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Research on the Impact of Online Public Opinion on College Students' Mental Health — *A Natural Language Processing–Based Approach*

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Abstract. As the Internet becomes deeply integrated into college students' daily lives,online public opinion has become an important factor influencing their mental health.This study investigates its impact on college students by collecting textual data from news comments,Weibo,Zhihu,and university forums.Using high-frequency word analysis,word-cloud visualization,and sentiment analysis,CNN and CNN-LSTM models were developed to examine topics including online culture,online gaming,cyberbullying,online social networking, mental health, public opinion governance, and online discourse.The results show that negative sentiment outweighs positive and neutral sentiment in online discussions and tends to generate greater engagement,as reflected in higher numbers of comments and likes.In particular,cyberbullying, online gaming,online social networking,and online discourse emerge as key negative factors affecting college students' mental health.The CNN-LSTM model also outperformed the CNN model in sentiment classification.The findings suggest that universities should strengthen online public opinion guidance, improve mental health services, and enhance students' information literacy and emotional regulation.

Keywords: Online public opinion; college students; mental health; sentiment analysis; CNN-LSTM.

1. Introduction

According to the 56th Statistical Report on Internet Development in China released by the China Internet Network Information Center (CNNIC), China had 1.123 billion internet users by July 2025, with an internet penetration rate of 79.7%, representing an increase of nearly 45 million users compared with 2023 [1].

Against this background, college students have become one of the most active groups in online environments. However, their ability to identify, assess, and filter online information remains relatively limited. Given the rapid dissemination, high emotional intensity, and uncertain credibility of online public opinion, college students may be particularly susceptible to its influence on value judgment, cognitive evaluation, and behavioral choice. As a result, the potential impact of online public opinion on college students' mental health has become an issue of increasing academic and social concern.

In methodological terms, current research is still dominated by theoretical discussion and qualitative interpretation, while systematic quantitative investigation remains insufficient. In particular, empirical studies on college students' resistance to online public opinion and its influencing factors are still lacking. In terms of research content, previous studies have mainly concentrated on dissemination mechanisms [2] and governance strategies [3], whereas comparatively less attention has been paid to students' psychological responses, cognitive processing, and behavioral decision-making in the face of online public opinion. Therefore, both the depth and breadth of existing research need to be further expanded.

Western research on online public opinion started relatively early and has grown steadily since around 2012. Existing studies mainly adopt a macro-political perspective [4], focusing on media structure and public cognition [5], the institutional constraints of the public sphere [6], the role of media technology in reshaping opinion and agenda setting [7], political polarization, echo chambers, and algorithmic filtering [8] [9], as well as broader issues such as international relations and diplomatic decision-making [10] [11]. This body of work provides an important framework for understanding the dissemination mechanisms and power structure of online public opinion, but it pays relatively limited attention to the mental-health effects on specific groups such as college students.

By contrast, domestic research is more closely tied to concrete social events and governance practices, especially opinion guidance, crisis communication, and policy response. However, systematic micro-level evidence on college students'mental health remains insufficient. Therefore, this study focuses on college students and seeks to connect macro-level theory with event-based research through an analysis of psychological mechanisms. Drawing on Western perspectives on media structure and algorithmic polarization, and using multi-source data and empirical models, it examines the links among exposure to online public opinion, emotion regulation, and mental-health outcomes, thereby addressing an important gap in literature.

2. Theoretical Framework

First, we took "online public-opinion" governance as the survey topic and focused on current hot issues. By scraping comment data related to "college students and online public opinion" from mainstream media platforms such as Tencent News, Weibo, and Zhihu, we conducted big-data text mining through manual labeling [8] and then performed text analysis to judge the sentiment tendency of comment data and mine and analyze the hidden information, so as to accurately and effectively identify college students' level of understanding, key concerns, and attitudes toward such events from comment data on major news websites.

