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Research Article

Analysis of Online Education Reviews of Universities Using NLP Techniques and Statistical Methods

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In the long-running battle against COVID-19, it is worth further discussing how well online education is accepted by users as a new type of education method which is popularized suddenly. The launch of a large-scale online teaching during the COVID-19 pandemic gave us the opportunity to investigate the opinions and emotions of online teaching users. This paper employs NLP techniques and statistical methods to process 93754 comments collected from the three online teaching platforms designated by the Ministry of Education for universities. This study aims to gain a better understanding of the changing characteristics of students' opinions and emotions regarding online teaching, as well as to learn what students required and how the platforms functioned during the epidemic period. The findings revealed that (1) users of online teaching platforms were mostly concerned about whether the teaching resources provided by the platforms were rich and of high quality all along. The main influencing factors affecting online teaching experiences during the implementation of large-scale online teaching are hardware device deficiencies such as server congestion and network lag. (2) The majority of users expressed positive attitude towards online education which played a positive role during the outbreak. (3) The epidemic had a significant impact on the emotions of online teaching users. In short, the research themes showed that online teaching users are always concerned with the richness and quality of the platform's resources. Furthermore, the most important issues for users during the period of large-scale online teaching are whether the network infrastructure is efficient and smooth, as well as the platform's function perfection. The popularity of online teaching helped to solidify the online teaching space and improve its social image. This study provides a point of reference for the development and improvement of online education and compensates for a lack of relevant studies.

1. Introduction

When Chinese universities postponed their courses during the COVID-19 pandemic in 2020, online teaching had become the primary way to ensure that the teaching activities in universities were carried out. Despite the fact that China began the pilot project of "Modern Distance Education" in 1999 and vigorously promoted online open courses (MOOC) in 2012, online teaching has always been in a supporting role and has been frequently questioned by teaching effect and satisfaction [1, 2]. With the implementation of large-scale online teaching in China, it is critical to investigate how the opinions and emotions of the online teaching users change in order to promote and improve online teaching in the future.

Early in the days of the resumption of online classes for primary and middle school students, the "Dingtalk received one-star rating from the pupils" was on the hot search list of Weibo, and "online teaching platforms collapsed" had become a hot topic. If the pupils' minds are immature and the comments refer to "emotional catharsis," the reviews of online teaching platforms are particularly valuable for the relatively rational college students. Generally speaking, whether online teaching can promote school education is closely related to the opinions and emotions of users. As information technology advances, an increasing number of people start to express their needs and emotional attitudes towards something by using network comments. The genuine perspective of users can be fully reflected in the open, shared, and anonymous network space. In recent years, mining user opinions and feelings from network platform comments has taken on a new focus. In this context, Natural Language Processing (NLP) technologies and statistical models are used to explore the views and emotions of users of online teaching, effectively extract and analyze the comments, and extract the topic words with directional meaning and emotional tendency from the comments.

The innovations and contributions of this paper are listed below.

(1) Online education has been studied and used since the 1990s, but there has not been a chance for widespread implementation. Instead, it has been used to supplement traditional classroom learning. As a result, there is a lack of research on large-scale online education. In order to make up for the absence of relevant studies, this paper uses online teaching platform reviews for the semester when universities implemented online teaching on a large scale for the COVID-19 period

(2) In terms of research methods, the data sources are mostly data from online teaching questionnaires, which are more targeted and the research results are easier to quantify. However, the established questionnaire questions have limitations and the designed response range restricts the complete and true expression of respondents' opinions, whereas online comments on the Internet can fully express respondents' opinions. Therefore, this paper takes the comments of online teaching platforms as research data, which can accurately reflect users' emotions and concerns

This paper provided a useful reference for the relevant administrative departments, universities, and enterprises to develop online teaching.

2. Literature Review

2.1. Student Satisfaction and Influencing Factors of Online Teaching. Online education has fundamentally changed how knowledge is gained and made learning more individualized by fusing the Internet and education across the boundary. According to a study of the literature, relatively little research has examined how well online teaching platforms are working by examining student feedback [3]. The literature that is most pertinent to this topic focuses on two primary areas: ① the influencing factors of online learners' learning experience; ② learning satisfaction. The learning experience of students as participants in online learning is affected by a variety of elements. According to Paechter et al., the online learning environment, resources, learning process, and interaction are the primary influencing aspects of online learning [4]. Following the study by Alhabeeb and Rowley, they highlighted the significance of technical infrastructure, staff technical level, student computer proficiency, and e-learning acceptance as major elements in aiding the success of e-learning [5]. According to Kamali and Kianmehr, an effective network environment is required from the viewpoint of students in order to improve online education [6]. Learner satisfaction, however, indicates how students feel about their educational experience [7]. Through a survey of 1,786 MOOC participants, Gameel discovered that access to learning resources online after class and students taking ownership of their learning both positively influenced learner satisfaction [8]. Alzahrani and Seth discovered that during the pandemic, service quality had no bearing on students' satisfaction, but that self-efficacy and information quality had a substantial impact [9].

2.2. Sentiment Analysis of Online Teaching Based on NLP. A significant use of NLP is sentiment analysis and opinion mining, which identify opinions and categorize text as positive, negative, or neutral. In order to research the quality of associated goods and services or to comprehend netizens' emotional inclinations, short text sentiment analysis for netizens' comments includes website evaluations, tourist hotel reviews, Twitter, microblog, and other social networking sites. Along with current data mining and learning analytics techniques, course evaluation or faculty performance evaluation was carried out by El-Halees and Rashid from students' feedback dataset [10, 11]. Naive Bays, *k*-nearest, and Support Vector Machine were used and compared in the evaluations. Additionally, effective approaches to sentiment analysis from feedback evaluations have been put forth by Kechaou et al., utilizing a Hidden Markova Model and a Support Vector Machine without experiment results, and by Ortigosa et al. with the combination of lexicon and SVM proposed. Moreover, there has been an increasing interest in exploring sentiment recognition, classification, and prediction in the field of education [12–15].

