RESEARCH ARTICLE

The influence of bullet screen on communication effect of knowledge videos: An ELM perspective

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ABSTRACT

As an important interaction method of knowledge videos, bullet screens have a significant influence on their communication effect. This research developed the research model based on the elaboration likelihood model (ELM), and collected 2843 knowledge videos and 2.93 million bullet screens in BiliBili to conduct data analysis. The results show that the amount of bullet screen information, intensity of bullet screen interaction and special bullet screen amount have a positive impact on the communication effect of knowledge videos, while the bullet screen load has a negative impact. The results suggest that knowledge video creators and platforms should cooperate to guide reasonable and effective bullet screen interaction in order to promote the communication effect of knowledge videos and achieve a competitive advantage.

KEYWORDS

Bullet screen; Knowledge video; Communication effect; Elaboration likelihood model

1 Introduction

Knowledge communication is the process by which members of society use certain knowledge communication media to share specific knowledge in a specific social environment. Online video, as a mode of information transmission in the Internet era, has become an important medium for knowledge communication. According to a report published by the China Internet Network Information Center (CNNIC) in December 2022, the number of China's Internet users has reached 1.067 billion, among which the number of online video users was 1.031 billion, accounting for 96.5% of the overall Internet users (CNNIC, 2023). Online video has great potential for communication because of its large base and rapid growth of users, which supply high-quality communication subjects and objects for the knowledge communication of online video. On the one hand, online video can work with search engines to provide users with accurate and diversified knowledge content. On the other hand, more and more people can participate in the production and communication of knowledge through video creation. However, the quality of many knowledge videos is uneven and the content is more homogenized, which will impact the

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communication effect of knowledge videos. Based on this, it is necessary to study the influencing factors of the communication effect of knowledge video to take effective measures to promote its communication effect.

The existing literature has focused on the impact of video characteristics (Kuang & Lu, 2022; Tao & Li, 2022; Xu, 2022), such as video usefulness, video duration, video title, and video cover on the communication effect of the video, and has seldom examined the impact of user behavior of bullet screens. They just examined the amount of bullet screens while neglecting the role of other attributes of bullet screens such as level of debate, bullet screen load, and so on. Bullet screen has commonly appeared in videos as a type of information interaction behavior during the network era. Bullet screens are more interactive and immersive than typical information interaction methods such as comments. At the same time, this pseudo-synchronized interaction creates an impression of “real-time” viewing (Johnson, 2013). With the popularization of bullet screen interaction, numerous video websites, like BiliBili, iQiyi, Tencent and Youku, have included the bullet screen function in all of their videos. As one of the important ways of video user interaction, the role of bullet screen cannot be ignored. It has also been found that bullet screens had a positive effect on video learning outcomes (Leng et al., 2016). Therefore, this paper examined the influence of the attributes of bullet screens, including the amount of bullet screen information, level of debate, bullet screen load, intensity of bullet screen interaction, similarity of bullet screens and special bullet screen amount, on the communication effect of knowledge videos based on elaboration likelihood model (ELM). The results will help to understand the mechanism of the impact of bullet screens on the communication effect of knowledge videos. They can also provide suggestions to video producers and platforms in order to promote the communication effect of knowledge videos and gain a competitive advantage.

2 Literature review

2.1 Bullet screen

The phrase “bullet screen” originated in the military because of the dense artillery shells that resembled a curtain. The bullet screen video system originated from the Japanese bullet screen video-sharing website Niconico Animation, and was later introduced into China by AcFun and BiliBili (Zhuge, 2015). With the continuous development of the Internet, bullet screens, a novel form of interaction, have quickly gained widespread attention, and bullet screens are no longer limited to 2D animation videos and animation websites, but have gradually been popular on video websites, live streaming platforms, and short-video platforms.

