



Cross-platform Communication Strategies and Effects of Chinese Calligraphy in Overseas Countries under New Media Contexts

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SUMMARY: *The emergence of new media has greatly promoted the dissemination of Chinese calligraphy culture, and the study investigates the dissemination effect of Chinese calligraphy in overseas platforms based on the new media marketing communication context. Taking Chinese calligraphy videos on YouTube platform as an example, the study evaluates the overseas communication effect of Chinese calligraphy through data statistics and BERT-CNN text sentiment analysis model, and further proposes a cross-platform communication strategy for Chinese calligraphy in overseas. On the one hand, the overseas communication of Chinese calligraphy has shortcomings such as low degree of specialization, data indicators mostly at the middle and low levels, and lack of interactivity, with the distribution of videos with a duration of 1,000 seconds and less than 1,000 viewings accounting for 86.33% and 90% respectively, and 90% of the videos have a number of likes of less than 10. On the other hand, the overseas communication of Chinese calligraphy has an obvious advantage of professional media, and the feedback from the audience is more positive. More than 60% of the videos are released by individuals and media, and the level of audience expressing regret and disgust is less than 5%. Although the overseas dissemination of Chinese calligraphy has achieved some results, it is still necessary to strengthen the dissemination and promotion of calligraphy culture in the new media context.*

KEYWORDS: *BERT-CNN; sentiment analysis; communication effect; Chinese calligraphy*

1 Introduction

Calligraphy is the essence of traditional Chinese culture and a unique art of the Chinese nation, and is one of the most important ways to understand Chinese culture. Since its birth, Chinese calligraphy has continued to develop through different eras. From tortoise shell inscriptions, writing on simple silk and hemp paper, to tablet inscriptions and topographies, movable type printing, and nowadays in the era of digital technology, Chinese calligraphy and communication methods have promoted each other and made achievements together [1, 2]. In the process of continuous updating of the means of communication, the artistic value of Chinese Calligraphy as a means of educating and helping people has been fully manifested. With the continuous development of international exchanges and the increasing number of “Confucius Institutes” around the world, Chinese calligraphy, which combines philosophical, historical, connoisseurship and literary qualities, has gradually become familiar to the world,

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and has also gradually become a cultural symbol for the world to recognize China [3, 4]. Since the new century, with the enhancement of China's comprehensive national power, Chinese calligraphy has been spreading overseas with more and more momentum. Chinese calligraphy has gone out of Asia and gradually entered Europe, America and other countries [5]. Calligraphy monographs in many languages have been translated, and Chinese and Western calligraphy exhibitions and other exchanges have been frequently held, making the overseas dissemination of calligraphy show a good trend [6, 7].

The arrival of the new media era has led to a new change in media communication, and the transformation of communication methods and information receiving terminals has completely subverted our traditional cognition and opened up new paths for the inheritance and development of the art of calligraphy. Social media platforms such as TikTok, Facebook and other social media platforms spread calligraphy in the form of pictures, short videos, short animations and other fragmented forms, which improves the speed of dissemination. However, the fragmentation feature in new media also limits the depth of dissemination, and information barriers and algorithmic bias also make dissemination more limited [8, 9]. And cross-platform communication can entertain different audiences and improve the depth of communication [10].

The study selects YouTube, currently the most popular video website in the world, as the research platform, and uses crawler technology to collect the relevant data of Chinese calligraphy videos, and evaluates the overseas dissemination effect of Chinese calligraphy from the three dimensions of video posting account, video posting content, and video viewers. Aiming at the collected video comment text data, a BERT-CNN model that fuses a BERT pretraining model with a convolutional neural network is proposed, using BERT pretraining to extract the sentiment feature representations of the Chinese calligraphy video comment text, and then the convolutional layer extracts various lengths of disambiguation features by using different sizes of convolutional kernels, and finally pools, maps and outputs the sentiment classification results as a way of investigating the audience's sentiment tendency towards the Chinese calligraphy videos. Based on this, key strategies are proposed in four aspects: content strategy, platform selection, interaction strategy, and branding strategy, in order to guide the practical work of Chinese calligraphy culture dissemination overseas.

2 Data collection and analysis methods

2.1 Subjects of study

This paper takes Chinese calligraphy videos on YouTube, the world's largest video sharing website, as the research object, and comprehensively evaluates the marketing communication effect of Chinese calligraphy on overseas cross-platforms by quantitatively analyzing the three dimensions of video posting account, video posting content, and video viewers, combined with sentiment analysis based on YouTube users' video comments.

2.2 Data Collection

2.2.1 Data acquisition

In this paper, we utilize Octopus software to crawl the information indicators related to Chinese calligraphy videos on YouTube platform. The total number of YouTube videos related to Chinese Calligraphy from May 2024 to May 2025 was 5,563 after filtering. The videos were sorted by the number of views, and the top 300 videos were selected after removing duplicates and irrelevant content. The captured information includes video link, video title,

video category, video duration, video synopsis, number of times the video was viewed, number of likes, number of clicks, number of comments, publisher, publisher's link, number of subscribers of the publisher, and the number of times the publisher's videos have been played on YouTube.

