment value, and collect barrage-related network terms, and finally merge Dalian University of Technology's emotional vocabulary ontology database and Chinese sentiment analysis vocabulary set to form a barrage sentiment dictionary as a follow-up Dictionary of Barrage Sentiment Analysis.

Based on the constructed barrage sentiment dictionary, we extract negative words, degree adverbs, sentiment words related to the calculation of sentiment orientation, and the calculation method of sentiment orientation of each barrage is as follows:

$$s = \Sigma O(w_i) = \Sigma (-1)^f \times d \times w_i \qquad (1)$$

where w_i is the weight of emotional words, and f is the number of times the negative word appears and d is the degree adverb weight.

B. EMOTIONAL VALUE CALCULATION CONSIDERING THE HERD EFFECT

There is a herd effect in the barrage. Many users will follow the previous users to send the barrage, forming a large number of repeated or similar barrage in a short period. This phenomenon will increase the emotion in this period. Based on the above, we analyze the barrage of each video one by one and identify sentences that are highly similar to each barrage within 30 seconds (the similarity is set to 75%), and the proportion of the number of similar sentences is used as an emotional bonus weight.

$$simS = \left(simNum \times s \times \left(\frac{simNum}{num} + 1 \right) \right) \qquad (2)$$

where simNum is the number of similar sentences in each barrage text, and num is the number of barrage within the 30s, and s is the emotional value of a single barrage.

C. EMOTIONAL VALUE CALCULATION CONSIDERING THE EMOTION ATTENUATION MODEL

When analyzing the overall sentiment of a video barrage, not only the sentiment of the text itself must be analyzed, but also the impact of sentiment attenuation in the last period should be considered. Taking 30s as the unit time, calculate the emotional intensity value of each unit time after the attenuation,

and finally, calculate the overall emotional intensity value of each video.

Based on the relationship between emotion attenuation and personality factors that have been generally recognized in social sciences [29], the audience emotion attenuation method proposed by Yin Yanjun *et al.* [30] is adopted, and the formula is as follows:

$$I(t) = \beta \times \exp \left(\frac{-p \times numSent}{P_E \times time} \right) \qquad (3)$$

where I(t) is the intensity of emotional attenuation per unit time, and β is the occasion modifier, and P is the mood regulator, and P_E is the degree of extroversion of a person's personality, and numSent is the number of barrages per unit time.

The emotional intensity per unit time after considering the emotional attenuation model is as follows:

$$ST(t+1) = ST(t) \times I(t) + \frac{\Sigma simS}{numSent} \qquad (4)$$

We analyze the emotion of the barrage based on the sentiment dictionary and calculate the emotional intensity of the barrage considering the herd effect and the sentiment attenuation.

VI. RESULTS
A. DESCRIPTION STATISTICS

Table 2 provides the definitions and descriptive statistics for the variables used in the regressions. From the perspective of quantity, the number of barrages is significantly higher than the number of comments. The easy-to-send, fewer words, and strong interaction of the barrage make the overall number of barrages more than comments. At the same time, whether barrage or comments, the number of non-emotional neutrals has the highest proportion. From the perspective of emotional intensity, the emotional intensity of comments is significantly higher than the emotional intensity of barrage. On the one hand, the length of the barrage is limited, and on the other hand, the barrage is more colloquial and irregular than comments.

B. CORRELATION ANALYSIS

Table 3 presents Pearson correlation coefficients between variables. There is a strong correlation between the number of barrages and comments, the emotional intensity of the barrage and comments, and the play volume. We use these four variables as independent variables and the play volume as the dependent variable for the regression model analysis.

C. REGRESSION ANALYSIS
1) THE IMPACT OF BARRAGE AND COMMENTS ON VIDEO POPULARITY

We first examine the impact of barrage and comments on the video popularity, using the number of barrages, the emotional intensity of barrage, the number of comments, and the emotional intensity of comments as independent variables, and

TABLE 2. Variable definition and descriptive statics.