Previous researchers have studied two main aspects of bullet screens, the characteristics of bullet screen videos (Chen & He, 2014; Li & Wang, 2015; Chen et al., 2017), and the impact of bullet screen on user behavior (Zhou et al., 2019; Guo, 2020; Yuan et al., 2020; Zhang, 2021). With regard to the characteristics of bullet screen videos, Chen & He (2014) analyzed the distribution of the audience groups of bullet screen videos as well as the timeliness, relevance and interactivity of bullet screen videos. Li & Wang (2015) summarized the basic features of bullet screen videos based on the user experience method and examined their potential value in online learning. Chen et al. (2017) suggested that bullet screen videos enable viewers to get information, entertainment and social connections. In terms of the impact of bullet screens, Guo (2020) found that bullet screens have a negative impact on people's ability to concentrate and think independently, and can also lead to biased public discourse. Yuan et al. (2020) argued that both the number of bullet screens and the emotion of bullet screens have an effect on users' consumption behavior. Zhang (2021) investigated the effects of bullet screens on movie viewing scenes, movie audiences, and movie works themselves. Zhou et al. (2019) investigated the role of bullet screen in paid gifting on the live streaming platform of Douyu.

From literature, it can be found that they have examined the role of bullet screens on users' consumption behavior, rewards, and so on, but few literature have examined the effect of bullet screens on the communication of knowledge videos, which will be investigated in this paper.

2.2 Video communication effect

The term "communication" is derived from the field of journalism and communication (Hu, 1997). The communication effect is the effective result of human communication behavior. With the emergence of the fourth media (Internet) and the fifth media (mobile network), which are different from the traditional media, the "potential communication" effect of the new media has been increasingly emphasized (Yin & Liu, 2010). Video, as an important carrier of new media communication, has received a lot of attention for its communication effect. Chen (2020) analyzed the communication effect of health short videos from the aspects of video communication content and communication mode by taking the TikTok platform as an example. Gao et al. (2021b) investigated short library videos and found that title sentence type, background music emotion type, production category, content theme, and message type affect their communication and interaction effects.

For the communication effects of knowledge videos, current research has examined the influence of the video itself such as video content, title or credibility of the source. For example, Xu (2022) found that information usefulness, information interestingness, source professionalism and source reputation influence the communication effect of knowledge short videos. However, few literature investigate the communication effect of knowledge videos from the perspective of bullet screens. It has been found that bullet screens, as a mass communication medium, provide a high degree of autonomy to the audience to achieve the desired optimal communication effect (Xie et al., 2014). Consequently, there is a correlation between bullet screens and video communication effect, and this will be investigated in the paper.

2.3 ELM

The ELM was proposed by social psychologists Petty & Cacioppo (1986). The model argues that changes in an individual's attitude or behavior are due to the processing of information through the central and peripheral routes. When people use the central route, they spend more time and energy working on relevant clues. Accordingly, the central factors are closely related to the information itself and require the user's thoughtfulness, time and effort to identify, understand and process them. Peripheral factors, however, are usually judged or examined based on simple clues only, or tend to address the issue of source credibility. The central route will be more stable and more likely to influence an individual's attitudes or behaviors over time than the peripheral route. The selection of these two routes depends on the likelihood that the individual will think carefully when receiving and processing information. When processing through the central route, the elaboration likelihood is usually high, whereas a low or medium elaboration likelihood is involved in the peripheral route (Gao et al., 2021a).

ELM has been applied to the study of video communication effects and user behavior. Liu et al. (2023) found that the quality of bullet screen information in e-commerce live streams affects consumers' purchase intention. Ke et al. (2021) investigated the influence of the communication content and form of health science popularization short videos on the communication effect. Jiang & Liu (2022) found that expectations of knowledge, enjoyment, aesthetics, socialization, and effort, as well as social influences, all positively influenced college students' intention to watch micro videos in college libraries. Based on these literature, this paper will investigate the influence of bullet screen on the communication effect of knowledge videos based on ELM.

3 Research model and hypotheses

Based on ELM, this paper will investigate how the communication effect of knowledge videos is affected by three central factors: the amount of bullet screen information, level of debate, and bullet screen load, and three peripheral factors: intensity of bullet screen interaction, similarity of bullet screens, and special bullet screen amount. It also included the number of the author's fans as a control variable.

