How Attitudes Toward Online Learning Changes During Pandemic, and Reasons Behind It

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Abstract: This paper aim to understand people's attitude toward online learning and find the reason behind it. The emergence of new coronavirus disease has revolutionized every aspect of people's lives. During the pandemic, all those who try to receive education, students, have to study online. Online learning has become a famous topic during a pandemic. People receive online education and this research is trying to find what are people's attitude towards this new form of education and does this attitude change during pandemic. At same time, social media are heavily used as a platform for people to express their emotions. In this research, data from posts of Twitter users under the topic of online learning are analyzed using sentiment analysis and MDCOR. The results of sentiment analysis tell us the attitudes change during the pandemic and MDCOR shows potential reason behind it.

Keywords: Online learning, Sentiment analysis, Covid-19 pandemic, Twitter, emotions and attitudes

1. Introduction

Since 2019, the COVID-19 pandemic changed people's life. Many activities normally carried out in person have changed to online in order to avoid intimate contact between people to avoid spread of virus. Online learning is one of the activities most impacted by the pandemic. The traditional way of school education was prohibited during the pandemic, and students and teachers changed their form of learning to online. More than 181 countries were affected by the epidemic and were forced to suspend their studies [1]. Except for Africa, the vast majority of regions adopted online teaching methods. The same goes for top universities. They also need to be familiar with this new environment online to provide the best education to their students [2].

As mentioned in the previous paragraph many daily activities are influenced by covid 19 pandemic, not only the form of education transforms to online, but the way people communicate with each other is also affected. Therefore, social media is considered an important space for people to communicate online during the pandemic. Nowadays, social media is defined as an internet-based channel that

allows users to opportunistically express themselves in real-time or asynchronously with a wide and narrow audience, and gain value from user-generated content and perceived interactions with others [3]. As scholars have pointed out, social media platforms are often treated as a vast field of community gatherings, and social media is not composed of a series of complex and interconnected communities, which are composed of individuals with specific needs, motivations, and expectations [4]. As mentioned above, we can infer a large number of words that related to emotion are posted on social media.

During the 2019-2022 period when the world is affected by the pandemic, it has greatly affected people's learning methods and communication methods. People began to use social media more frequently, and online learning has become a mainstream learning style during the pandemic. In this regard, we want to study the reason behind people's attitude changes towards online learning during and after the pandemic. To find the answer to this question, we use the database of people's public posts on Twitter with the theme of "online learning" during 2020-4-29 and 2021-12-31.   Furthermore, we will analyze, organize and mine the tweets of Twitter users under the theme of online learning during the pandemic and conduct sentiment analysis to test whether people's attitudes towards online learning during the epidemic have changed.

2.   Literature Review

2.1.   Emotion Change during the Pandemic

Studies have shown that people's emotions can change significantly when dramatic changes happen in their daily lives such as the Covid-19 pandemic and those emotional changes could be triggered by restricted movements and social interactions [5]. For example, Canet-Juric, et al. [6] suggested that quarantine during the pandemic cause separations, financial difficulties would bring people negative feelings of uncertainty and boredom. They also found that people report higher depression and anxiety levels and lower enthusiasm and interest after experiencing 2-week quarantine. Moreover, when the duration of quarantine is prolonged, it would result in feelings of confusion and anger [7]. Gallant et al. [8] also showed that elder people's attitudes towards vaccinations have been changed significantly across the pandemic in the UK. In one-year period, their complacency, mistrust of vaccines and concerns decreased while their sense of responsibility to take vaccines and worries about the future effects increased. Therefore, people's emotions/attitudes in general or towards certain issues can be changed during the covid-19 pandemic overtime. Online learning as an outstanding form of learning that becomes more popularized during the pandemic, and it is reasonable to deduce that people's emotion/attitudes towards it would change. This deduction is not only supported by the above examples of quarantine and vaccines, but also the a few longitudinal studies that show the increasing positivity towards online-learning [9].

2.2.   Social Media Flatforms and Sentiment Analysis

Social media is defined as an internet-based channel that allows users to opportunistically express themselves in real-time or asynchronously with a wide and narrow audience, and gain value from user-generated content and perceived interactions with others [3]. During the covid-19 pandemic, messages, comments, updates and posts have been spread explosively on social platforms such as Twitter [10], which makes them important sources of information [11]. Emotion is regarded as an expression of people's subjective feelings and thoughts. Sentiment analysis is also known as opinion mining, which focuses on emotions, subjective texts attitudes, opinions and appraisal [12]. Emotions are closely linked to sentiments in which the intensity of emotions influence how strong the opinions/sentiments are [12]. Therefore, sentiment analysis is frequently used to interpret Twitter users' emotions/attitudes towards an issue by extracting their emotions from their texts, where people

mostly profess their emotions through [13]. The explosive expressions of attitudes/emotions towards covid-19 pandemics on social media have become valuable social data, which provides researchers good opportunities to conduct sentiments analysis, to examine how people perceive or react to issues during pandemic [14,15].