	Variables	description	Mean	Std.Dev	Min	Max
	barNum	Number of barrages	4060.27	14112.44	9.00	287585
	barPosNum	Number of positive barrages	550.63	839.67	1.00	8834
barrage	barNegNum	Number of negative barrages	126.21	200.75	0.00	2109
	barNeuNum	Number of neutral barrages	652.96	847.77	2.00	5897
	barEmo	Emotional intensity of barrage	0.79	0.32	0.01	2.77
	barPosEmo	Emotional intensity of positive barrage	1.64	0.29	1.00	3.88
	barNegEmo	Emotional intensity of negative barrage	1.30	0.35	0	7
	comNum	Number of comments	1228.21	3641.04	6.00	108668
	comPosNum	Number of positive comments	217.32	318.06	1.00	4673
	comNegNum	Number of negative comments	69.50	147.01	0	3318
comments	comNeuNum	Number of neutral comments	230.42	362.58	0	5232
	comEmo	Emotional intensity of comments	1.46	0.73	0.25	7.19
	comPosEmo	Emotional intensity of positive comments	2.56	0.94	1.00	9.99
	comNegEmo	Emotional intensity of negative comments	2.18	1.29	0.00	11.5
Play volume	pv	Play volume	537655.30	1142579.16	1099.00	19587223

TABLE 3. Pearson correlations between variables.

		1	2	3	4	5
1	barNum	1				
2	barEmo	0.376832	1			
3	comNum	0.689928	0.215851	1		
4	comEmo	0.406745	0.373069	0.369597	1	
5	pv	0.68127	0.339527	0.636556	0.395656	1

TABLE 4. Regression model results.

Model	Regression coefficients	Standardization coefficients (β)	t	Significance(p)
constant	214764.744		2.928	.003
barNum	41.468	.399	24.676	.000
barEmo	46448.607	.024	2.007	.045
comNum	184.819	.392	24.254	.000
comEmo	-39519.500	-.084	-6.564	.000

the video play volume as the dependent variable for linear regression analysis.

Table 4 presents the results of the regression analysis. In terms of play volume, the significance of the number of barrages, the emotional intensity of barrage, the number of comments, and the emotional intensity of comments are all less than 0.05, and the regression coefficient values of the number of barrages, the emotional intensity of barrage, and the number of comments are all positive. It shows that they all have a positive impact on the play volume. But the regression coefficient of the emotional intensity of comments is negative, indicating that it has a negative impact on the play volume.

In terms of the barrage, the number of barrages has a significant positive impact on the amount of video playback ($\beta = 0.399$, p < 0.05). The number of barrages will positively affect the popularity of the video, that is, the more barrage in a video, the more popular the video will be. The emotional

intensity of the barrage has a significant positive impact on the video play volume ($\beta = 0.024$, p < 0.05). The emotional intensity of the barrage will have a positive impact on the popularity of the video. The stronger the emotion of the barrage in the video, the higher the popularity of the video. Thus, H1 is supported.

In terms of comments, the number of comments has a significant positive impact on the amount of video playback ($\beta = 0.392$, p < 0.05). The number of comments will positively affect the popularity of the video, that is, the more comments in a video, the more popular the video will be. The emotional intensity of the comments has a significant negative impact on the amount of video playback ($\beta = -0.084$, p < 0.05). The emotional intensity of the comments will have a negative impact on the popularity of the video. The stronger the emotion of the comments in the video, the lower the popularity of the video. Thus, H2a is supported, but H2b is not supported.

TABLE 5. Stepwise regression model results.

Model	Regression coefficients	Standardization coefficients (β)	t	Significance(p)
constant	-81899.655		-1.079	0.281
barPosNum	84.392	0.075	3.647	0.000
barNegNum	1421.171	0.300	14.147	0.000
comNegNum	-750.547	-0.116	-4.759	0.000
comNeuNum	1306.255	0.498	19.495	0.000
barPosEmo	143779.638	0.045	3.191	0.001
comPosEmo	-48100.237	-0.047	-3.499	0.000

TABLE 6. Regression model results.