3.1 The amount of bullet screen information

The amount of bullet screen information refers to the content contained in the bullet screen, reflecting the quality of the bullet screen sent by the user. Zeng et al. (2022) measured text quality in terms of text length and argued that the length of online comments affects users' attitudes and behaviors. Mousavizadeh et al. (2020) found that the longer the text, the richer the information and the more likely it positively influences users' decisions. Mousavizadeh et al. (2020) argued that long online reviews will require more cognitive effort. Since bullet screen information requires users to invest some time and effort to process, it is taken as the central factor. High-quality bullet screens with more information will enhance the user experience and make users more inclined to engage in sharing and communicating behaviors. Therefore, we suggest,

H1. The amount of bullet screen information positively affects the communication effect of knowledge videos.

3.2 Level of debate

Debate behavior in knowledge videos is an emotionally relevant bullet screen interaction between users who have opposite attitudes towards certain events or opinions while watching a video. The level of debate, in turn, reflects the overall intensity of debate among video viewers. Adam et al. (2015) found that in an auction setting, competitive interaction behavior among lot bidders significantly affects bidding. Zhou et al. (2019) used the level of debate to examine the effect of bullet screens on live streaming gift sending. They argued that debates increase arousal levels and trigger further action by viewers, and found that the level of debate was positively correlated with the number of gifts given by viewers. In knowledge videos, bullet screen debates based on knowledge content will make learners think more deeply about the content of the video, look at issues in a dialectic way, and be more willing to share this video with others. Thus, we propose,

H2. The level of debate positively affects the communication effect of knowledge video s.

3.3 Bullet screen load

Bullet screen load refers to the cognitive load imposed on a user by bullet screens that are unrelated to the video content, or that interfere with learning. This “noise” makes users’ experience less enjoyable and reduces their willingness to communicate. Zhao (2011) explored the influencing factors of cognitive load and found that reducing cognitive load can improve learning efficiency. Ke et al. (2020) found that meaningless content in bullet screens seriously affects users’ experience, causing them to expend more effort and increasing their cognitive load. Higher bullet screen load means that users will spend a lot of time reading bullet screens that are not related to the knowledge content of the video, which will negatively affect the user learning experience and reduce the video communication effect. Thus, we posit,

H3. Bullet screen load negatively affects the communication effect of knowledge videos.

3.4 Intensity of bullet screen interaction

The intensity of bullet screen interaction refers to the amount of information interaction of bullet screen users throughout the video, which is mainly reflected in the total number of bullet screens in the video. Lin et al. (2018) explored bullet screens in online video teaching and found that bullet screen interactions can effectively enhance learner interaction and increase course engagement. Ma & Cao (2017) found that bullet screen interaction can attract more people to watch the video in a short period of time, and that bullet screen users will encourage other users to watch the video and participate in the interaction. Lee et al. (2015) examined online learning environments and noted that as the number of time-anchored comments from prior learners increases, current learners experience higher levels of engagement and social interactivity and are facilitated to actively participate in learning. To a certain extent, bullet screen interaction can help users better understand the content of the video, thus promoting wider communication of the video. Therefore, we suggest,

H4. The intensity of bullet screen interaction positively affects the communication effect of knowledge videos.

3.5 Similarity of bullet screens

The similarity of bullet screens refers to the proportion of similar or identical bullet screens to the number of all bullet screens, reflecting the extent to which the bullet screens in the video are similar or identical. When the similarity of the bullet screen is high, the “flood” phenomenon occurs. That is, in a short period of time, users send a large number of bullet screens that have similar or repetitive contents and they spread over the entire screen. This behavior is often used to express some kind of emotion. Tu et al. (2018) examined bullet screens in the context of live gift sending and found that most gift sending is accompanied by a large number of bullet screens. Zhou et al. (2019) argued that if the content of a live stream is exciting, viewers tend to send similar complimentary bullet screens at the same time to express their appreciation for the streamer, and this emotional stimulus can influence their gift sending behavior. In knowledge videos, similar bullet screens generate a “flood” phenomenon that may also trigger users’ appreciation and emotional identification, thus promoting their further communication behaviors. Thus, we propose,

H5. The similarity of bullet screens positively affects the communication effect of knowledge videos.