In addition, in order to improve the authority of the evaluation of the dissemination effect of Chinese calligraphy on overseas cross-platforms, the account type and video subject, which need to be manually coded to obtain the indicators, are collected, and the content coding is specifically shown in Table 1.

Table 1: Content encoding of propagation effect assessment

Index	Coding specification
Account type	1=ordinary person, 2= opinion leader, 3=government agencies, 4=media agencies, 5=club association, 6=public welfare organization, 7 = art activities, 8=company enterprise, 9=education training, 10=the Chinese community, 11=vertical community, 12 = others
Video theme	1=News and politic, 2= entertainment, 3= characters and blogs, 4=music, 5= education, 6= travel and activities, 7= movies and animations, 8= DIY and life encyclopedia, 9=public welfare and social activities, 10=science and technology, 11=other

2.2.2 Comment data processing

Based on the unstructured online comments under the Chinese calligraphy video, it is necessary to carry out data preprocessing operations, including the deletion of special symbols, English letters, and some repetitive comment data, the elimination of short-length comments, and so on, and then complete the deep cleaning of the data, to minimize the adverse effects of data structure problems on the subsequent model training, and lay a good data foundation for model training.

A total of 21,285 pre-processed comment text data are obtained after processing, which are divided into training set, testing set and validation set according to the ratio of 6:3:1. For the subsequent BERT-CNN model testing, the training set is applied to the model to output the classification results after labeling some text data for artificial sentiment classification.

2.3 BERT-CNN Sentiment Analysis Modeling

In this paper, we perform sentiment analysis on the comment texts of Chinese calligraphy videos based on the BERT-CNN sentiment analysis model.

2.3.1 BERT model

BERT is a bi-directional representational pre-trained language model derived from the Transformer model, BERT contains only the encoder part of Transformer.

Standard language models are unidirectional, but BERT's encoder is bidirectional. The BERT model adds two pre-training tasks, Masked Language Modeling (MLM) and Next Sentence Prediction (NSP), in order to obtain a good bi-directional language characterization and general adaptability of the model. In the MLM task, BERT randomly selects lexical elements at 15% position in each pair of sentences for masking action. Of these, 80% are directly replaced with <mask>, 10% are replaced with random lexical elements, and 10% keep the original lexical elements. This makes BERT focus on the prediction of contextual bi-directional information, and its function is similar to that of completing the blanks. In the NSP task, the pre-training samples are sampled with a 50% probability that the selected

sentence happens to be the next adjacent sentence, and a 50% probability that an arbitrary sentence is randomly selected. The BERT model has a stronger polysemous learning capability, and is more suitable for the task of sentiment analysis compared to other algorithms and models.

Sentiment analysis using the BERT model belongs to one of the downstream tasks of the model, which generally involves generating a vector representation of the text using the pre-trained BERT model, and then applying relevant classification algorithms for sentiment classification.

2.3.2 CNN models

The basic architecture of a convolutional neural network (CNN) consists of five layers: the input layer, the convolutional layer, the activation function layer, the pooling layer, and the fully connected layer. As the number of layers of the network increases, the problem of “gradient disappearance” or “gradient explosion” is likely to occur, resulting in model training becoming difficult, so it is generally also added to the network batch normalization layer.

(1) Input layer

The role of the input layer is to input data. The incoming data is usually preprocessed in the input layer, and through data preprocessing, the magnitude of the data can be eliminated to improve the convergence speed of the neural network.

(2) Convolutional Layer

The convolutional layer is named after the convolutional operation, which is the most basic operation in CNN. The role of the convolutional layer is to extract features from the data. Depending on the type of data in the input layer, CNN needs to choose different types of convolution kernels, which can be categorized into one-dimensional convolution, two-dimensional convolution and three-dimensional convolution.

(3) Pooling layer

The role of the pooling layer is to select the features extracted by the convolutional layer and reduce the size of the output, thus preventing overfitting. Compared to the convolutional layer, it is characterized by the fact that there are no parameters to be learned and it does not participate in backpropagation. Two common pooling operations are maximum pooling and average pooling.

(4) Fully Connected Layer

Fully connected layer means that each node is connected to all the nodes of the previous layer, generally located at the end of the CNN, is responsible for converting the two-dimensional features output from the convolutional layer or the pooling layer into a one-dimensional large vector, and then determining the model output based on the feature vector.

(5) Activation function layer

The previously mentioned convolutional, pooling and fully connected layers are all linear, so a nonlinear activation function layer needs to be added to the network. Adding a nonlinear activation function to the network architecture allows the neural network to learn complex functions, if no nonlinear activation function is added then each layer of the network is simply a matrix multiplication. The everywhere derivable nature of the activation function guarantees that its partial derivatives can be computed during back propagation. The monotonicity of the activation function guarantees that the single-layer network is a convex function.

The commonly used activation functions are Sigmoid function, ReLU function and Tanh function.