With the help of CNN models and in combination with the LSTM model [12], this study compares the performance differences between CNN and an improved model in addressing the problem examined here. It analyzes how respondents' age, "mental-health education (online)," "online public opinion," "online games," and other factors affect attention to education-related events concerning "fragility." The analysis shows that "mental-health education (online)," "online public opinion," "online games," "online social networking," and "online culture" are significant factors through which online public opinion affects college students. A further comprehensive test is then conducted to ensure the overall goodness of fit of the regression equation. Finally, by integrating the results of text mining and field sampling surveys, the study draws conclusions and puts forward substantive suggestions.

During forward propagation, the input graphical data pass through multiple convolutional and pooling layers to extract feature vectors [10]. These feature vectors are then fed into a fully connected layer to produce classification results. When the output matches the expected value, the result is generated. The overall process is shown in the figure below:

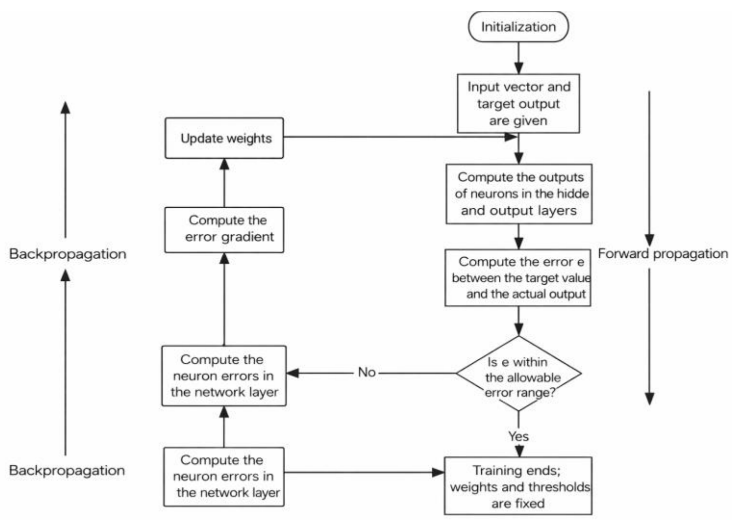

Figure 1. Workflow of the Convolutional Neural Network Model.

The input layer is a matrix, where the number of rows corresponds to the total number of words in the text and the vector dimension corresponds to the embedding dimension of each word. The parameters of the unknown channels are initialized and then gradually updated through iterative training of the network.

After the LSTM has traversed all the words in the text sequence(x_1,x_2,…,x_T), the final hidden state is used for sentiment classification. Usually, the last hidden state h_t is mapped through a fully connected layer and an activation function (such as D or Sigmoid) to obtain the probability distribution of sentiment categories. For example, assuming we have three sentiment categories—positive, negative, and neutral—the result can be written as follows:

$$y=Softmax(W_y h_T+b_y) \tag{1}$$

Here, the probability vector r$y \in R^3$ epresents the sentiment-classification output, while the weight matrix W_y and bias term b_y belong to the fully connected layer[13].

After local patterns are extracted by scanning the input data with convolution kernels (that is, after the CNN layer), pooling is needed to retain the main features and reduce computational complexity. After normalization accelerates convergence, the data are fed into the LSTM [11]. Through the input gate, forget gate, and output gate, the model controls information flow, overcomes the gradient-vanishing problem of traditional RNNs, and captures long-term dependencies.