3.6 Special bullet screen amount

The special bullet screen amount is the number of bullet screens in a video that has a different presentation mode, font size, or color compared with the default type of bullet screen. Zhang & Shui (2016) point out that bullet screens not only include normal pop-up subtitles, but can also be in a mode that allows you to choose the top or bottom, or change the color of the font, which are known as “rainbow bullet screens”, and can highlight the importance of the comments. Different from a normal white bullet screen that pops up at an even pace from right to left, a bullet screen displayed at the top or bottom with a larger font size or in color draws the user’s attention more quickly and reminds him or her to focus on the key content of the video. In addition, eye-catching special bullet screens are more likely to get replies from other users, which can lead to a better analysis of the problem. This additional explanation can serve to improve the video and facilitate subsequent viewers’ understanding (Chen et al., 2019b). Thus, we posit,

H6. Special bullet screen amount positively affects the communication effect of knowledge videos.

3.7 The number of author’s fans

The number of author’s fans refers to the total number of people who follow a video author on a particular video site. To some extent, the number of author’s fans reflects the author’s influence and social status on the site, as well as the author’s popularity. Previous studies have found a positive correlation between the number of author’s fans and the number of likes, comments, and shares (Lin, 2022). The number of author’s fans also has a positive effect on bullet screen video plays (Chen et al., 2022). Accordingly, a user’s video viewing, bullet screen interactions, and behaviors such as likes and forwards are likely to be affected by the number of author’s fans. Based on this, the number of author’s fans is used as a control variable in this paper.

Figure 1 presents the model.

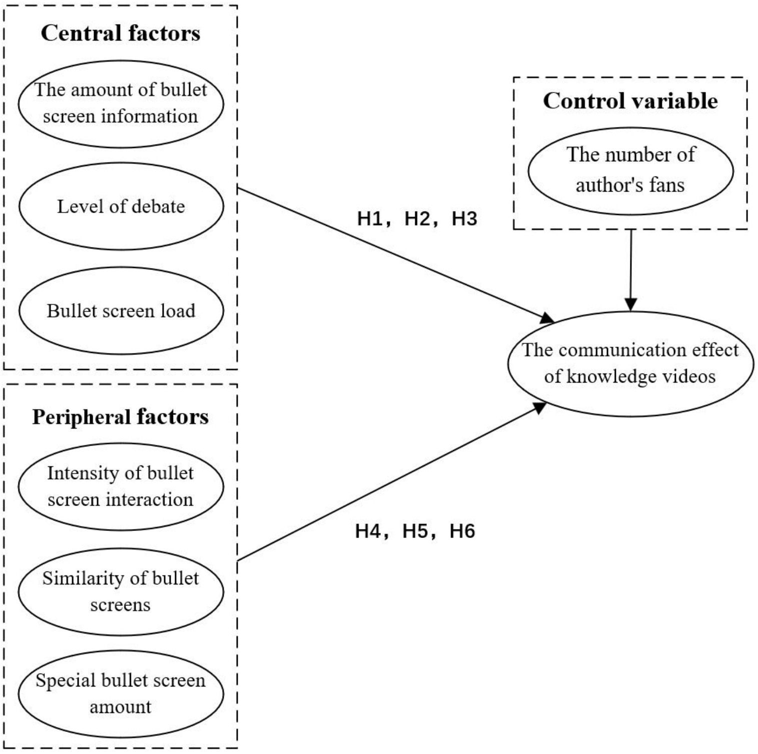

Figure 1 Research model

4 Data collection and analysis

4.1 Data collection

The data in this article was collected from BiliBili, where knowledge video section had already developed into one of the most popular vertical sections as early as 2020, with tech knowledge videos contributing 10% of the overall video playback at that time (Bilibili, 2021). In addition, as one of the first websites to introduce the interactive function of “bullet screen” into China, BiliBili has a long history of bullet screen system function and bullet screen video development. For this reason, we collected videos from “Popular Science”, “Campus Learning”, and “Wild Skills Association” in the “Knowledge” section of BiliBili. After removing samples with meaningless contents and too few bullet screens, a total of 2843 videos with more than 2.93 million bullet screens were obtained.