The Sigmoid function is defined as:

$$g(z) = \frac{1}{1 + e^{-z}} \quad (1)$$

The ReLU function is defined as:

$$g(z) = \max(0, z) \quad (2)$$

The Tanh function is defined as:

$$g(z) = \tanh(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}} \quad (3)$$

(6) Batch Normalization Layer

The batch normalization layer (BN) is the process of normalizing the data. The process of batch normalization can be described as follows: suppose the input batch data is $B = \{x_1, x_2, \dots, x_n\}$, then it can be computed its corresponding mean μ and variance σ^2 , and then the data is normalized:

$$\hat{x}_i = \frac{x_i - \mu}{\sqrt{\sigma^2 + \varepsilon}} \quad (4)$$

In order not to distribute the data on both sides of 0, which affects the nonlinear ability of the activation function, the parameters γ and β are introduced to translate and scale the normalized data to obtain the final output:

$$y_i = \gamma \hat{x}_i + \beta \quad (5)$$

CNNs were first used in the image domain until the emergence of the TextCNN model. TextCNN utilizes different sized kernels to extract the key information in a sentence so that local relevance can be better captured. In the sentiment analysis model, the text feature representation formula for the convolutional layer is shown below:

$$c_i = f(w \cdot X_{i:i+h-1} + b) \quad (6)$$

i denotes the i th feature and c_i denotes the feature vector generated from the i th feature value. f is the nonlinear activation function and b is the bias. W denotes the convolutional kernel size, h denotes the sliding window size, and $X_{i:i+h-1}$ denotes the feature matrix generated by the matrix X from the i th row to the $i+h-1$ th row.

All the feature vectors are combined into a feature map to generate the final feature vector c as follows:

$$c = [c_1, c_2, \dots, c_{n-h+1}] \quad (7)$$

The pooling layer chooses the maximum pooling method, i.e., only the feature values with the largest weights in each pooling kernel are retained and the rest are discarded. The formula is shown below:

$$p_j = \max(c_j) \quad (8)$$

2.3.3 BERT-CNN models

The BERT-CNN model consists of two main parts, the first part is the BERT base model and the other part is the CNN model. The BERT-CNN model is shown in Fig. 1. The model utilizes four convolutional kernels of different sizes to classify words or phrases at different scales. The text is passed through the BERT layer to obtain a vector representation, then each convolutional kernel takes the final output of BERT as a channel and performs a convolutional operation on it, then passes it through the ReLU activation layer and the maximum pooling layer. Finally, they are tandemly tapped flat and the final sentiment classification result is output after full connectivity through the Dense layer.

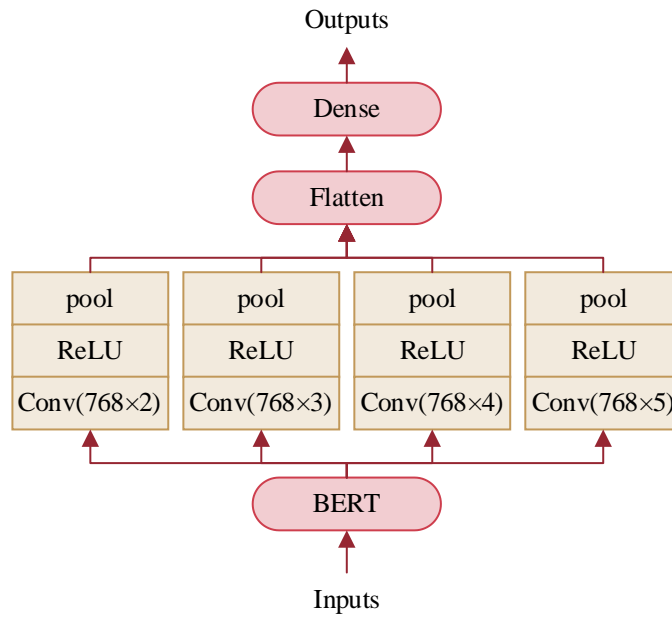


Figure 1: BERT-CNN model structure

2.3.4 Experimental Procedures

In the sentiment analysis of users' comments on Chinese calligraphy videos, their text data are characterized by strong media attributes, large scale and complex relationships. The basic process of textual sentiment categorization of Chinese calligraphy video comments is shown in Fig. 2, including steps of data preparation, model configuration, model training, model prediction, model evaluation and model application.

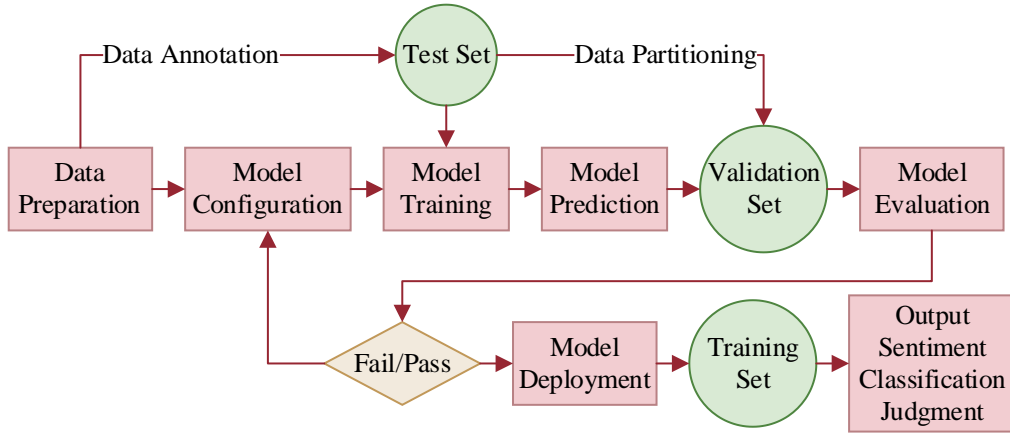


Figure 2: The basic process of the emotional classification of Chinese calligraphy video reviews