2.3. Sentiment Analysis in Different Domains

Sentiment analysis have been applied in various domains in recent years, which includes environment, politics, technology and industry. For examples, Asur & Huberman [16] used a combination of tweet sentiment and volume to conclude the attentions to a certain topic to forecast box offices revenue for movies industry; For political application, Bermingham & Smeaton [17] used tweet volume together with positive and negative tweets to predict the election result. Sentiment analysis is frequently used in stock market, for example, sentiment analysis was used to find out the positive and negative public moods towards the stock market to make predictions about different stock market industries [18]. Apart from the domains mentioned above, sentiment analysis is also used in analyzing people's emotions/attitudes towards online learning during the covid-19 pandemic. For example, Sahir et al. [19] used sentiment analysis to conclude the public opinions towards online-learning during covid-19 under the debate of preparation of technology in Indonesia. The results showed that negative sentiments dominant the public attitude towards online learning, which could provide related education departments with advisory information when implementing online learning. Hence, sentiment analysis is useful in various domains in terms of finding and monitoring opinions on different media and distilling that information, which provides more applicable information to assist decisions making [18].

2.4. The Current Study

Online learning refers to individuals receiving education online and having all access to materials through the computer. Similar words such as distance learning, E-learning, and computer-based training are all one form of online learning [20]. Since the explosion of covid-19 pandemic, over 181 countries have been affected and the switch from traditional ways of learning to online learning has affected 88% of the students [1]. While some students acknowledge the advantages of online such as no restrictions on locations and time and express their positive attitudes [21], some express their negative attitudes by emphasizing the negative effects such as technical issues and discouragement of socialization [22]. The prevalence of online learning during the covid-19 pandemic has placed itself to central debate. As a topic that has been widely discussed on social media platform during the pandemic, a rich data pool with different posts and texts towards this topic has been established. According to the previous discussions, it is reasonable to deduce that researchers could use sentiment analysis to extract people's emotions/attitudes towards it from social media platforms such as Twitter. Additionally, as discussed at the beginning, people's emotions/attitudes could change overtime during the pandemic, no matter it is the overall mental state or attitudes towards a certain issue. Therefore, although there are some studies investigating the emotions/attitudes towards online learning during this period, many of them have limited time span, which is hard to find out the changes across time [19, 23]. Hence, the currently study aims to conduct a 20-months longitudinal study with 3 time slots to examine whether there are any changes. The time slots chosen to grab the data are approximately where the confirmed cases and death rates at their first peaks, first troughs, and starts of their second peaks in the USA. The choice of time slots is sensitive as evidence shows that people's negative emotions including fear and anxiety, can be triggered rapidly when they witness the increase in confirmed cases during the pandemic [24]. People also tended to be distressed when they witnessed that the death rate increased during the pandemic [25]. However, there are currently few evidence

showing that how emotion at different stages of the pandemic would impact their emotions towards online learning in specific, which is the one of the gaps that the current study aims to fill.

3.   Method

3.1.   Study Design

This research using texts posted on twitter under the topic of "online learning" from 2020-4-29 to 2021-12-31 as qualitative data. Fig 1 and Fig 2 is shows the changing of infection and death rate in United States from 3 Jan 2020 to 9 August 2023. For an interactive version of data, click on this link: https://covid19.who.int/region/amro/country/us[26]