Data collection was conducted by writing a crawler program in Python language, in which the bullet screen information is different from the video information and cannot be directly crawled in bulk from the original webpage. For getting the bullet screen information, since BiliBili itself provides a bullet screen interface and the bullet screen data of the corresponding video is stored in the xml file, we can use the interface to find the corresponding video bullet screen data. Since the CID number of each video is unique, the program first found the corresponding video CID number based on the video address, then constructed the URL based on the CID number, and subsequently extracted the bullet screen and the required bullet screen attributes from the xml file and saved them to a local file.

4.2 Variable measurement

4.2.1 The communication effect of videos

For the communication effect, if we only consider the number of plays, it will not be able to completely reflect the communication effect. Therefore, previous studies often used multiple indicators to measure and evaluate the communication effect (Kim & Yang, 2017; Chen et al., 2019a), assigning weights to calculate the communication effect of the video. Accordingly, we referred to previous studies (Zhang et al., 2021) and developed the equation for calculating the communication effect of knowledge videos, which is as follows.

$$\mathrm{KVCE} = 0.3 * \ln\left(x_p + 1\right) + 0.0665 * \ln\left(x_l + 1\right) + 0.112 * \ln\left(x_s + 1\right) + 0.14 * \ln\left(x_c + 1\right) + 0.21 * \ln\left(x_f + 1\right) + 0.1715 * \ln\left(x_r + 1\right) \quad (1)$$

In equation (1), KVCE represents the communication effect of knowledge videos, x_p represents the number of video plays, x_l represents the number of video likes, x_s represents the number of video coins, x_c represents the number of video favorites, x_f represents the number of video forwards, and x_r represents the number of video comments. To prevent large gaps in values between indicators, the indicators are logarithmized and multiplied by the corresponding weights. Also to prevent the emergence of a certain indicator for the value of 0 to affect the logarithm, the equation first adds 1 to the value of each indicator and then takes the natural logarithm for calculation.

4.2.2 The amount of bullet screen information

Since it was observed that in knowledge videos, longer bullet screens were generally scientific or explanatory and relatively informative, while shorter bullet screens were mostly social or expressing emotions, we used the average text length of all the bullet screens in a video to measure the amount of bullet screen information of that video, which was calculated using equation (2). We first used the len () function in Excel to obtain the length value of each bullet screen, and then used the average () function to find the average length to get the average text length of the video bullet screens.

$$\text{The amount of bullet screen information} = \frac{\text{Sum of all bullet screen lengths}}{\text{Total number of bullet screens}} \quad (2)$$

4.2.3 Level of debate

A debate is a situation where video users hold opposing views and send bullet screens to argue. When a debate occurs, there are roughly the same number of positive and negative bullet screens (Zhou et al., 2019). Therefore, when we calculated the level of debate of a video, we first analyzed the sentiment of each bullet screen of that video by marking positive, negative or neutral sentiment. Sentimental analysis was handled by using the Gooseeker software. The software's segmentation rules are based on natural language processing (NLP) algorithms and have been applied to various research fields (Li & Huang, 2022). Firstly, each bullet screen was sliced into words, the emotions of the words were analyzed and scored according to the imported emotion dictionary, and then integrated to get the emotion scores of the whole bullet screen, and finally the bullet screen was categorized as positive, negative, or neutral according to the categorization rules.

After the sentimental analysis, the respective totals of positive and negative bullet screens in the video were then counted, and finally the absolute value of the difference between the two was divided by the total number of bullet screens in that video. The lower the value, the higher the level of video debate indicated. To make it easier to see and understand, the value was taken as the opposite number to get the final value of the level of debate.

$$\text{Level of debate} = -\frac{|(\text{Number of positive bullet screens} - \text{Number of negative bullet screens})|}{\text{Total number of bullet screens}} \quad (3)$$

4.2.4 Bullet screen load

For the calculation of the bullet screen load of a particular video, it is first necessary to determine which bullet screens in that video are not related to the content of the video, for example, just expressing the mood, showing the identity, or having no meaning. And the number of bullet screen samples is too large to categorize completely manually. Therefore, we used the Python language to write programs to classify each bullet screen of each video (relevant or irrelevant) using the plain Bayesian classification method in machine learning. A classifier needs to be constructed before classification. We manually categorized the randomly selected samples by classifying 80% of them as a training set and 20% as a test set. The text of the bullet screens was then preprocessed and the jieba package was used for word splitting. Further feature extraction of the preprocessed text was done by using the CountVectorizer, an NLP bag-of-words model. Finally, the training and testing of the model was carried out and the accuracy of the model obtained from the test was about 81.6%, which worked well.