2.3.5 Evaluation indicators

After completing the construction and training of the model, the final experimental results need to be evaluated accordingly. In measuring the performance of each model, multiple metrics are often used to evaluate the model. In machine learning models with supervised learning, the confusion matrix is usually presented in a visual way to visualize its prediction results. Taking the sentiment analysis of Chinese calligraphy video comments in this study as an example, TP denotes that the actual sentiment tendency of the comments is positive, while it is recognized as positive by the classifier. FN denotes that the actual sentiment tendency of the comments is positive, but it is recognized as negative by the classifier. FP denotes that the actual sentiment tendency of the comments is negative, but it is recognized as positive by the classifier. TN denotes that the actual sentiment tendency of the comments is negative, and at the same time, it is recognized as negative by the classifier. FN denotes that the actual sentiment tendency of the comments is negative, but it is recognized as negative by the classifier.

The sentiment analysis method studied in this experiment belongs to the multicategorization problem, so the indicators commonly used in multicategorization should be selected for evaluation: accuracy, precision, recall and $F1$ value.

(1) Accuracy: indicates what is the probability of predicting the correct sample. The formula is as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (9)$$

(2) Precision: Indicates the percentage of samples with positive prediction results to the percentage of samples with positive predictions. The formula is as follows:

$$P = \frac{TP}{TP + FP} \quad (10)$$

(3) Recall: indicates the percentage of samples with positive predictions that are actually positive. The formula is as follows:

$$R = \frac{TP}{TP + FN} \quad (11)$$

(4) F value: represents the weighted harmonic mean of precision P and recall R . The formula is as follows:

$$F = \frac{(\alpha^2 + 1)P * R}{\alpha^2(P + R)} \quad (12)$$

When $\alpha = 1$ is the most common F1 value:

$$F1 = \frac{2 * P * R}{(P + R)} \quad (13)$$

3 Analysis of the effects of overseas dissemination

3.1 Publisher dimension

3.1.1 Distribution of account types

The publishers of the 300 videos were screened and analyzed, and a total of 264 published accounts were screened out by removing duplicate accounts, and the coding of the remaining 264 account types were counted, and the distribution of account types of Chinese calligraphy videos is shown in Figure 3. Among them, ordinary individuals (1) are the most dominant type of Chinese calligraphy video accounts on the YouTube platform, accounting for 43.94%, and media organizations (4) are the second most dominant type, accounting for 16.67%, and the number of accounts of these two major types exceeds 60% of the total number. The number of accounts of the types of societies and associations (5) and vertical communities (11) ranked third and fourth, accounting for 8.33% and 7.58%, respectively.

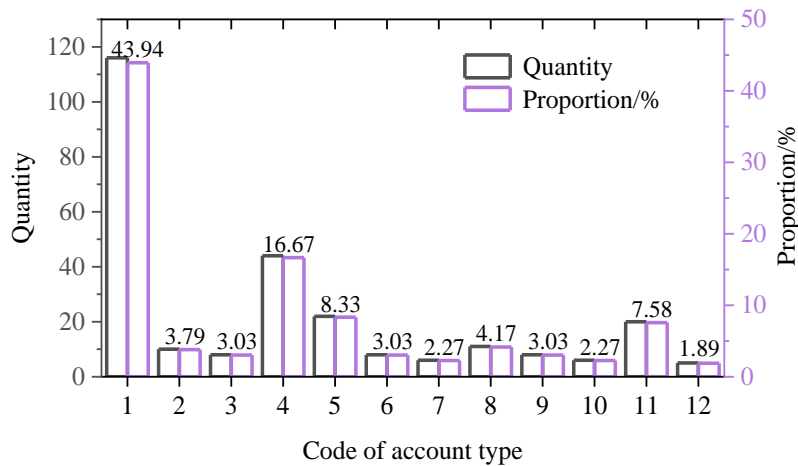


Figure 3: The number of account type of Chinese calligraphy video

3.1.2 Number of account subscriptions

As of the day of data collection, the total number of subscriptions of 264 YouTube platform accounts is 3577625, with an average value of about 23375, and the distribution of account subscriptions is shown in Figure 4. There are 49 accounts with 0 subscriptions, accounting for 18.56%, a total of 193 accounts with subscriptions between 0 and 10,000, more than 73% of

the total, and a total of 22 accounts with more than 10,000 subscriptions, accounting for 8.33%.