Machine driven classification of open-ended responses (MDCOR) and sentiment analysis are used in this research to analysis short text data from twitter users.   The longitudinal data gathered from 2020-4-29 to 2021-12-31 were split into 3 waves based on the infection rate and death rate data of United States due to COVID-19. The first wave of data collection was placed on April 29th 2020 to January 11th 2021, which is from the first day this research to collect data during pandemic until the first peak of both the infection and death rate of COVID-19 in United States. The second wave of data collection was placed on January 12th 2021 to June 14th 2021, which is the downward infection and death trending start and reach the trough. The third wave of data collection was placed on June 15th 2021 to December 31st, which is the upward trending start of infection and death rate until the second peak. (United States of America: Who coronavirus disease (covid-19) dashboard with vaccination data). This research is using United States' covid-19 infection and death rate to divide the data into wave because most of users on twitter are from United states, especially under post on this topic is English based [27].
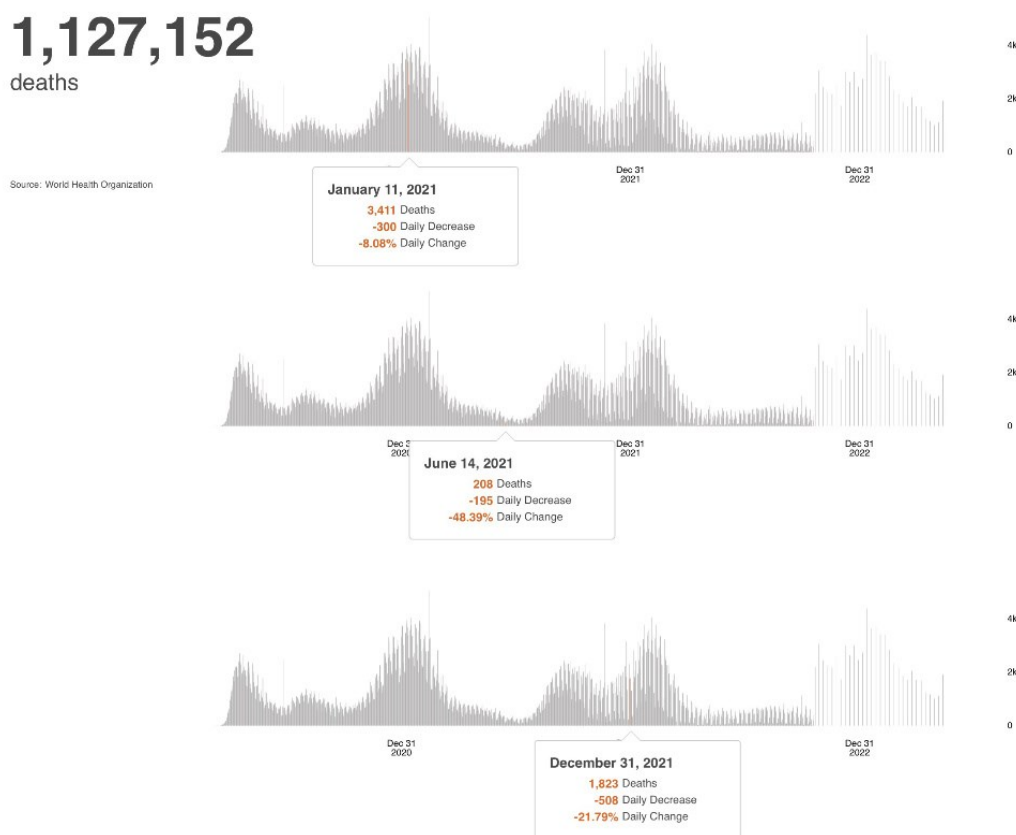

Figure 1: Key timespot of WHO Data of death rate during Covid-19 pandemic
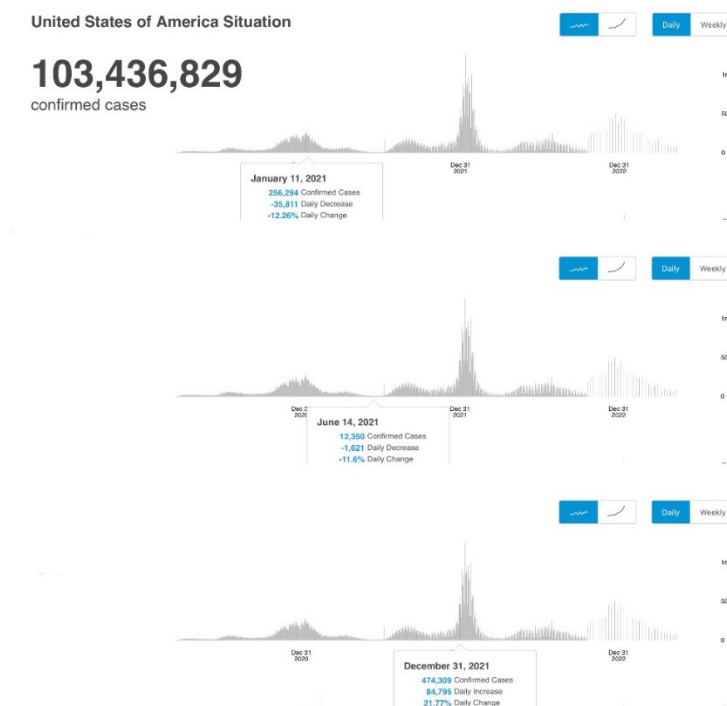
Figure 2: Key timespot of WHO Data of infection rate during Covid-19 pandemic

3.2. Academic Twitter

Twitter builds up an influential community for academic development in higher education [28]. Twitter provided free access of the data for researchers to conduct academic research (Twitter data for Academic Research | Twitter Developer platform). This research collect data from Twitter users public post from 4-29-2020 to 12-31-2021 under the topic "online learning".