Subsequently, the text of the video bullet screens that needed to be classified was imported into the classifier for classification, and the bullet screens which were not related to the video content were labeled as 0, and the bullet screens which were related to the video content were labeled as 1. After categorization, the total number of irrelevant bullet screens in the video was counted, and the ratio of the number of irrelevant bullet screens to the total number of all bullet screens was the bullet screen load of the video, which was calculated as shown in equation (4).

$$\text{Bullet screen load} = \frac{\text{Number of irrelevant bullet screens}}{\text{Total number of bullet screens}} \quad (4)$$

4.2.5 Intensity of bullet screen interaction

The intensity of bullet screen interaction refers to the number of information interactions of bullet screen users throughout the video, which is mainly reflected in the total number of bullet screens in the video. The total number of bullet screens for a given video is therefore used to indicate the intensity of the bullet screen interaction for that video.

$$\text{The intensity of bullet screen interaction} = \text{The total number of bullet screens} \quad (5)$$

4.2.6 Similarity of bullet screens

Since it is difficult to judge whether the whole bullet screen content is similar or identical to each other, we chose to split the text of the bullet screen and replaced the bullet screen similarity with the word similarity. Segmentation was handled by using Gooseeker, which split the words and counted the word frequency of all meaningful words. The number of recurring words was counted, and the ratio of the number of recurring words to the total number of meaningful words was the similarity of bullet screens. The calculation is shown in equation (6).

$$\text{The similarity of bullet screens} = \frac{\text{Number of recurring words}}{\text{Total number of meaningful words}} \tag{6}$$

4.2.7 Special bullet screen amount

In the bullet screen information crawled, the bullet screen properties item contains several pieces of information about the bullet screen. This paper obtained three items of bullet screen position, bullet screen font size, and bullet screen font color, and then the default attribute value (1, 25, 16,777,215) was used as a reference to select all non-default bullet screens, that is, special bullet screens. The amount of special bullet screen is calculated as in equation (7).

$$\text{Special bullet screen amount} = \frac{\text{Number of non}-\text{default form bullet screens}}{\text{Total number of bullet screens}} \tag{7}$$

4.2.8 The number of author's fans

The number of author's fans was obtained by crawling the number of followers of the author of the corresponding video in BiliBili. For videos co-created by multiple authors, the number of followers of the main creator, that is, the author who uploaded the video, was taken as the number of author's fans of that video.

4.3 Data analysis

Descriptive statistics for each variable are shown in Table 1.

Table 1 Descriptive statistics results

Variables	Min.	Max.	Mean	SD.
The communication effect of knowledge videos	2.951	12.660	8.311	1.393
The amount of bullet screen information	1.312	27.247	9.003	2.650
Level of debate	-0.919	-0.001	-0.107	0.092
Bullet screen load	0.001	0.980	0.120	0.080
Intensity of bullet screen interaction	102	23,000	1,033.100	1,745.981
Similarity of bullet screens	0.056	0.879	0.302	0.054
Special bullet screen amount	0.001	0.457	0.123	0.069
The number of author's fans	6	15,676,000	595,987.770	1,272,666.893

As shown in Table 1, some of the variables have large gaps in their values and there are extreme values. To eliminate the influence of the magnitude and reduce the variability between the variables, and also to avoid the influence of extreme values leading to a large deviation in the analysis results, we first calculated the natural logarithm for three variables - the amount of bullet screen information, intensity of bullet screen interaction, and the number of author's fans, and then conducted regression analysis. The results are shown in Table 2. The adjusted R^2 value of the model was 0.742, showing a good fit. The VIF values of the variables were less than 10, indicating that there was no multi-collinearity problem.