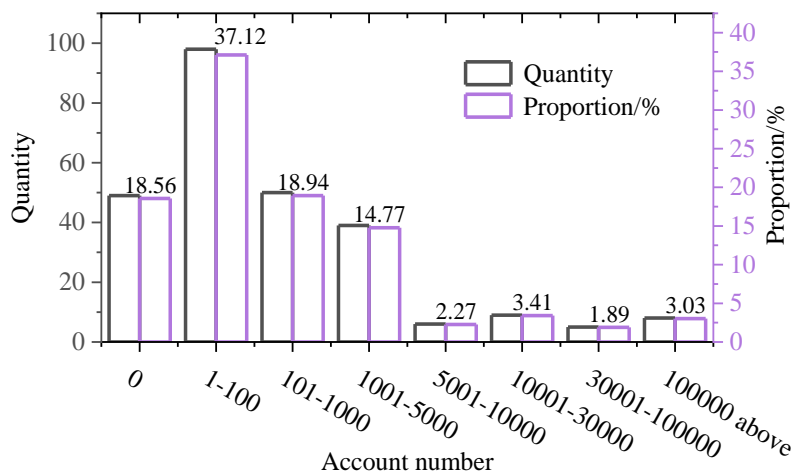


Figure 4: The distribution of the number of accounts

3.1.3 Cumulative account views

As of the day of data collection, there are 238 accounts with known cumulative views among 264 YouTube platform accounts, and the distribution of account cumulative views is shown in Figure 5. The number of accounts with cumulative views within 100,000 times is 107, accounting for nearly 44.96%, while the number of accounts with more than 100 million views is only 5, accounting for 2.10%.

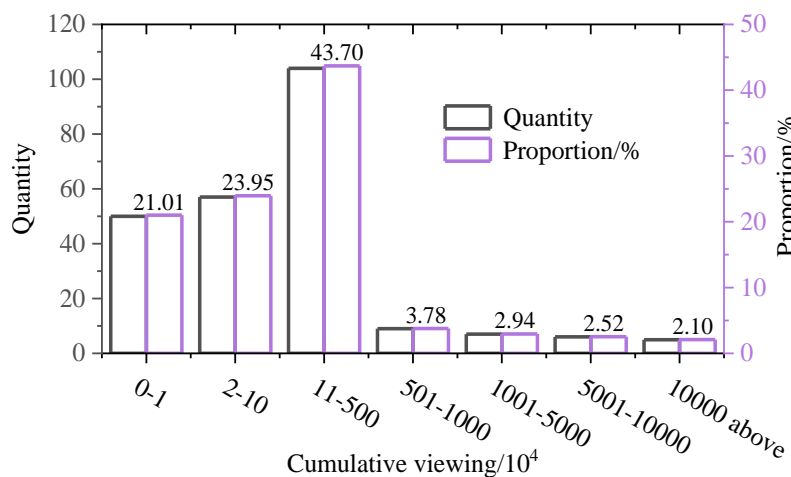


Figure 5: The distribution of the account accumulated viewing quantity

3.2 Dissemination of the content dimension

3.2.1 Video releases

The number of Chinese calligraphy videos released in different months is shown in Figure 6. The number of Chinese calligraphy videos released in different months on the YouTube platform shows a fluctuating trend, with a total of 123 videos released in September, October and November, accounting for 41% of the total, of which the number of videos released in November reaches the peak, and the number of Chinese calligraphy videos released on

YouTube in March is the lowest, accounting for 2.67%. The video releases in different months vary greatly, and the overall number of releases fluctuates more clearly, indicating that the releases of Chinese calligraphy videos on overseas platforms at different times have not formed a more stable trend, and are greatly influenced by various factors.

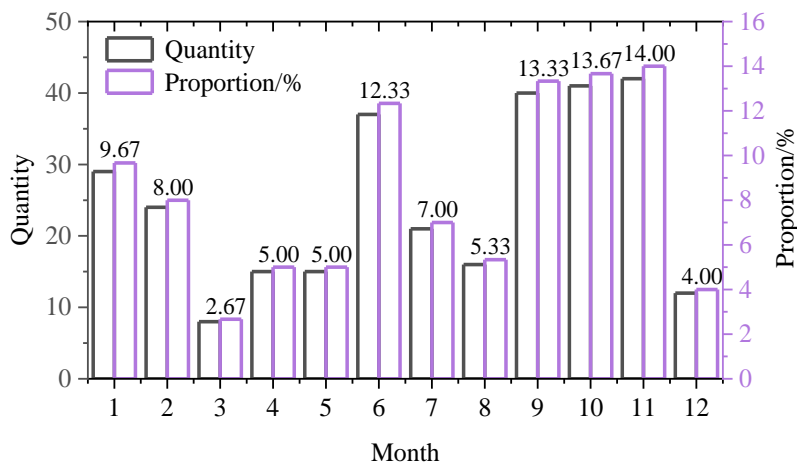


Figure 6: The number of calligraphy videos in different months

3.2.2 Distribution of video topics

According to the reported coding statistics of 300 video themes on YouTube, there is a wide range of video themes involving Chinese calligraphy culture on the YouTube platform, and the distribution of video themes of Chinese calligraphy is shown in Figure 7. Among them, people and blogs(3) are the No. 1 themes of Chinese calligraphy culture videos on YouTube platform, accounting for 36.00%, and videos themed on entertainment(2) are in the second place, accounting for 18.33%, and the number of videos on these two major themes is more than 50% of the total number of videos. The level with Education(5) as the theme is in the third place with 13.00%. Videos with News and Politics (1) and DIY and Life Encyclopedia (8) as themes were equal in number, with these two together accounting for 18.00% of the total videos.