Based on the above literature, scholars from different countries analyzed online teaching from multiple perspectives including influencing factors of online teaching, satisfaction of online teaching, and emotional analysis of online teaching students. They then compared and improved categorization models. However, there is lack of studies of online teaching platform in a large-scale application. In most studies, online teaching was only a supplement to classroom teaching, rather than a main teaching method. When online education is the primary or even the sole school teaching technique, does it affect students' opinions and feelings, or satisfaction differently than when it is merely a supplemental teaching method? There was no precedent for mass adoption of online education before the COVID-19 outbreak in several nations. The COVID-19 pandemic forced some nations, including China, to implement online education on a national scale during the acute stage of the epidemic, opening the door for research on widespread online education. This study uses big data technologies to examine the opinions and emotions and their evolution of the online teaching platforms during the semester when all Chinese colleges adopted online teaching during the COVID-19 epidemic in order to make up for the lack of pertinent research.

3. Research Method and Definition of the Problem

3.1. Data Collection and Pre-Processing

3.1.1. Select the Information Source. In a survey of online teaching during the COVID-19 pandemic, the Chinese Network of Internal Quality Assurance Agencies in Higher Education (CIQA) and China Education Network found that, respectively, 26.22 percent, 17.74 percent, 9.94 percent, 9.63 percent, and 22.44 percent of college teachers used CHAOXING Learning, Tencent Class, DingTalk, Cloud Class, and other platforms [16]. The primary online teaching platforms that enable MOOC are, among them, China University MOOC (73%) and Xuetang online (47%) whereas those that support live courses include Rain Classroom (73%), Zoom (50%), Tencent Class (47%), and DingTalk (40%) [17]. Based on the aforementioned survey, this article chooses three platforms from the Ministry of Education's list as its research targets CHAOXING Learning, China University MOOC, and Tencent Class.

3.1.2. Define the Time Interval. The start time is when the platforms for online teaching go live. Online classes offered by Tencent, China University, and CHAOXING Learning are available on December 1, 2016, May 28, 2015, and April 10, 2016, respectively. The deadline is June 30, 2020, which is when the online semester ends. All the data are split into two halves for study, using Wuhan's lockdown on January 23, 2020, as the time node. Pre-epidemic data are those collected prior to January 23, 2020, and in-epidemic data are those collected following that date.

3.1.3. Get the Data. Python programming was used to obtain comments from the relevant online learning platforms under the condition of time interval. User name, publishing time, content, whether to modify it or not, and score are among the crawling contents. The crawled data is stored in the MySQL database.

3.1.4. Data Cleaning. We ultimately obtain the initial data after removing duplicate and blank entries. There are 36414 valid CHAOXING Learning data points, 23812 valid Chinese University MOOC data points, 33528 valid Tencent Class data points, and a total of 93754 valid comments among them.

3.2. Method. Internet comments are the most intuitive, concrete, and real data sources offered by online users in the era of big data. They serve as a reflection of the online users' most worrying content and are a crucial source for researching user attitudes and sentiments. In order to thoroughly and impartially analyze the evolution of users' ideas and feelings before and after the pandemic and disclose the overall and psychological impression of online teaching platforms, text mining and processing were done using big data technology. In this research, natural language processing techniques including emotion analysis and high-frequency word analysis were predominantly used.

3.2.1. Analysis of High-Frequency Terms by Statistical Method TF-IDF. Due to the more freedom and anonymity of cyberspace, users' comments are usually regarded as the real reflection of their perception. However, is there a general representative view in the mass of disorderly comments? How to extract representative opinions from massive user comments?

To determine the significance of a word to a file in a corpus, Jones proposed the statistical technique Term Frequency Inverse Document Frequency (TF-IDF) [18]. The primary premise is that a word or phrase has a strong categorization capacity and can represent a file if it occurs frequently in one file but infrequently in other files, as measured by term frequency (TF). However, it might be challenging to accurately describe the significance of terms using merely word frequency. A popular weighting technique for data mining and information retrieval is TF-IDF. By including the Inverse Document Frequency (IDF) in the computation of keyword weight, it is possible to effectively minimize the weight of some referential and unnecessary terms, as well as the inaccuracy that results from basing weight determination exclusively on word frequency [19].

The following steps are included in the analysis of high-frequency word:

(1) The stop words are eliminated after segmenting the initial data

(2) Word frequency is counted and word distribution characteristics in the corpus are obtained

(3) The keywords are weighted and extracted to obtain words with weight

The term frequency in the TF-IDF method is used to define the frequency of words. The calculation formula is shown in Equation (1).

$$tf_{i,j} = \frac{n_{i,j}}{\sum_k n_{k,j}}, \tag{1}$$

where $n_{i,j}$ in Formula (1) represents the overall frequency with which the term t_i appears in comment set (d_j) of online teaching platform. $\sum_k n_{k,j}$ stands for the total number of words in the online teaching platform's comment set.

IDF measures the universality of a word by examining its presence in the corpus. The higher the IDF value is, the less common the word is and the stronger the ability to distinguish documents. The calculation formula is shown in Equation (2):

$$idf_i = \lg \frac{|D|}{1 + \left|\left\{j : t_i \in d_j\right\}\right|}. \tag{2}$$

In Equation (2), $|D|$ represents the total number of comments in the online teaching platform corpus to be analyzed. $|\{j : t_i \in d_j\}|$ indicates that the comment set includes the word t_i. The Laplace smoothing method is used by $1 + |\{j : t_i \in d_j\}|$ to calculate the denominator in order to prevent the denominator from being 0, which would be the case if the word does not present in the corpus.