Table 2 Regression analysis results

Variables	Path coefficient (β)	Significance (p)	VIF
ln（The amount of bullet screen information）	0.270	0.000	1.184
Level of debate	0.009	0.390	1.338
Bullet screen load	-0.272	0.000	1.238
ln（Intensity of bullet screen interaction）	0.470	0.000	1.735
Similarity of bullet screens	0.012	0.244	1.135
Special bullet screen amount	0.170	0.000	1.248
ln（The number of author's fans）	0.083	0.000	1.288

4.4 Robustness check

We used a Logistic regression model instead of the original model for the analysis to examine whether the hypotheses still hold. The dependent variable for the logistic regression model needed to be a binary or multivariate discrete variable. Thus, the dependent variable, that is, the communication effect of knowledge videos, was re-coded as a discrete numerical variable, which was subsequently tested (Model 2). At the same time, we randomly selected 20% of the original sample to form a sub-sample and re-analyzed it (Model 3). The results of the tests are shown in Table 3, showing that the results of the three models are consistent, indicating that the regression results are generally robust.

Table 3 Results of the robustness check

Variables	Model 1	Model 2	Model 3
ln(The amount of bullet screen information)	0.270^{***}	2.239^{***}	0.238^{***}
	(0.040)	(0.172)	(0.092)
Level of debate	0.009	0.580	0.027
	(0.166)	(0.611)	(0.361)
Bullet screen load	-0.272^{***}	-9.317^{***}	-0.249^{***}
	(0.185)	(0.841)	(0.429)
ln(Intensity of bullet screen interaction)	0.470^{***}	1.552^{***}	0.472^{***}
	(0.017)	(0.081)	(0.039)
Similarity of bullet screens	0.012	-0.569	0.014
	(0.261)	(1.050)	(0.617)
Special bullet screen amount	0.170^{***}	10.126^{***}	0.203^{***}
	(0.214)	(0.844)	(0.492)
ln(The number of author's fans)	0.083^{***}	0.119^{***}	0.076^{***}
	(0.006)	(0.022)	(0.013)
R^2	0.742	0.524	0.728

$^{***}p<0.01$, values in parentheses are deviations.

5 Discussion

Table 2 shows that except hypotheses H2 and H5, other hypotheses are supported. That is, when we control the number of author's fans, the amount of bullet screen information, bullet screen load, intensity of bullet screen interaction, and special bullet screen amount have a significant impact on the communication effect of knowledge videos, while the effects of level of debate and similarity of bullet screens are not significant.

Regarding the central factors, the amount of bullet screen information has a significant positive effect on the communication effect of knowledge videos (β =0.270, p<0.001), which is similar to the results of previous studies (Mousavizadeh et al., 2020). A large amount of bullet screen information brings users high quality text, which in turn positively affects user decision-making and promotes the communication effect of knowledge videos.

The effect of level of debate on the communication effect of knowledge videos is not significant (β =0.009, p=0.390). This may be due to the fact that, in the process of watching knowledge videos, users' debating behaviors through bullet screens not only include debates related to the knowledge content of the video, but also include a portion of debates unrelated to the content of the video. The content of such debates includes arguments about the characters, scenes or plots, and so on, that appear in the video. Such debates tend to deviate from the main content of the video and are mostly on an emotional level, unrelated to the knowledge content itself. Consequently, a high level of debate in a video does not necessarily mean that it is also more helpful to the user and therefore difficult to enhance its communication.

Bullet screen load has a significant negative effect on the communication effect of knowledge videos (β =-0.272, p<0.001). It shows that the irrelevant bullet screens do have a negative impact on users' behavior, as this "noise" reduces their learning efficiency and creates a negative viewing and learning experience, leading to a lack of intention to share the video.

Regarding peripheral factors, the intensity of bullet screen interaction has a significant positive effect on the communication effect of knowledge videos (β =0.470, p<0.001). It suggests that as the intensity of bullet screen interaction increases, the interactive atmosphere of the video's bullet screen rises to an overall higher level, which leads to knowledge video users experiencing a higher sense of engagement and interaction, as well as generating a stronger interest in learning and a higher intention to share.