Not only are Twitter users more interested in topic relevant to education topic, but also twitter is considered as an important platform of informal learning which is also considered as an important part of online learning [28]. Twitter is used as a platform of collecting data in this research because it can provide data more relevant to online learning and academic usage.

3.3. Sentiment Analysis

This research using sentiment analysis to analyze people's emotion, attitudes, and opinions toward online learning. Syuzhet R package is used to analysis the short text information collected from twitter. "The R package syuzhet has been designed to allow you to choose from four of these sentiment lexicons: Bing, Afinn, Stanford, and the NRC Word-Emotion Association Lexicon [29]. In this research, NRC Word-Emotion Association Lexicon is used for us to make connection between word and emotion. This lexicon includes 8 basic emotions proposed by Plutchik [30,31,32] which includes joy, sadness, anger, fear, disgust, surprise, trust and anticipation, and also positive and negative. This research will analysis these 10 categories of emotion by using text data published by individuals' on Twitter to see people's attitude toward online learning.

3.4. MDCOR

In order to analyse how the attitude towards E-Learning changes during and after the pandemic and the reasons behind it, the MDCOR — Machine Driven Classification of Open-ended Responses has

been chosen as the most fitted. This method allows people to the maximum extent to the unresolved problem of how to turn off open-ended responses as rigorously and efficiently as possible. The MDCOR method provides a rigorous, user-friendly, no-code, and cost-free software application that implements texting mining and data organising within mixed equal-status text data [33]. In the topic that we are studying, about attitude towards change of online Learning, is that we need to analyse the open-ended text data from Twitter users and MDCOR can help organise vast quantities of information that has been collected. Meanwhile, MDCOR will value the data and MDCOR will outputs the Metrics Assessment and the Interactive Summaries. As a result, having a layout of the Metrics Assessment and the Interactive Summaries has made a set of fully classified databases. Throughout the Fully Classified Database, it turn out to be the Test of Group Code Association and the Code to Code Strength by Group. Therefore, the findings and the results part can rely on MDCOR's final result in order to explore and examine how the attitude towards online Learning changes during and after the pandemic and the reasons behind it.

By considering two research questions – "What is the distribution of emotions regarding online learning on Twitter during the pandemic?" and "Does this distribution change when the analysis disaggregated during the pandemic?", this method sheds light on the emotional attitude differences, highlighting the importance of the emotional attitude of E-Learning changed during and after the pandemic period. Although, the emotional attitude toward E-Learning changed - ……during and after the COVID-19 pandemic - and how the public has adapted to the specifics of the emotional attitude change in both questions, gives a perspective on how the technological advancement is being adapted to meet the public's emotional changed during and after the pandemic period.

MDCOR was chosen as a main method of research because of its specificity and essentiality classification of open-ended responses. In the process that the Twitter users's data has been collected, it is an unprocessed group of texts based on open-ended resources. Hence, this open-ended resource is Machine Driven Classification needed, based on MOCOR's epistemology, this classification is based on Bayesian statistics and statistical physics, showing a full description of all the outputs resulting from its implementation [33]. The next step consists of the flow diagram implemented by MDCOR, making the natural text processing and text mining and normalisation with optional frequency words deleted for MDCOR to continue the processes [33]. Afterwards, the Metrics Assessments showed the identification of the optimal number of codes, showing the case that MDCOR will process the main outputs automatically. Aim to analyse the final MDCOR classification results, the main output is the test of independence needed, to continue the forward analysis. Thus, the outputs of MDCOR would be consequential whenever it is enriched by the voices of the participants.