In the corpus dataset to be examined, the following formula is used to determine the word t_i's TF-IDF value:

$$tfidf_{i,j} = tf_{i,j} * idf_i = \frac{n_{i,j}}{\sum_k n_{k,j}} * \lg \frac{|D|}{1 + \left|\left\{j : t_i \in d_j\right\}\right|}. \quad (3)$$

Take TF-IDF as a measure of the significance of words. The importance of the associated keywords increases with the weight value, demonstrating that users give related issues more consideration.

The comments in the online teaching platform app were extracted and stored in the MySQL database in this work with the aid of the Python programming language. The database's data was categorized and tagged using the Python tool Jieba. After extracting the keywords containing nouns and emotive adverbs using the TF-IDF algorithm, the appropriate TF-IDF weight value was obtained.

3.2.2. Emotion Analysis Based on NLP. Emotion analysis was first proposed by Nasukawa [20]. Emotion analysis is the process of extracting the sentiment tendency from the text data released by users, calculating the emotional intensity of each text data, and obtaining whether the sentiment tendency of the text is positive, negative, or neutral. At the same time, users' emotional changes are tracked and observed by statistical distribution and variation trend of emotional values. Currently, studies on sentiment analysis are mainly focused on product reviews or movie reviews from blogs and websites [21–23]. Dictionary-based emotion analysis marks the emotional polarity and intensity of terms in the text using the already-existing general sentiment dictionary. Dictionary-based emotion analysis is popular in many study domains since it is accurate and practical for assessing Internet comments.

The Chinese Emotion Vocabulary Ontology Database of Dalian University of Technology [24] was utilized as both the primary and auxiliary emotion dictionaries in this study. Auxiliary dictionaries include negative dictionary, adverb dictionary, and conjunction dictionary. The Chinese Emotion Vocabulary Ontology Database of Dalian University of Technology includes nouns, verbs, adjectives, adverbs, and other parts of speech, as well as common sayings and network terms. Making it the default dictionary can increase the precision of text sentiment analysis because the comments are all from online sources and the sentiment words have a similar style to those in the dictionary.

This paper employed Python programming to assess each comment's emotional propensity from online education platforms. The corpus was accurately segmented using "Jieba" segmentation, and the data for comment segmentation was acquired after stop words had been removed.

Given a collection of online learning platforms, T, which includes a collection of reviews, $T = \{S_1, S_2, \cdots, S_k, \cdots, S_n\}$. All the words in the comment S_k are used to traverse the sentiment dictionary, and only those with clear sentiment tendencies are chosen. The sentiment polarity of the corpus is then reinterpreted in light of the presence or absence of negative terms. The weight is finally assigned using the adverb dictionary. It is possible to determine the emotional polarity of a single comment. Equation (4) provides a formula for the calculation:

$$\text{Sentiment}_k = \sum_{i=1}^{m} P_i + \sum_{j=1}^{n} P_j, \quad (4)$$

where Sentiment_k stands for the emotional value of review S_k, P_i for the collection of all words with positive feature in S_k, and P_j for the collection of all terms with negative feature in S_k. The numbers m and n represent the proportion of polarized words in a single comment that are positive and negative, respectively.

When S_k's emotional value is larger than 0, it can be identified as positive; when it is equal to 0, it can be considered as neutral; and when it is lower than 0, it can be identified as negative. Equation (5) displays the precise formula:

$$\text{Sentiment}_i = \begin{cases} Q_{\text{pos}}\left(Q_{\text{pos}} > 0\right) \\ Q_{\text{neu}}\left(Q_{\text{nue}} = 0\right) \\ Q_{\text{neg}}\left(Q_{\text{neg}} < 0\right) \end{cases}. \quad (5)$$

3.2.3. Temporal Evolution Analysis of User Emotion. Short comment texts often contain emotional elements that change over time, and this regularity is frequently related to how readers perceive of the text. To monitor changes in the theme emotion of short text reviews, some researchers use time series analysis [25, 26]. The cumulative emotional value of all comments on that day is calculated in the unit of day according to the calculated emotional value of each comment, and a time sequence diagram showing the fluctuation of emotional intensity is drawn.

4. Results and Discussion

4.1. Analysis of Users' Opinions of High Frequency. By using word-level information extraction technology and visual technology from many dimensions, analysis of user opinions may extract the keyword, expose the user's overall opinion of the online teaching platform, and extract the key phrase.

This study used the COVID-19 outbreak node as a dividing line and sorted the network comments of the application market since the launch of Chinese University MOOC, CHAOXING Learning, and Tencent Class. It then calculated the TF-IDF values of all extracted keywords in each stage of the platform using the high-frequency word calculation rules in Section 3.2. The words (students, schools, CHAOXING, Tencent, Netease, mobile phone, computer, and other entities) were deleted. As shown in the following figures, the general word cloud and high-frequency keyword histogram of the relevant platforms were obtained, respectively, before and after the pandemic, and the commonness and evolution of users' concerns were examined. In order to make the results more comprehensive and intuitive, this paper took the top 100 high-frequency words as samples and made a word cloud through

WordCloud package in Python, where the word size represents the word's frequency. Most of the words in the word cloud are of low importance. They reflect the diversity of users' views and the impression of online teaching platform before and after the epidemic.

The TF-IDF study found that a few key phrases with a high relevance, which reflect the users' primary viewpoints and needs, best represent the users' emphasis. In this study, the top ten TF-IDF values were chosen in order to create a keyword histogram with TF-IDF high-frequency terms as the horizontal axis and TF-IDF value as the vertical axis. This was done in order to concentrate on the users' concerns.