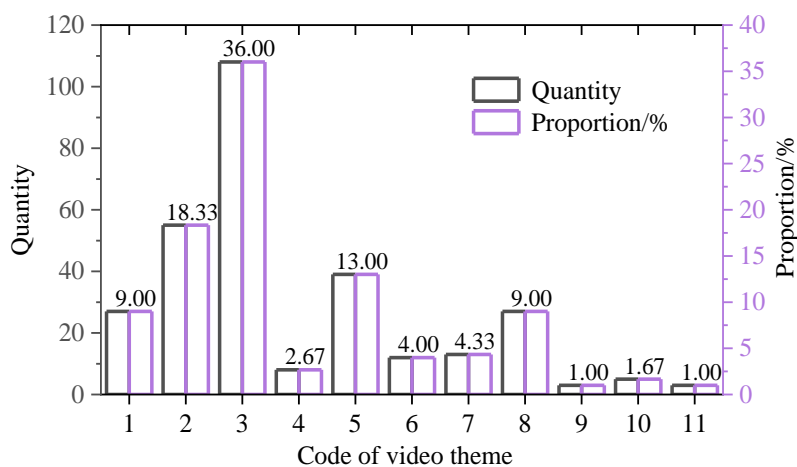


Figure 7: The video theme distribution of Chinese calligraphy

3.2.3 Video Duration and Profile Length

Chinese calligraphy video duration and video synopsis length on YouTube can reflect the content richness of Chinese calligraphy culture videos. The distribution of video duration and synopsis length is shown in Table 2. The number of videos with playing time within 1000 seconds is the largest, accounting for 86.33%, the number of videos with synopsis characters within 1000 accounts for 93.33%, and there are 57 videos without synopsis, accounting for nearly 20%.

On the whole, the length of Chinese calligraphy videos is basically within 1,000 seconds, and the number of long videos with more than 5,000 seconds is very small on YouTube. Most of the videos are accompanied by a brief description, and the number of characters in the brief description is mostly within 1,000, and the frequency of the brief description for videos with large segments exceeding 1,000 is relatively low.

Table 2: Length of video and length of profile

Video time length/s	Quantity	Proportion/%	Profile length/ character	Quantity	Proportion/%
1-100	59	19.67%	0	57	19.00%
101-1000	200	66.67%	1-100	70	23.33%
1001-3000	24	8.00%	101-500	101	33.67%
3001-5000	5	1.67%	501-1000	52	17.33%
5001-10000	6	2.00%	1001-2000	17	5.67%
10000 above	6	2.00%	2000 above	3	1.00%
Total	300	100%	Total	300	100%

3.3 Dissemination of the audience dimension

3.3.1 Number of views and likes and dislikes

The number of video views, likes and pedals of Chinese calligraphy can reflect the attention and popularity of Chinese calligraphy videos on overseas social media platforms within a certain period of time. The distribution of the number of video views, likes and clicks is shown in Fig. 8(a)~(c).

Among the 300 videos sampled, there is a “long-tail” distribution in which very few videos have a huge number of views and the majority of videos have a very low number of views. The number of videos with less than 100 views accounted for 51.67% of the total number of videos, the number of videos with less than 1,000 views accounted for 90% of the total number of videos, and the number of videos with more than 5,000 views was only 5 videos, accounting for 1.67%. The number of videos with 0 likes accounted for 39.33% of the total number of videos, the number of videos with less than 10 likes accounted for nearly 90% of the total number of videos, and the number of videos with 0 likes accounted for 85.67% of the total number of videos. It shows that Chinese calligraphy has low attention and popularity on YouTube, but only a small portion of the audience expresses negative emotions towards Chinese calligraphy videos.