The effect of similarity of bullet screen on the communication effect of knowledge videos is not significant (β =0.012, p=0.244). This is different from the results of previous studies (Tu et al., 2018), which may be due to the research context of this paper. Previous studies on the similarity of bullet screens and the "flood" phenomenon of bullet screens have focused on live streaming environments such as e-commerce live streaming and live game streaming, in which bullet screens are a kind of behavior that drives the atmosphere and "rhythm", and in which the bullet screens sent by users are all instantaneous. Therefore, the bullet screen interaction with other users and streamers will be more effective, and will also generate greater emotional stimulation, thus prompting the user's gift sending behavior. As for the video environment, video bullet screens are pseudo-instantaneous, which is different from live streaming bullet screens. Thus, the emotional stimulus generated by the act of flood screening in a video is greatly diminished. In addition, some of the bullet screen "flood" behavior is only out of entertainment needs or emotional expression, and has nothing to do with the knowledge contents, which will lead to a decline in the perception of other users and reduce their willingness to communicate.

Special bullet screen amount has a significant positive effect on the communication effect of knowledge videos (β =0.170, p<0.001). It implies that striking special bullet screens will remind other learners of the key knowledge of the video and improve the content of the knowledge video, thus promoting its better communication.

6 Conclusion

This research developed a model to examine the communication effect of knowledge video based on ELM. It was found that the amount of bullet screen information, intensity of bullet screen interaction and special bullet screen amount have a positive impact on the communication effect of knowledge videos, while the bullet screen load has a negative impact. And the level of debate and similarity of bullet screens do not have a significant effect on the communication effect of knowledge videos.

This research makes three contributions. First, existing researches have mainly examined the influence of video features such as video duration, video title, and video introduction on the communication effect, and have seldom examined the role of bullet screen. This research found that bullet screen, as an important form of interaction, has a significant impact on the communication effect of knowledge videos. The results enriched the research on the communication effect of knowledge videos. Second, based on the ELM, this research found that the communication effect of knowledge video developed through central and peripheral routes. The central factors included the amount of bullet screen information, level of debate, and bullet screen load, while the peripheral factors included intensity of bullet screen interaction, similarity of bullet screens, and special bullet screen amount. The results revealed the formation mechanism of the communication effect of knowledge video. Third, we found that bullet screen similarity does not play a significant role in the communication effect, showing the different characteristics of knowledge videos compared with other types of videos, such as game videos. These results also help to improve the understanding of the communication effect of videos.

The results have a few implications for practice. For knowledge video authors, should pay attention to the impact of bullet screen interaction on the communication effect of the video. For example, they can increase the contents of the bullet screen in the knowledge video or encourage users to discuss on a certain part of the knowledge content through the bullet screen. This may effectively enhance users' willingness to interact and improve their experience, and enable users to independently enrich and improve the content of the knowledge. For video platforms, better video communication effect means more user visits and streaming revenue. Video websites can further develop various special types of bullet screens, such as audio bullet screen and special bullet screens, in order to continuously enhance the role of special bullet screens in the communication of knowledge videos. In addition, effectively reducing the load of bullet screens is also a problem that video websites need to solve. Video websites should consider developing new functions to intelligently identify meaningless “flood” bullet screens in videos and enable users to freely choose whether or not to block these “floods”. Further, knowledge video authors should collaborate with video platforms to combine their high-threshold, highly specialized knowledge contents with the bullet screen, and improve the communication effect.

This research has a few limitations. First, the data in this research was collected from a representative platform, BiliBili. Thus, the results need to be generalized to other knowledge video platforms. Second, the communication effect of knowledge videos may be influenced by multiple factors. Besides the central and peripheral factors identified in this research, there are other possible influencing factors such as viewer's age, education level and cultural background. Future research may examine their effect. Third, we did not consider the content types of knowledge videos. Future research may compare different subjects such as STEM and humanities, and obtain a rich understanding of bullet screen interaction.

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