4.1.1. Keyword Extraction and Analysis of Chinese University MOOC. The shared key phrases of Chinese University MOOC before and after COVID-19 were "platform," "video," "horizontal screen," "split screen," and "function," as shown in Figures 1 and 2. Related comments were "Netease gets a thumbs up for offering a free platform for everyone to study with all different types of university resources." "There are abundant teaching videos of university courses on this platform. This platform can be used to preview, review, or check the missing. Additionally, there is information that may be applied in daily life to raise EQ and improve social interactions. You can also pick up tips in yoga, flower arranging, and table manners. I've never used a learning program quite like this. Finally, I want for more perfection in the courses." "Split screen and horizontal screens are not supported yet, making the iPad a difficult learning tool." These frequently used keywords and associated comments showed that users' attention was focused on the quantity and quality of video courses and online courses offered by the platform, as well as whether the online courses work flawlessly.

As seen in Figure 2, some high-frequency phrases that were different from those before the pandemic, such as "network" and "server," appeared after the COVID-19 outbreak. "Focus on how to prevent students from cheating, while not attaching value to the drop-off occurred in the exam," were the relevant comments. "I lost connectivity today while taking the test, however as the network was reset, the questions I had already answered were removed! I was really upset since there were only 10 minutes left before the exam was over." "It will block if there are too many users online. The time has come to invest more money on your own server." From the above keywords and associated comments, it is clear that due to the COVID-19 outbreak and the subsequent increase in Chinese University MOOC users, issues with the network block, the poor experience brought on by insufficient servers, and issues with other platforms were made public.

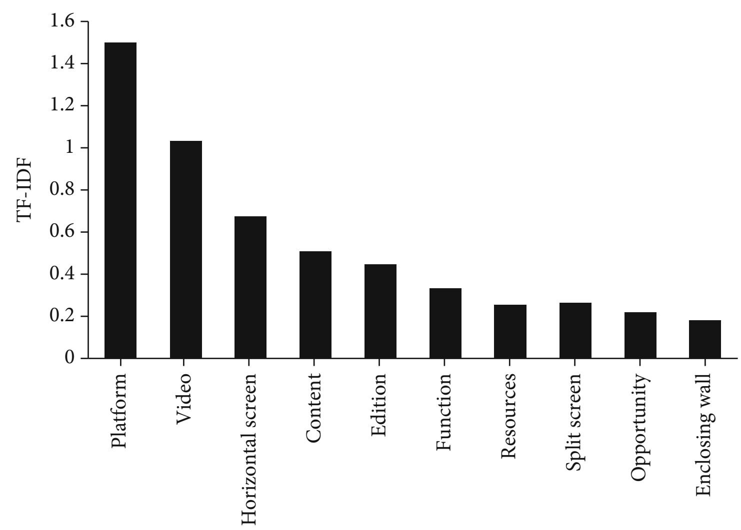
4.1.2. Keyword Extraction and Analysis of CHAOXING Learning. The phrases "video," "function," "problem," and "content" were among those that were frequently used in CHAOXING Learning before and after COVID-19, as shown in Figures 3 and 4. It demonstrated how concerned platform users were with the platform's availability of rich video resources, content, and features. In the related comments, CHAOXING Learning was considered to be rich in learning resources and powerful in functions. As shown in Figure 3, the unique terms prior to the outbreak included "network," "verification code," and "customer service," which primarily represented issues with network congestion, failure to receive or correctly validate verification codes, and subpar customer service. After the COVID-19 outbreak, these keywords stopped appearing since the platform itself had been updated and improved to address the issues that users had been reporting.

Following the COVID-19 outbreak, as seen in Figure 4, the new keywords were "interface," "server," etc. "You'll accidentally flip over other pages by sloppily sliding up and down. You would have to rewrite your schoolwork if you didn't save it," which were some remarks that were related. The touch button is not responsive when the application is running, and the bottom pull-up taskbar is also backwards. Please fix it as soon as you can. "The server blocked in the middle of the exam." The primary themes in the key phrases and comments included compliments for the user interface as well as issues with incomplete functions, server slowness, system failure, etc. It was evident that users had primarily focused on the experiences provided by the features of the platforms since the epidemic's onset.

4.1.3. Keyword Extraction and Analysis of Tencent Class. As observed in Figures 5 and 6, Tencent Class prior to and during COVID-19 primarily used the words "video," "platform," and "function," which were comparable to Chinese University MOOCs. This suggested that consumers were constantly worried about the quantity and quality of platforms. As shown in Figure 6, during the COVID-19 outbreak, the key high-frequency phrases were "problem" and "epidemic condition," showing that due to the epidemic's spread, the problems of online teaching platforms were fully exposed as the number of users increased.

4.1.4. Summary. In conclusion, there are many shared terms in the three online teaching platforms. There were "video," "platform," "content," and "resource" before and after the outbreak of COVID-19. This suggests that the primary concerns of each online teaching platform are whether the platform offers an abundance of learning resources, whether the content of the course is abundant, and whether the teaching functions are perfect. It is clear that university online teaching platforms provide comprehensive online courses to cater to individuals' individualized needs. Many terms, including "server" and "issue," were used interchangeably across the three platforms since the COVID-19 outbreak. Because the majority of college students were studying at home during this time, the number of users and daily logins to the online teaching platform increased, which exposed underlying issues with online teaching. For instance, network congestion brought on by insufficient bandwidth infrastructure, latency in live broadcasting, and poor platform functionality. We discovered from the shared high-frequency phrases that hardware (like servers), network speed and reliability, and platform features are the most crucial elements determining

(a) Overall word cloud



(b) Top 10 of TF-IDF values

Figure 1: Keyword extraction before the epidemic of Chinese University MOOC.

the online learning experience. We were able to learn from these issues that COVID-19 showed when we later built online teaching systems for colleges and universities.