4. Result

4.1. Sentiments Analysis

From 2020 April 29th to 2021 December 31st, there are 1437814 texts posted by twitter users under the topic of online learning. This research randomly selected 5000 texts from each of the wave as sample text for further sentiment analysis. All blank or unreadable texts are excluded from sample text. Fig.3, Fig.4, and Fig.5 are the histogram of sentiments analysis of each wave. Here is the interactive version of the graph, https://rpubs.com/RRiosssss/1070234,https://rpubs.com/RRiosssss/1070238,https://rpubs.com/RRiosssss/1070465
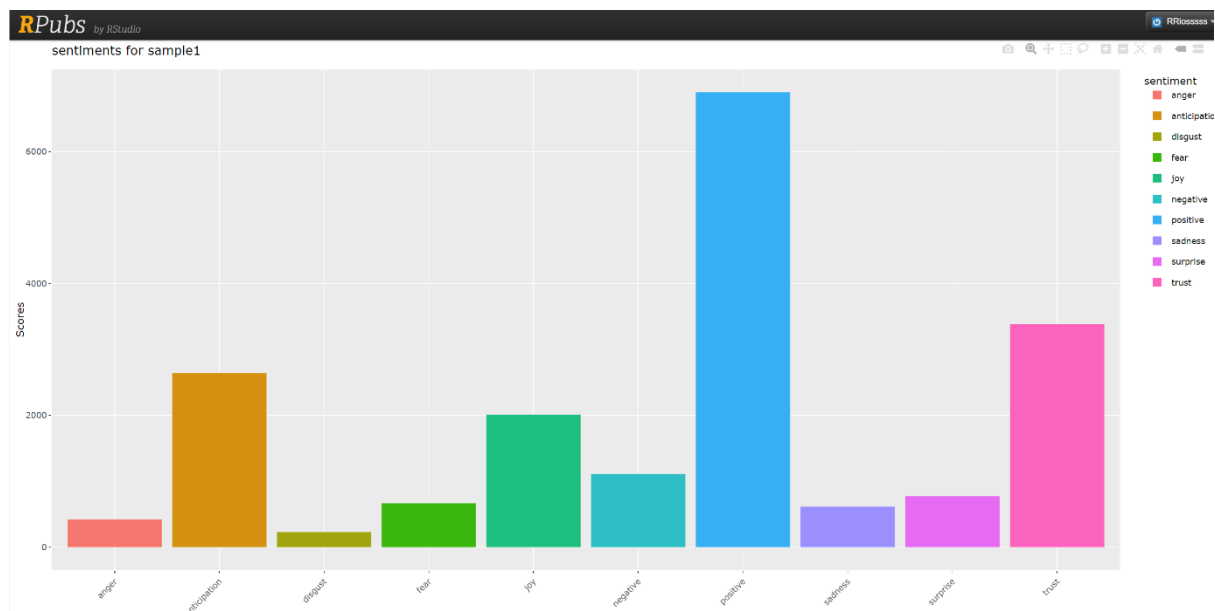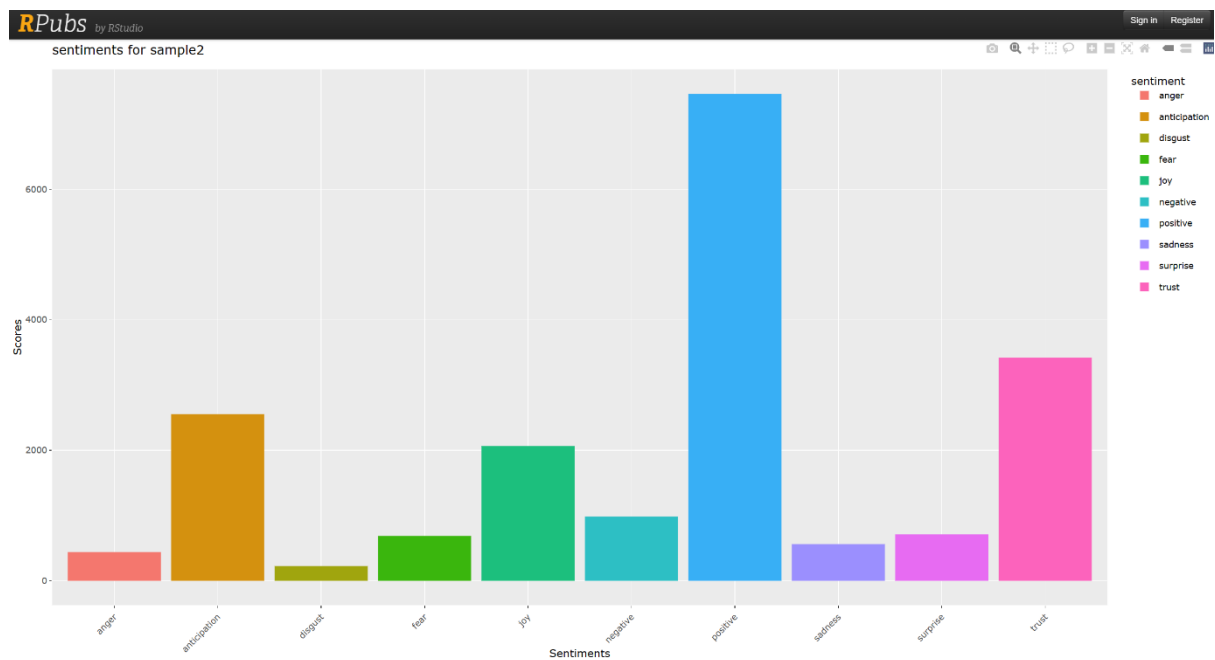
Figure 3: Wave 1 sentiment analysis result