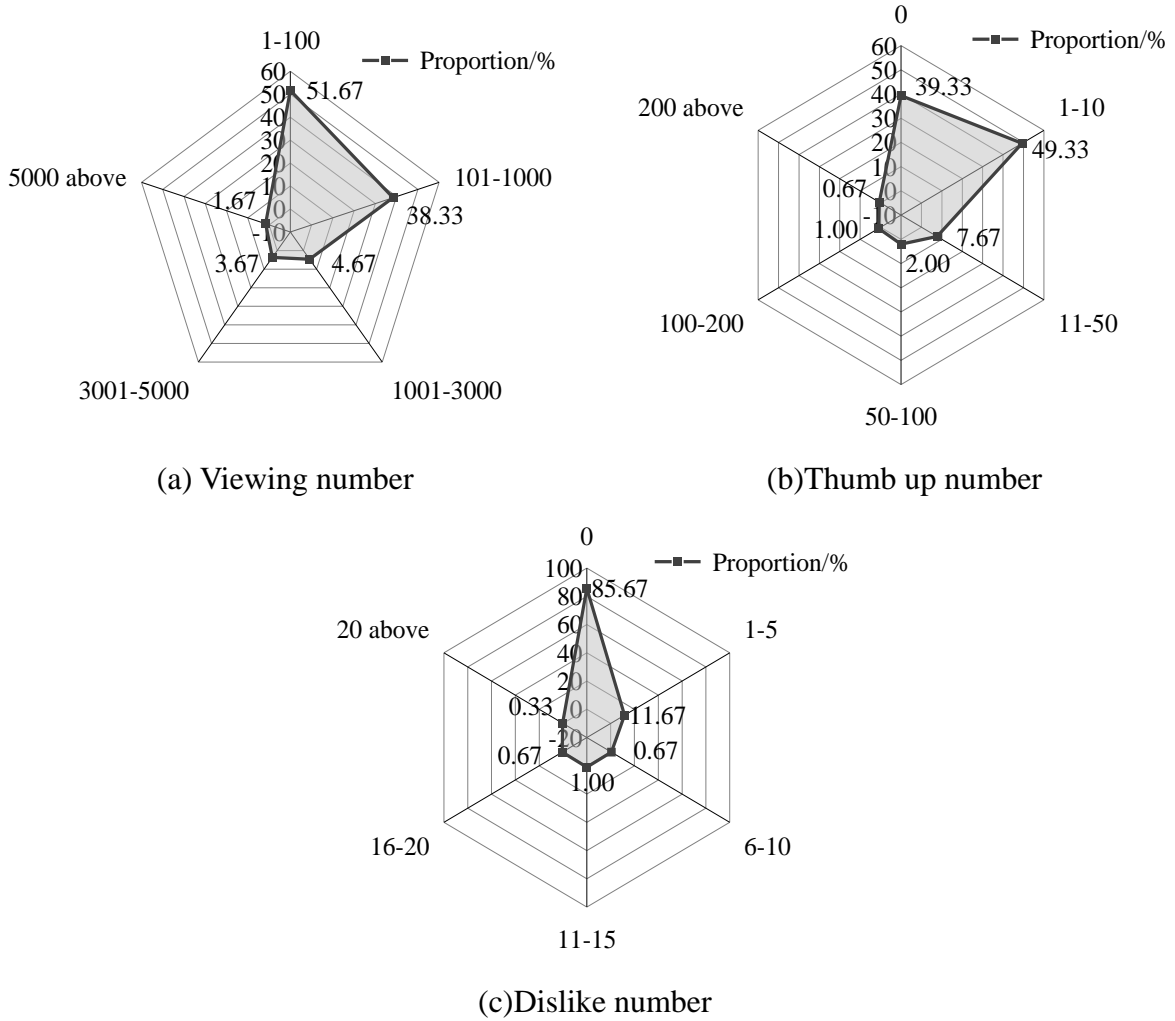


Figure 8: Number of views, thumb points and dislike

3.3.2 Commentary Sentiment Analysis

The comment text attitude of Chinese calligraphy video is categorized into four types: Like, Pity, Normal and Dislike, and the BERT-CNN model is evaluated using the training set data with Precision, Recall and F1-score as evaluation indexes, and the model evaluation results are shown in Fig. 9. It can be seen that among the four types of classification, the indicators of Like class are at a high level, all above 85%, while the indicators of Pity class (lament) and Dislike (disgust) are slightly lower compared to the Like class, with the F1-score of 81.9% and 79.3%, respectively. This is due to the fact that the sample size of Pity and Dislike comments in the manually labeled dataset is relatively small compared to Like and Normal, and the model's recognition effect on Pity and Dislike is relatively weak, but after tuning, it now reaches a usable level. The overall evaluation of the model is good, and the classification F1-score for each type of emotion is between 79% and 90%, which can pass the model evaluation and be applied to the training set.

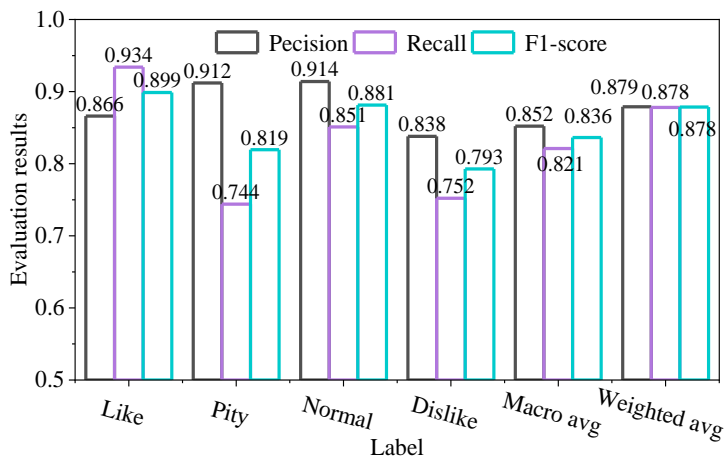


Figure 9: BERT-CNN model evaluation results

After training, this experiment needs to import the comment text data in the test set into the BERT-CNN text sentiment classification model to output the corresponding sentiment attitude classification of each Chinese calligraphy video comment. The distribution of sentiment tendencies of Chinese calligraphy video comments is shown in Figure 10. Among them, Normal category comments account for the most 68.25%, while Dislike category comments account for 2.41%, Pity category comments account for 2.56%, and Like category comments account for 26.78% of the comments with significant emotional color. It can be seen that the audience's willingness to discuss Chinese calligraphy videos is high, the amount of interaction between the author and the audience and between the audience and each other is high, and the vast majority of the audience expresses the attitude of active participation and favoritism.