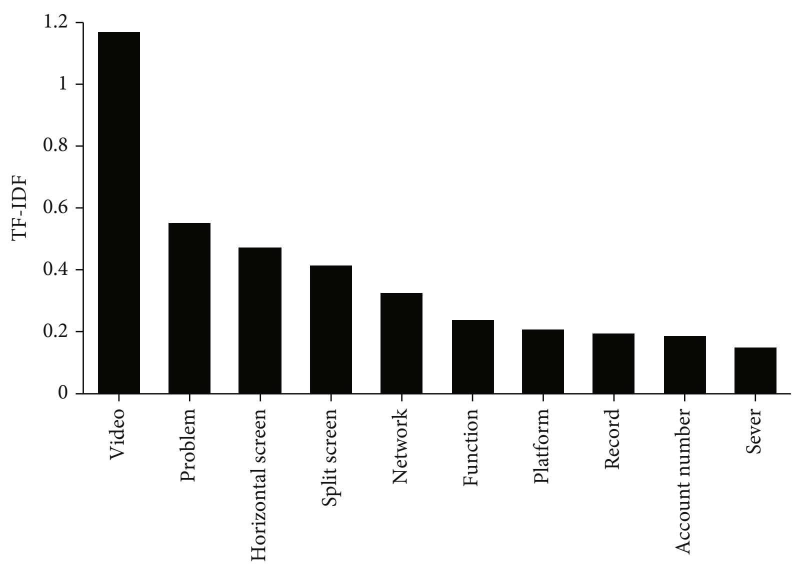
4.2. Analysis of Users' Emotion. In this paper, the SnowNLP package of Python was used to calculate the emotional values of 93754 comments based on Formula (4) in order to better understand users' attitudes towards online instruction. According to Formula (5), the comments were divided into three categories: positive, neutral, and negative, so as to quantify the emotional tendency of users to evaluate online teaching platforms and compare the emotional changes before and after COVID-19.

4.2.1. Statistical Analysis of User Emotion of Online Teaching Platform. Taking the outbreak time of COVID-19 on January 23, 2020, as the boundary, this paper calculated and counted the emotional values of the reviews of three online teaching platforms from the launch of the platform to June 30, 2020; the results are shown in Table 1.

Before the COVID-19 outbreak on January 23, 2020, there were 1,709 and 10,830 comments on CHAOXING Learning and Tencent Class, respectively, but there were 34,705 and 20,992 comments after the COVID-19 outbreak. The number of comments exceeded the total amount of four years before the COVID-19 outbreak in barely half a year. It shows that CHAOXING Learning and Tencent Class were widely used by teachers and students for online instruction during the period when the school year was postponed due to the COVID-19 epidemic. However, the number of comments on the Chinese University MOOC before the outbreak was 18,166, which was significantly higher than the number of comments after the outbreak of the epidemic, indicating that the users of Chinese University MOOC were accumulated in the early stage and it was not widely used for online teaching in Chinese universities during the epidemic period.

Prior to the outbreak, there were few users of CHAOXING Learning, and only 24% of user ratings were positive. The number of comments on CHAOXING Learning substantially grew throughout the epidemic, and the percentage of positive review also climbed to reach 55%. This shows that users of the online education platform were quite satisfied with its functions during that period, even if the number of

(a) Overall word cloud



(b) Top 10 of TF-IDF values

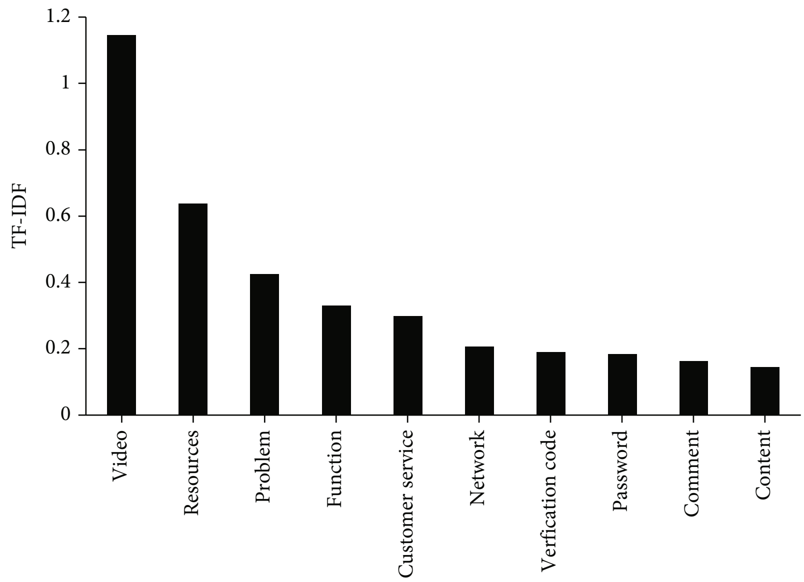
Figure 2: Keyword extraction during the epidemic of Chinese University MOOC.

users increased noticeably. After the pandemic, Chinese University MOOCs saw a 33 percent decline in the percentage of positive remarks, going from 65 to 32 percent. This suggests that users were dissatisfied with the platform throughout the epidemic. Users had low expectations for the platform's features before the pandemic because they were primarily self-studying through MOOCs and had a strong desire to learn, so they gave the platform's courses and resources excellent ratings instead. Following the COVID-19 epidemic, colleges began using Chinese University MOOCS for online instruction, and some students started studying passively online. They focused more on the platform's technological features and services, but the platform could not meet these needs. The percentage of positive comments on Tencent Class was high both before and after the COVID-19 outbreak, demonstrating that users significantly value Tencent Class as both a self-study tool and an online learning platform. In general, during the epidemic period, the number of reviews of online teaching platforms increased significantly and the proportion of positive emotions was high, indicating that online teaching was widely used during the epidemic period and users had positive feelings towards online teaching, which played a positive role during the epidemic period.