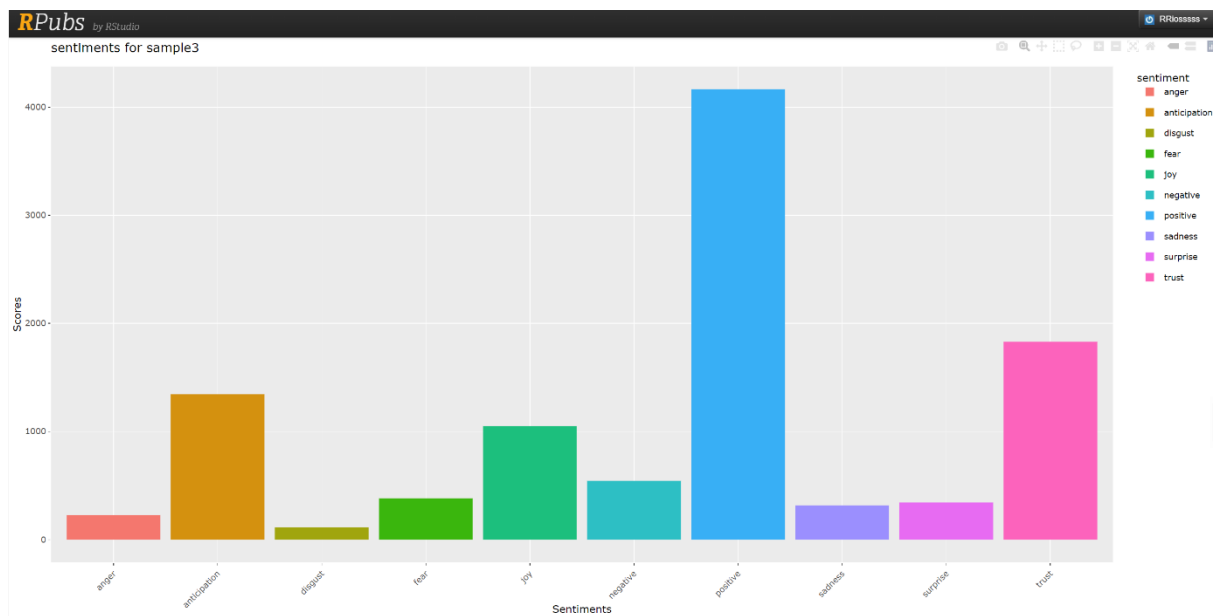Figure 4: Wave 2 sentiment analysis result

Figure 5: Wave 3 sentiment analysis result

The total score of sentiments from each wave is different from each other, so this research will calculate the ratio of each sentiment score in each of the wave in order to check if there is any variations of sentiment.

Table 1 is the aggregation table of 3 wave of sentiments.

Table 1: aggregation table of 3 wave of sentiments

	Angry	Anticipation	Disgust	Fear	Joy	Sadness	Surprise	Trust	Positive	Negative
Wave1	2.24%	14.10%	1.22%	3.55%	10.40%	3.27%	4.11%	18%	36.80%	6%
Wave2	2.30%	11.80%	1.18%	3.59%	10.80%	3%	3.72%	17.90%	39%	5.14%
Wave3	2.19%	7%	13%	1.10%	3.70%	3.10%	3.22%	17.70%	40.40%	5.27%

Based on the ratio of each sentiment in wave, the table shows that there are more positive sentiment than negative sentiment. Also, trust occurs at a high frequency in every wave. Generally, there is not much change in sentiments between the three waves. The most obvious variation is the disgust. From wave 2 to wave 3, disgust suddenly increase from 1.18% of all sentiment to 13% which is a huge gap. At the same time, sample data shows less fear, less anticipation and less joy from wave 2 to wave 3.

