Will Education Return to Normal?
Investigating Public Opinions on Covid-19 School Reopening

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Abstract. All educational institutions are currently reopening because the global community is more prepared and has the resources needed to control the spread of Covid-19. However, after years of online dominated learning, reopening schools and universities is not a simple task. Authorities need to understand the risks and benefits of school reopening across education, public health, and socio-economic factors. Educators also have the responsibility of making the transition from online to face-to-face learning easy and effective for students. Understanding how the public, especially students, perceives the current school reopening practice could direct the current policies and approaches in the right direction. The present study shows that the public has a positive sentiment during the current school reopening. This result can reassure policymakers and educators since preparedness, mental wellbeing, and emotions are essential in learning.

Keywords: Covid-19 · school reopening · sentiment analysis · twitter

1 Introduction

The Covid-19 social restrictions and health protocols have affected all sectors of life, including education. However, due to the scientific and medical advancements in combating Covid-19, the global community is recovering. The recovery process in the educational sector is reflected by the significant shift of affected learners caused by Covid-19. At its peak, the affected learners reached 1,291,004,434 or 81.8% of total enrolled learners (April 2020); currently, the latest data from February 2022 shows that only 43,518,726 are affected (2.8% of total enrolled learners) [1].

The low number of affected learners from school closures is a critical development for education. It signifies the start of a new chapter in education: the return to face-to-face learning after almost two years of school closures. Besides important, this new chapter can also be very challenging. Authorities need to understand the risks and benefits of school reopening across education, public health, and socio-economic factors [2].

Previous researchers understood these concerns and have investigated the different aspects of school reopening. For example, Marianno et al. addressed the school reopening decision and its relationship with teacher unions [3]. Another research done by Lichand et al. [4] investigated the relationship between school reopening and Covid-19 incidence and mortality.

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There is also research that addresses the non-health-related topic of school reopening, such as students' sleep quality and mental health [5], learning losses [6, 7], and behavioral measures perception [8]. The present study is interested in examining the behavioral aspect of school reopening. Previous research has found that students' attitudes toward online learning and its effectiveness compared to traditional face-to-face learning still vary from research to research [9–11]. This can create unique challenges since the current transition from two-year online learning to traditional face-to-face learning is indeed a unique situation.

Understanding the public's attitude toward school reopening can be vital to the success of learning in the post-pandemic era. Currently, there are various techniques available for understanding human attitudes. Sentiment analysis, also known as attitude analysis, can be helpful in this study's context [12]. Sentiment analysis determines whether a sentence or a text expresses a particular sentiment: a positive one or a negative one [13]. There are two approaches to this, the lexicon-based approach, and the machine learning approach.

This study will use the first approach. A lexicon-based approach compares extracted text from sources (commonly from social networking sites) to a set of word lists, with each word having some scores [14, 15]. This word list is called lexicons. The extracted word and lexicon comparison results produce a sentiment score, whether it is positive, negative, or emotional scores (anger, trust, etc.).

In studies such as done by Khoo et al. [16], it has been understood that some lexicons perform better than others in terms of accuracy. However, some other lexicons can have advantages outside of accuracies, such as how the NRC lexicon coded positive or negative sentiment and eight sentiment categories (anger, fear, anticipation, trust, surprise, sadness, joy, and disgust). Since the present study explores public sentiment and emotion, the NRC lexicon will be used.

Both the use of the machine learning approach and lexicon-based approach can provide a better understanding of the unfiltered opinion of the public. Understanding how the public perceives school reopening could direct the current policies and approaches in the right direction. Ideally, positive sentiment is expected; however, since the current situation is unique, many aspects can be at play: stress, fatigue, and social anxiety could nullify the many positive aspects of school reopening. Therefore, the present research asks, "What is the public perception of school reopening?".

2 Research Method

The present research used a dataset from Twitter because it contains a considerable number of personal thoughts with public access; it becomes a valuable source to know people's opinions and sentiments towards various topics or current issues. Since many people are voicing their opinion and view toward the education system on Twitter, sentiment analysis might be an appropriate method to discover public perceptions. Sentiment analysis could reveal peoples' opinions towards online learning as positive or negative. Using this method on microblogging sites like Twitter is proven to provide supportive information for decision-making and handy tools for consumer research, particularly public perception. The steps of our analysis consisted of data collection, pre-processing, and classification.

2.1 Data Collection

Twitter Streaming API, with the help of R library “rtweet” was used for getting public tweets data from Twitter.

R Installation:

```
install.packages("rtweet")
```

User tweets was collected by providing the “rtweet” library keywords related to online learning such as ‘school reopening’ and ‘back to college’. A total of 53,059 was gathered and used in the next step.

R command:

```
search_tweets("school reopening", n = 10000,
include_rts = FALSE, retryonratelimit = TRUE, lang =
"en")
```

2.2 Data Pre-processing

Pre-processing is when the data are prepared and ready to be analyzed. The stages include punctuation removal, trimming, and stop word removal. After conducting this process, duplicate tweets were removed, and the total tweets became 49,825.