4.2.2. Temporal Evolution Analysis of User Emotion. This paper intercepted the data from July 1, 2019, to June 30, 2020, counted the sum of emotional values of daily reviews, and obtained the statistical characteristic figures of users' emotional values in Chinese University MOOCS, CHAOXING Learning, and Tencent Class in order to further observe the changes and transitions of users' emotions over time and analyze the evolution of users' emotional attitude towards online teaching. The following figures demonstrate how users' emotions clearly exhibit stage characteristics. Before and after COVID-19, all of the emotional values of online education expanded, peaked in either a positive or negative direction, and then stabilized.

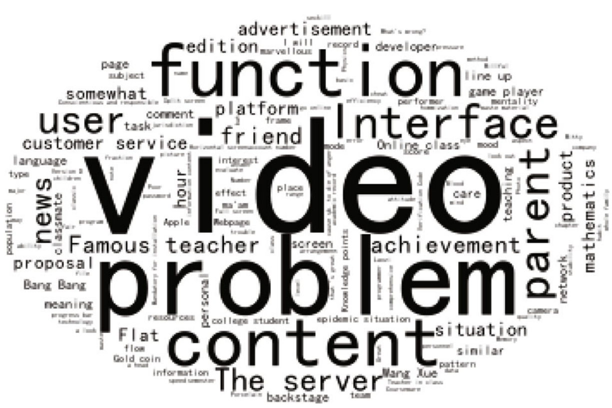
As shown in Figure 7, the evaluation was basically positive and the emotional values were relatively stable after the launching of Chinese University MOOC. While the COVID-19 broke out in February 2020 and the new semester started, Chinese University MOOC was applied for online teaching in Chinese universities. When the number of MOOC

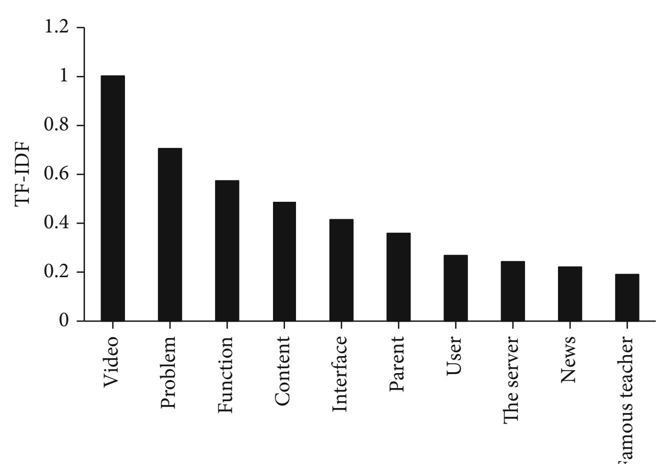
(a) Overall word cloud



(b) Top 10 of TF-IDF values

Figure 3: Keyword extraction before the epidemic of CHAOXING Learning.



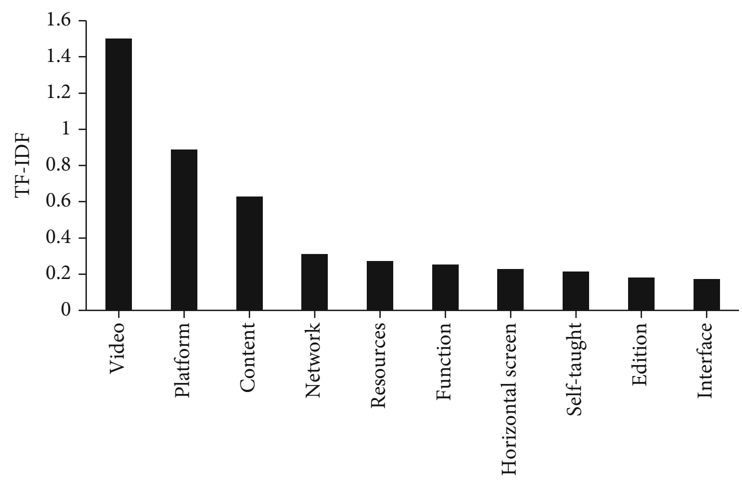


(a) Overall word cloud

(b) Top 10 of TF-IDF values

Figure 4: Keyword extraction during the epidemic of CHAOXING Learning.

(a) Overall word cloud



(b) Top 10 of TF-IDF values

Figure 5: Keyword extraction before the epidemic of Tencent Class.

downloads expanded dramatically during this time, the emotion values formed a negative peak, indicating that the flaws of online education platforms were fully exposed. On this stage, users' emotions were mostly negative.

The emotion value of CHAOXING Learning formed two tiny negative valleys in March and April before forming a sizable positive peak in May, as illustrated in Figure 8. Due to CHAOXING Learning's lack of an online teaching feature, its user base did not significantly grow in February and March during the college term, and new users gave it a poor rating. The CHAOXING Learning platform's homework, exam, and invigilation features are robust, and since May is when colleges collect the most homework and hold the most online exams, CHAOXING Learning has seen a significant increase in usage. The majority of the new users' sentiments were positive.