4.2. Most Representative Result from MDCOR

MCCOR is used to analysis open-ended responses from random 5000 sample from each wave. After execution of MDCOR 3 times by using sample data from 3 waves, and decide the number of topic need to sperate, Fig 6 to Fig.12 are output of relevent terms and topic in each of the wave. Fig. 6 and Fig.7 are two separation of topic published by twitter users under online learning topic during wave 1. Fig. 8, Fig.9, and Fig 10 are 3 separation topic during wave 2. Fig 11 and Fig. 12 are 2 separation topic during wave 3.

For further understand what are the content under these topics, most representative open ended response are summarized by researchers. We found that during wave 1, the most representative content under the first topic is " Enter to win Dash and Dot robots and accessories wonderworkshop Inapp learntocode challenges provide hours of self-directed learning time ". The most representative content under the second topic is " online learning, educators, and learning process".

During the wave 2, the most representative content under the first topic is "udemy udemycourse udemyfree udemycoupon onlinecourses udemycoupons udemycourses programming". The most representative content under the second topic is " Great tutors for students". For the third topic, the most representative content is " Join Webinar of npcindia for Higher productivity and SelfImprovement npccertificate NPCINDIAGOV onlinelearning EnergyEfficiency environnement Agritech HRCommunity."

During the wave 3, the most representative content under the first topic is "Join Webinar of npcindia for Higher productivity and SelfImprovement npccertificate NPCINDIAGOV onlinelearning EnergyEfficiency environment Agritech HRCommunity". Under the second topic, the content is "Group educators, take home online course, free course."
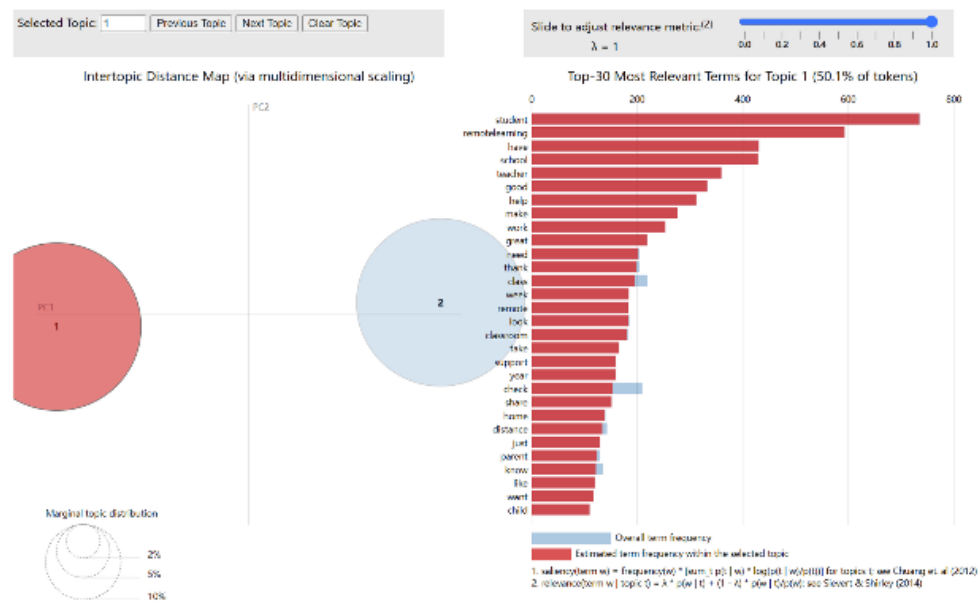

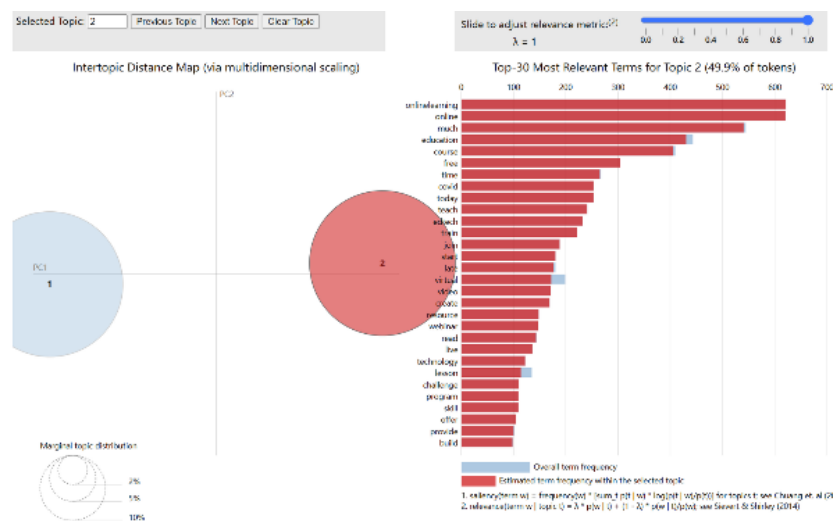Figure 6: Topic 1 of most representative world wave 1