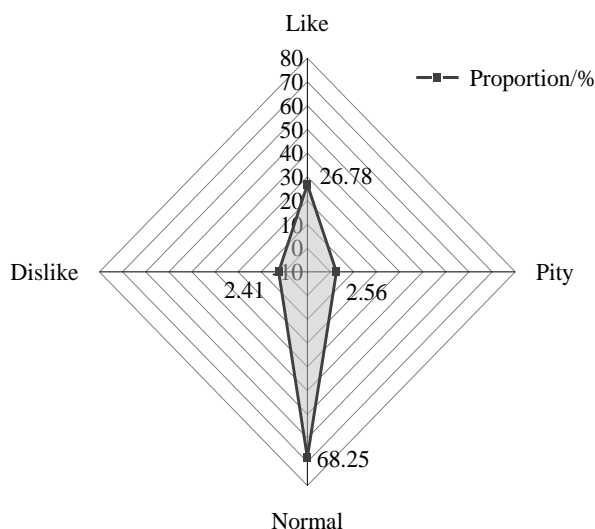


Figure 10: The emotional tendency of Chinese calligraphy video reviews

4 Chinese Calligraphy Overseas Communication Strategy

Chinese calligraphy, as a traditional art with a long history, carries rich cultural connotations, aesthetic values and the inheritance of human wisdom. In the era of new media, it is worthwhile to explore how Chinese calligraphy can be better disseminated overseas across

platforms.

4.1 Content strategy

Content strategy plays a crucial role in the dissemination of calligraphy culture in the new media era. First of all, the calligraphic works should be attractive, which can be realized by the artist through innovative use of ink and brush, unique style or exploration of the theme. Second, the work needs to be unique, including a particular calligraphic script, a distinctive composition, or highlighting a certain cultural characteristic. Most importantly, the calligraphic work should have a storytelling quality. By giving the work a storytelling dimension, viewers can better understand the cultural, historical, or personal story behind it, which will deepen their emotional connection and identification with the work. At the same time, the content should convey the history, techniques and cultural context of calligraphy. This helps to improve the cultural literacy of the audience so that they can better understand and appreciate the calligraphic works.

4.2 Platform selection

Choosing the right new media platform is crucial to the dissemination of calligraphy culture. Different platforms have different audience groups and characteristics, so they need to be selected according to the target audience. For example, visual social media platforms such as Instagram are suitable for displaying pictures and videos of calligraphy works, while blogging platforms with rich textual content are suitable for in-depth discussions on the history and techniques of calligraphy. Choosing the right platform will help spread the culture of calligraphy to the most interested audience and increase the effectiveness of communication.

4.3 Interactive Strategies

In order to effectively communicate calligraphic works and engage audiences, active social media interaction is essential. This includes creating interactions with audiences and responding to their comments, questions, and feedback; by actively engaging with followers, artists can create a more intimate and authentic connection and increase audience engagement. In addition, online events and competitions are a powerful way to inspire audience engagement. Organizing calligraphy competitions, online exhibitions and interactive events not only attracts more people to participate, but also improves the dissemination of calligraphy culture.

4.4 Branding Strategy

Establishing a calligraphy brand is about creating a distinctive logo and identity for the dissemination of calligraphy culture, making it unique and attractive in the marketplace. For example, a brand may focus on a particular calligraphy style, emphasizing its uniqueness and depth. And visual and sound identities are key elements in building brand recognition and trust. For a calligraphy brand, the visual identity may include a specific calligraphy font, logo design, or iconic artwork samples. Sound identities, on the other hand, include music, sound effects or voice logos that can be used to convey the emotions and characteristics of the brand through sound. These logos not only enhance the recognizability of the brand, but also help establish brand credibility and communication of brand values.

5 Conclusion

The booming development of new media brings a new development mode for the promotion of Chinese calligraphy culture. This paper takes Chinese calligraphy videos on YouTube as the research object, and combines the BERT-CNN text sentiment analysis model to evaluate the dissemination effect of Chinese calligraphy on overseas platforms. The main analysis results are as follows:

(1) In terms of video publishing, Chinese calligraphy content publishers are of various types, with a clear trend of concentration; individuals and media constitute the main source of publishers, accounting for more than 60% of the total, with low to medium subscriptions and cumulative views accounting for the vast majority. (2) In terms of dissemination content, video releases were concentrated in September to November, with people and blogs, entertainment, and educational themes dominating, accounting for more than 65% of the total, 86.33% of the videos were within 1,000 seconds of each other, and 93.33% of the video profiles were within 1,000 characters of each other. (3) In terms of dissemination audience, videos with less than 1000 views and less than 10 likes accounted for 90% of the videos, and 85.67% of the videos had 0. Most of the audience's emotions towards Chinese calligraphy were fondness and indifference, and less than 5% expressed regret and disgust, which shows that the new media promotion channel is generally supported and loved by the audience, and the authors were able to create high-quality Chinese calligraphy videos through the The authors are able to promote Chinese calligraphy-related contents to audiences through the creation of high-quality Chinese calligraphy videos.

Overall, the overseas platforms for Chinese calligraphy are diverse and unevenly distributed, with a low degree of communication specialization, but the advantages of professional media are obvious, and the feedback from the audience is more positive. In this paper, we put forward suggestions from four aspects: content strategy, platform selection, interactive strategy, and branding strategy, in order to promote the dissemination of Chinese calligraphy culture on overseas platforms.

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