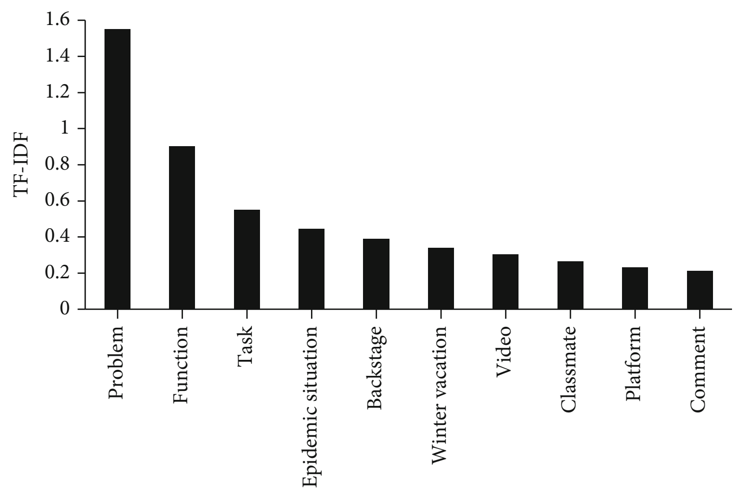
Figure 9 illustrates that following the COVID-19 outbreak, Tencent Class was widely used and well appreciated by users during online teaching in colleges. This is because the emotion values of comments in Tencent Class showed a substantial positive surge in February and March.

The data depict the prevailing emotional trend of the time. It can be seen that before the outbreak of the epidemic, the emotional values of the online teaching platforms fluctuated around $y = 0$. The emotional values appeared a positive or negative peak after the epidemic's onset, indicating that the application of online teaching had caused great emotional fluctuation to online teaching. The later period saw college teachers and students adapt to online teaching and their attitude towards online teaching platforms also tended to be rational. The emotional values gradually converged to $y = 0$ and fluctuated slightly. This was due to the gradual maturity and stability of the online teaching application.

4.2.3. Users' High-Frequency Emotional Attitude. Emotion analysis was done from the standpoint of online education based on user comments. This paper extracted the top 10 emotional feature words from the three platforms using the TF-IDF algorithm. In Table 2, the statistical findings are displayed.

There are similarities and differences in the emotional attitudes of the three online teaching platforms. Top ten emotional feature words are all positive emotional feature words, and the shared high-frequency emotional words are "good," "convenient," "very good," "rich," and "great." The user's assessment of online learning was overwhelmingly positive emotionally, and the users felt that the convenience and effectiveness of the program were both "excellent" or "very good," and that the information was "rich." CHAOXING Learning and Tencent Class were among those who

(a) Overall word cloud



(b) Top 10 of TF-IDF values

Figure 6: Keyword extraction during the epidemic of Tencent Class.

Table 1: Emotional tendency of comments from three online teaching platforms.

Platform	Time	Total Comments	Positive emotions Comments	Positive emotions Proportion	Neutral emotions Comments	Neutral emotions Proportion	Negative emotions Comments	Negative emotions Proportion
Chinese University MOOC	Before the epidemic	18166	11902	65%	4669	26%	1594	8%
	After the epidemic	5374	1740	32%	1852	34%	1782	33%
CHAOXING Learning	Before the epidemic	1709	410	24%	334	20%	513	30%
	After the epidemic	34705	19163	55%	6186	18%	4838	14%
Tencent Class	Before the epidemic	10830	6837	63%	2345	22%	1648	15%
	After the epidemic	20992	11909	57%	4832	23%	4250	20%

used the phrase “fluent,” indicating that the playback of their online lessons and resources is generally fluid. In Tencent Class and MOOCs offered by Chinese universities, the phrase “conscience” is used frequently. The assessment consists of “Many of the free classes are conscience-based, and our teachers are presenting lectures there. It’s excellent. It’s still free, and we can see how many minutes are left in the lesson. It’s incredibly careful.” Users have complimented it since it demonstrates how many free learning resources are available on the platforms.

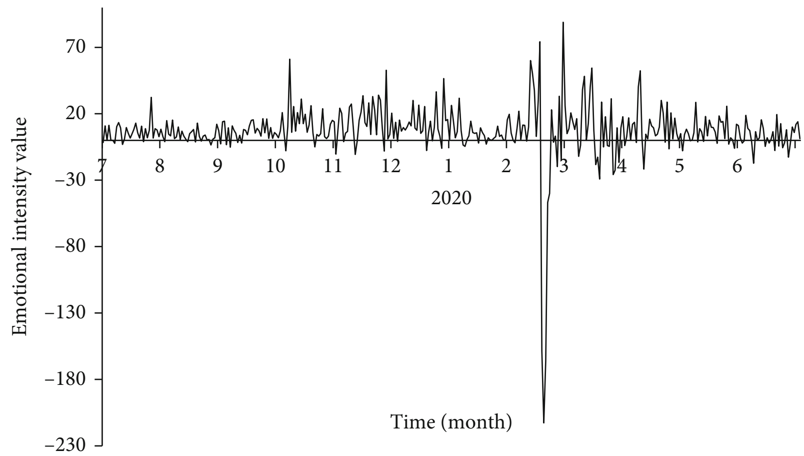


Figure 7: Emotional time series of Chinese University MOOC.

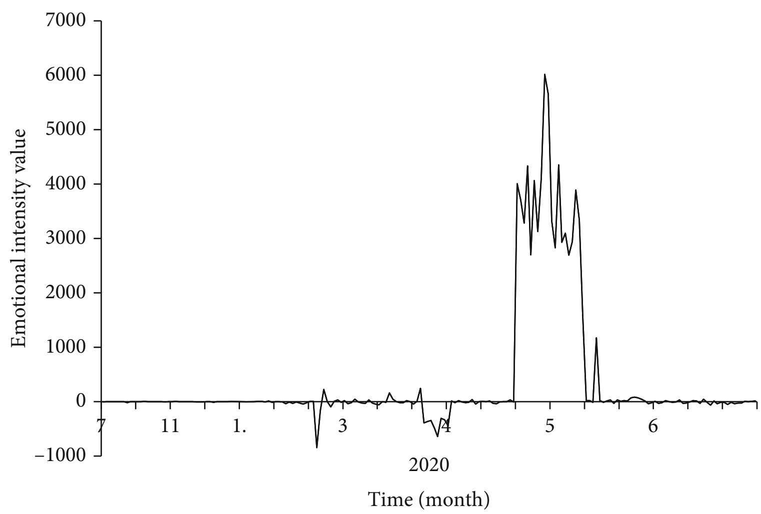


Figure 8: Emotional time series of CHAOXING Learning.