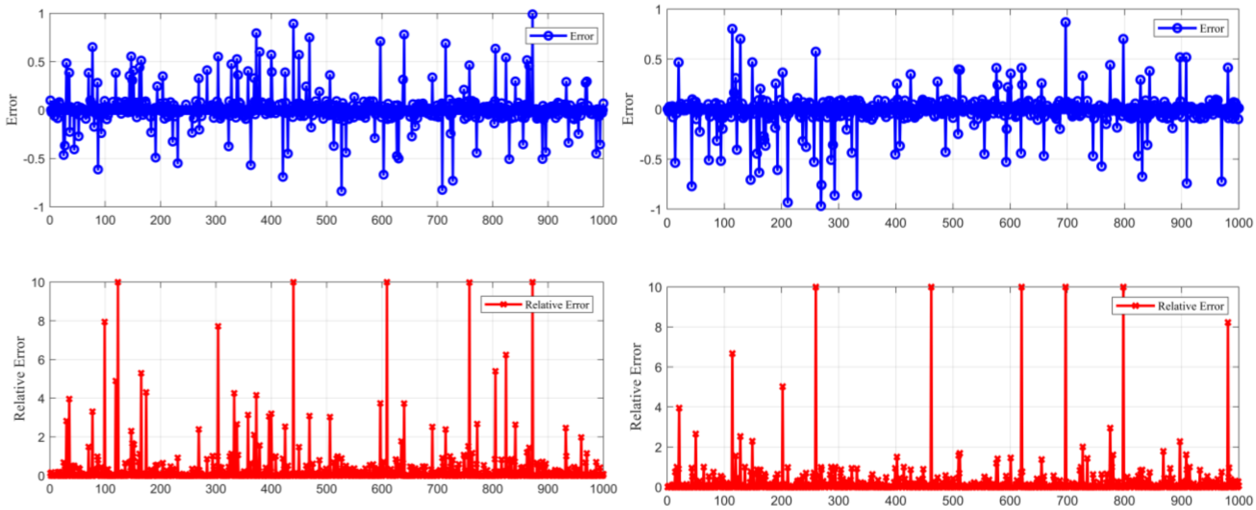

Figure 2. Relative (Error) of the Model Test.

Error and relative error tests were conducted on the trained CNN and CNN-LSTM models. Figure 2 shows that the CNN model was successfully trained, with low error and relative error. Compared with the CNN model, the CNN-LSTM model achieved better performance in both metrics and exhibited good stability.

3. Results and Discussion

According to the CNN model,the sentiment tendencies obtained on the test set (data from university Tieba forums) are shown in Table 1.

Table 1 Results of Sentiment Tendency Analysis Obtained by the CNN Model

Category	Positive	Neutral	Negative	Tieba data	Proportion
Public-opinion governance	70.17%	8.60%	21.23%	1868	17.90%
Category	Positive	Neutral	Negative	Tieba data	Proportion
Cyberattacks	40.21%	9.62%	50.17%	1815	17.43%
Online games	41.02%	9.77%	49.21%	1715	16.45%
Online social networking	41.15%	10.13%	48.72%	1378	13.21%
Mental health	45.39%	10.16%	44.45%	1265	12.12%
Online public opinion	31.09%	12.94%	55.97%	1229	11.78%
Online culture	41.85%	8.71%	49.44%	1159	11.11%

Finally, the sentiment tendencies obtained on the test set (data from university Tieba forums) are shown in Table 2.

Table 2 Results of Sentiment Tendency Analysis Obtained by the CNN-LSTM Model.

Category	Positive	Neutral	Negative	Tieba data	Proportion
Public-opinion governance	67.83%	9.97%	22.20%	1868	17.90%
Cyberattacks	42.71%	10.82%	46.47%	1815	17.43%
Online games	39.55%	10.68%	49.77%	1715	16.45%
Online social networking	41.19%	10.11%	48.70%	1378	13.21%
Mental health	44.39%	10.76%	44.85%	1265	12.12%
Online public opinion	32.09%	12.74%	55.17%	1229	11.78%
Online culture	43.95%	9.79%	46.26%	1159	11.11%

From Tables 1 and 2, it can be observed that "cyberattacks" produce the highest level of negative public opinion, followed by "online social networking" and "online games." It is not difficult to see that cyberattacks are intertwined with factors such as online games and online social networking, so it is not surprising that cyberattacks generate the strongest negative public opinion. Therefore, in order to reduce the negative public opinion and impacts brought about by cyberattacks, promoting more positive energy in games and social interaction could be a solution that serves multiple purposes at once.

4. Summary

In conclusion, online public opinion has become an important factor affecting the mental health of college students. Information overload, negative content, and the difficulty of verifying online information can easily trigger anxiety, confusion, and other psychological problems. At the same time, academic, social, and employment pressures further intensify students’ psychological vulnerability. Therefore, universities should strengthen mental-health education and counseling services, promote students’ participation in real-life activities, and improve their psychological resilience. In addition, colleges should enhance online ideological education, respond promptly to hot issues and rumors, and guide students to form rational judgments in the online environment.

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