Model	Regression coefficients	Standardization coefficients(β)	t	Significance(p)
constant	254432.441		3.330	.001
barNum	59.463	.551	23.038	.000
barEmo	-49732.112	-.024	-1.913	.056
barNum*comNum	-.004	-.261	-8.747	.000
barEmo*comNum	76.481	.501	25.032	.000

TABLE 7. Regression model results.

Model	Regression coefficients	Standardization coefficients(β)	t	Significance(p)
constant	136929.020		1.594	.111
barNum	88.229	.818	16.339	.000
barEmo	64248.565	.031	2.024	.043
barNum*comEmo	-4.225	-.194	-3.842	.000
barEmo*comEmo	-3651.918	-.035	-2.123	.034

The number of barrages has a higher impact on video popularity than the number of comments (0.399 > 0.392), but the emotional intensity of barrage has a lower impact on video popularity than the emotional intensity of comments (0.084 > 0.024). It shows that barrage and comments have their advantages and disadvantages. Thus, H3 is supported.

In summary, in terms of quantity, the number of barrages and comments have a clear positive correlation with the popularity of the video, and the number of barrages has a greater impact. In terms of emotion, the emotional intensity of the barrages is positively correlated with the popularity of the video, while the emotional intensity of the comments is negatively correlated with the popularity of the video.

2) THE IMPACT OF BARRAGE AND COMMENTS WITH DIFFERENT EMOTIONAL TENDENCIES ON VIDEO POPULARITY

We further examine the impact of video barrage and comments with different emotional orientations on video popularity. We perform a stepwise regression analysis on the variables.

Table 5 presents the stepwise regression optimal model, including the number of positive barrages, the number of negative barrages, the number of negative comments, the number of neutral comments, the emotional intensity of positive barrage, and the emotional intensity of positive comments.

In terms of quantity, the number of positive barrages, the number of negative barrages, and the number of neutral comments all have a significant positive impact on video play volume, of which the number of neutral comments has the most significant impact (0.498 > 0.300 > 0.075), but the number of negative comments has a negative impact on video play volume($\beta = -0.116$).

In terms of emotional intensity, the emotional intensity of positive barrage has a significant positive impact on the play volume($\beta = 0.045$), while the emotional intensity of positive comments has a negative impact on the play volume($\beta = -0.047$).

In summary, barrage plays a greater role in the video play volume. This is because barrage is more entertaining and social to a large extent, and users have a sense of companionship.

3) THE MODERATING EFFECT OF COMMENTS IN THE IMPACT OF BARRAGE ON VIDEO POPULARITY

We further examined the moderating effect of the number of comments and the emotional intensity of comments on the impact of barrage on video popularity.

Table 6 presents the results of the regression model after adding two adjustment items: barNum*comNum and barEmo*comNum. The number of comments will negatively adjust the impact of the number of barrages on the popularity of the video ($\beta = -0.261$, p < 0.05). It shows that with the increase in the number of video comments, the positive impact of the number of barrages on the popularity of the video will be weakened. H4a is supported.

Table 7 presents the results of the regression model after adding two adjustment items: barNum*comEmo and barEmo*comEmo. The emotional intensity of comments will negatively adjust the impact of the emotional intensity of the barrage on the popularity of the video ($\beta = -0.035$, $p < 0.05$). It shows that with the increase in the emotional intensity of video comments, the positive impact of the emotional intensity of barrage on the popularity of the video will be weakened. H4b is supported.

In summary, comments play a negative role in the impact of the barrage on video popularity. When the number of comments is large and the emotion of the comments is strong, the impact of the number of barrages and the emotion of barrage on the video popularity will be weakened.

VII. DISCUSSION AND CONCLUDING REMARKS
A. CONCLUSION
Our research is based on the videos uploaded by individual users of bilibili, a representative Chinese barrage video site. And based on the user participation theory, we study the impact of barrage and comments on video popularity from two dimensions: quantity and emotion, and explore the influence of different emotional tendencies on popularity.