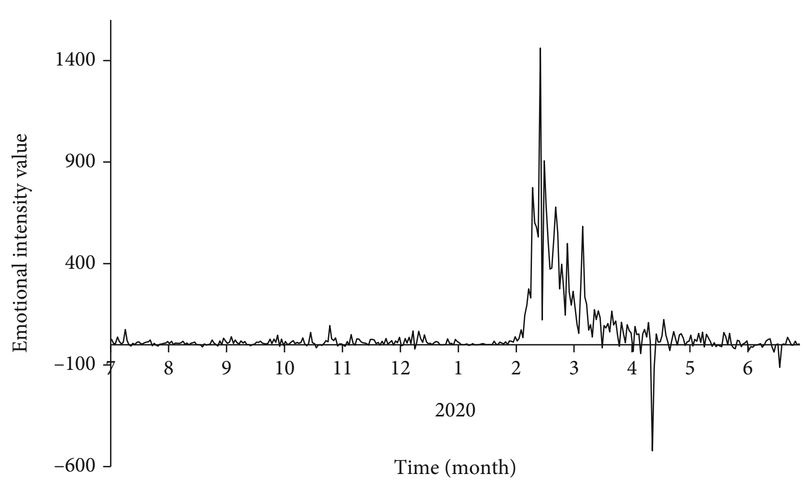


Figure 9: Emotional time series of Tencent Class.

Table 2: Statistics of emotional feature words.

Chinese University MOOC		CHAOXING Learning		Tencent Class	
High-frequency words	Word frequency	High-frequency words	Word frequency	High-frequency words	Word frequency
Not bad	1546	Not bad	3692	Not bad	2067
Convenient	736	Convenient	914	Convenient	876
Very good	677	Very good	720	Very good	523
Rich	603	Rich	519	Rich	386
Great	494	Great	513	Happy	360
Conscience	293	Interesting	496	Excellent	328
Excellent	223	Simple	471	Conscience	218
Best	139	Fluent	420	Fluent	211
Important	111	Powerful	345	Easy	184
Perfect	166	Easy	326	Clear	183

5. Conclusions

User's opinions and emotion are reflected in user comments on online teaching platforms. What were the attitudes of college students towards online teaching during the time of unified online courses in colleges and universities in 2020? This study employs text mining and sentiment analysis to conduct statistics of high-frequency terms, calculation of sentiment value, and analysis of sentiment time series on three online teaching platforms chosen by the Ministry of Education: China University MOOC, CHAOXING Learning, and Tencent Class. A significant effort is being made to research large-scale online instruction in the context of COVID-19. The main conclusions can be summarized as follows:

Firstly, the user opinions of online teaching platform showed consistency and difference before and after the epidemic. Users' consistent attention to "video," "platform," "content," and "resources" before and after the outbreak suggests that users of online teaching were primarily concerned with whether the teaching materials given by these platforms are rich and the content is perfect. Users' attention was drawn to "server," "issue," and "network" during the COVID-19 outbreak, showing that deficiencies of hardware devices such as server overload and network lag are the primary determining factors affecting online teaching experiences when large-scale online teaching is used.

Secondly, the users' emotions towards online teaching were positive. The sentiment analysis revealed that most users express positive attitudes towards online teaching. The quantity of reviews of online teaching platforms had significantly increased during the outbreak, and the proportion of positive emotions was high. The top ten high-frequency emotional words in the comments were positive, which indicated that online teaching had been widely used during the pandemic period, and users' feelings were positive. Online teaching had played a positive role during the epidemic period, which had positive significance to the development of Chinese teaching.

Third, the epidemic had a significant impact on online teaching users' emotions. The user emotion values of the three online teaching platforms involved in the study all showed positive or negative peaks during the epidemic. The negative emotion of Chinese University MOOCS reached the peak in the early stage of the epidemic, which indicated that due to the imperfect functions, such as the lack of "horizontal screen" and "split screen," users' emotions tended to be significantly more negative. Early in the outbreak, positive emotion of Tencent Class reached the peak, showing that people had approved of the online teaching function. When CHAOXING Learning reached its pinnacle in May, it was clear that the lack of a live online function at the beginning of the month had prevented it from being widely used. It was widely used and accepted throughout the intensive online homework processing and online tests at the end of university courses in May because CHAOXING Learning is so effective at online homework, exams, and invigilation.

To sum up, under the background of COVID-19, the online teaching platform had undergone a major test and had gained recognition from users. In the face of all kinds of voices, we should not only make full use of online teaching but also try to improve the service of online teaching platforms, such as the support of software and hardware, the humanization of functions, and the improvement of interactive efficiency, so as to better realize "cloud" education and make online teaching an indispensable part of school education.

The limitation of this paper lies in that during the period of large-scale online teaching, users pay more attention to the perfection of the functionality, infrastructure, and hardware advancements of the platform, and less attention to the teaching content and teaching effect of the online teaching platform.

Data Availability

This paper takes the reviews of three platforms including CHAOXING Learning, China University MOOC, and Tencent Class from the Application market as data sources. All the data included in this study are available upon request by contact with the corresponding author.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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