R command:

```
# remove ampersand
tweets.txt <- gsub("&amp", "", tweets.txt)
# remove retweeted
tweets.txt <- gsub("(RT|via)((?:\\b\\W*@\\w+)+)", "",
 tweets.txt)
# remove mention
tweets.txt <- gsub("@\\w+", "", tweets.txt)
# remove punctuation
tweets.txt <- gsub("[[:punct:]]", "", tweets.txt)
# remove number
tweets.txt <- gsub("[[:digit:]]", "", tweets.txt)
# remove URL
tweets.txt <- gsub("http\\w+", "", tweets.txt)
# remove \tab
tweets.txt <- gsub("[ \t]{2,}xx", "", tweets.txt)
# remove $ symbol
tweets.txt <- gsub("^\\s+|\\s+$", "", tweets.txt)
# remove extra white space
tweets.txt <- gsub("[\r\n]", "", tweets.txt)
```

2.3 Data Classification

Using a library called ‘syuzhet’, the application of the NRC lexicon can be made by a simple command. It created a matrix of emotional scores for each extracted text. The sample of NRC classification is shown in Table 1.

Table 1. Sample NRC Classification

Tweet ID	1	2	3	4
anger	0	1	0	0
anticipation	0	2	1	1
disgust	0	1	0	0
fear	0	1	0	0
joy	0	2	1	0
sadness	0	1	0	0
surprise	0	1	1	0
trust	2	3	1	1
negative	1	1	0	1
positive	0	2	1	1

R command:

```
s <- get_nrc_sentiment(tweets.txt)
```

Tweet ID 1:

Nothing pisses me off than the fact that next year, when school reopens and I'm stressed, I'd begin to romanticize this lacklustre phase of my life.

Tweet ID 2:

@Alanthropist @bapieli @hanaaa_aaaa it's there in the mall I'll bring it to you when school reopens its actually pretty good.

Tweet ID 3:

guys i need to rush to do my work bc school reopens tmr wish me luck! https://t.co/GmpYvnbsXp.

Tweet ID 4:

joking guys, i can't wait until school reopens in a week AAAAAAAA.

3 Results

This chapter discusses the results of the sentiment analysis conducted. Firstly, a word cloud was created to describe the dataset we used. A word cloud was created from the most frequent words in our dataset; a bigger text size represents more frequent word appearances (see Fig. 1). From the figure, it can be seen that some unique words other

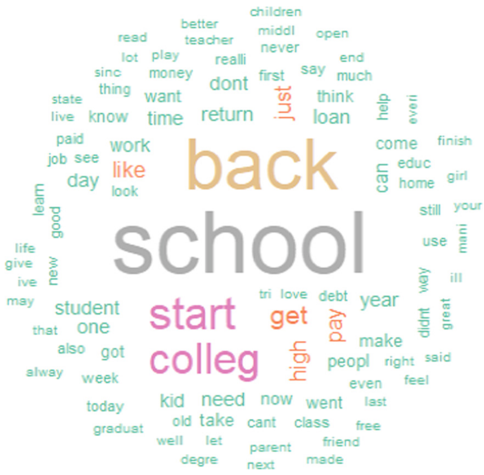

Fig. 1. Word Cloud Dataset

than 'school' or 'college', which is the keyword used for data gathering, appear. Words such as 'money', 'debt', 'pay' are interesting to see since they can indicate that the financial aspect can be a concern for the public in the state of school reopening. This is reasonable since online learning has reduced most of the costs related to education: commuting, uniforms, higher tuition, etc.

Finally, the results of sentiment scores are shown in Table 2. The table shows the average scores of the 49,825 tweets using the NRC lexicon. Using the NRC lexicon, ten emotion scores are provided. The most important values are these ten emotions' positive and negative sentiments. The results show that the dataset produces a 0.734772 score of average negative sentiment and 1.447285 of average positive sentiment. This result is important since now it can be understood that the public has a more positive sentiment or attitude towards the reopening of schools. This finding could be utilized by policymakers and educators to confidently advances the process of school reopening.

Other findings are generated from the eight emotions. The highest average score among the eight emotion scores is trust and anticipation. This can be interpreted that people generally feel more trusting toward the school reopening and the protective measures done to facilitate the face-to-face learning process. The high value of anticipation scores can also be interpreted as how the public is anticipating going back to school. This can be refreshing to hear for parents and educators since it has been found that mental wellbeing is affected by Covid-19 [17]. Finally, negative emotions such as disgust, sadness, and anger exhibit the lowest score. This is in contrast to previous findings using a similar approach but conducted in the middle of the Covid-19 outbreak, which shows the dominating negative emotions were anger, fear, sadness, and surprise [18].

Table 2. NRC Results

Emotion	Average
anger	0.334611
anticipation	1.107396
disgust	0.216979
fear	0.370778
joy	0.617782
sadness	0.38579
surprise	0.309985
trust	1.504225
negative	0.734772
positive	1.447285

4 Conclusion

The present study successfully utilized a sentiment analysis approach to explore the current sentiment of the public regarding school reopening. As expected, positive sentiment scores higher on average rather than negative sentiment and emotions. This research is important for policymakers and educators in deciding the current state of recovery. There are, of course, some limitations in this study; the lack of time-based analysis and supervised classification of tweets can be improved in future studies.

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