First, the number of barrage and comments has a significant positive impact on video popularity, indicating that as the number of barrage and comments in the video increases, the video popularity will increase accordingly. The emotional intensity of the barrage has a significant positive impact on video popularity, while the emotional intensity of the comment has a significant negative impact on video popularity, which is caused by the difference in the location and nature of the barrage and the comment. Second, we further explore the influence of different emotional tendencies on popularity. The number of neutral comments has the greatest impact on video popularity, and the number of negative barrages has a significant positive impact on video popularity. While the emotional intensity of positive comments has a significant negative impact on video popularity. Third, the impact of the number of barrages on video popularity is greater than the impact of the number of comments, while the impact of the emotional intensity of barrage on video popularity is less than the impact of the emotional intensity of comment on video popularity, indicating that in online video user participation, barrage and comments have their advantages and disadvantages, and both play an important role in online video sites. Fourth, it is further discovered that the number of comments will negatively adjust the impact of the number of barrages on video popularity, and the emotional intensity of comments will negatively adjust the impact of the emotional intensity of the barrage on video popularity.

B. THEORETICAL CONTRIBUTION
First, in the past, many people have done a lot of research on traditional user-generated content such as Weibo, forum posts, and online comments. But we take barrage as the research object, explore the impact of the number of barrages and emotional intensity on video popularity, and expand the relevant research on user-generated content.

Second, barrage and comments are two important ways for users to participate in video websites. Many previous studies focused on the differences in the characteristics of barrage and comments themselves. From the perspective of user participation, we explore the difference between barrage and comments on the impact of video popularity, and explored the moderating effect of comments on the impact of barrage on video popularity, and expanded the research on the difference between barrage and comment. And to a certain extent, it has expanded the related research in the field of video popularity.

C. MANAGERIAL IMPLICATIONS
In recent years, the online video industry has developed rapidly, with high user participation, high on-demand volume, and high income that have attracted more and more attention to online video companies. We focus on the important management index of online video popularity and study the impact of two important interactive methods-barrage and comments on video popularity, which have great practical significance.

First, video websites should pay attention to the management of social systems, improve user stickiness, and arouse high user satisfaction. Managers can use a series of measures to encourage users to send more barrages and comments that contain personal opinions and express personal emotions. And to further manage the content of the barrage, pay attention to guiding users to express the correct emotions.

Second, video managers can try to combine community with barrage and comments, analyze them based on users' social data, and make user portraits more accurate. The number and content of the barrage can be used as a basis for creators to explore user preferences, helping managers to more accurately grasp trends. For comments, use the characteristics and advantages of comments to inject traditional social methods into fresh gameplay to make them exert greater influence.

D. LIMITATION AND FUTURE RESEARCH
Readers should be aware of certain limitations of our research. We explored the impact of barrage and comments on video popularity, but our research only divided emotions into positive, negative, and neutral, without further segmentation of emotions. We did not consider the informational barrage and the connection between the barrage content and the video content. Regarding video popularity, only the impact of barrage and comments was explored, and the impact of other factors was not considered.

As avenues for future research, first, for emotional intensity, we can further refine the emotional classification in the future. For example, it can be divided into emotions such as happiness, anger, sorrow, and fear, and explore which type of barrage emotion has the greatest impact on the popularity of the video. Second, for the barrage, the barrage is closely related to video content. The content of barrage can reflect

user feedback on video content. In the future, we can study the role of information-based barrage and conduct more comprehensive research on the barrage. Finally, for video popularity, the influence of video characteristics on popularity can be further studied in the future. The emotion of video content and video subtitles has a direct impact on the audience's reaction. In the future, the emotion of video content and video subtitles can be analyzed. At the same time, the cover and title of the video are the audience's first impression of the video. A clear title and pleasing cover can greatly increase the popularity of the video. Analysis of the video cover and title content can be added. Future research can take these factors into account and conduct a more comprehensive analysis of video popularity.

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