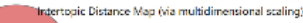Figure 7: Topic 2 of most representative world wave 1

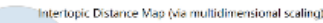Figure 8: Topic 1 of most representative world wave 2

Figure 9: Topic 2 of most representative world wave 2

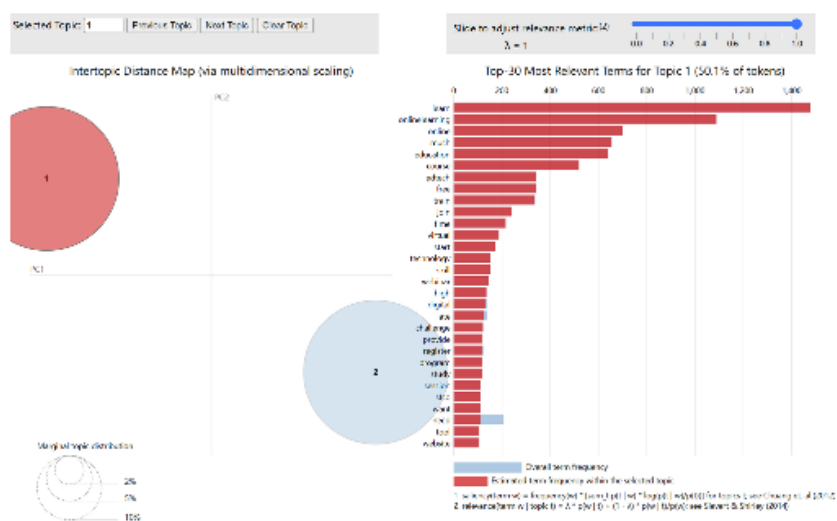Figure 10: Topic 3 of most representative world wave 2

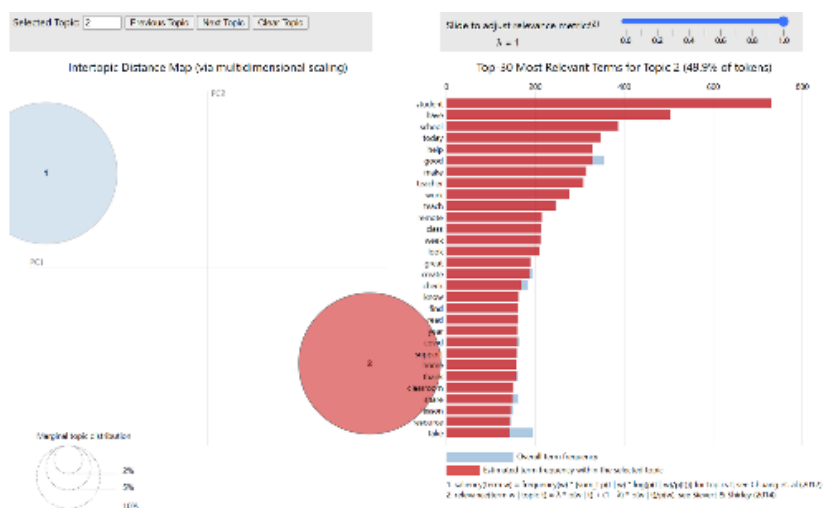Figure 11: Topic 1 of most representative world wave 3

Figure 12: Topic 2 of most representative world wave 3

5. Discussion

Based on our finding from sentiment analysis, twitter users show more positive sentiment, and trust under the topic of online learning can help us to understand the situation faced by online learning. Online learning, at least from this research, is trustworthy and acceptable education format.

The sudden increase of the disgust sentiments potentially influenced by the sensitive timing related to the COVID-19. Since the wave 2 is the trough of the Covid-19 infection and death rate, but this trending start to change during wave 3. People have to face the pressure brought by increasing death and infection rate, stay at home again. This could be the potential of the emotional change between wave 2 and wave 3.

We are surprised by the most representative content produced by MDCOR under the topic of online learning by twitter users. Advertisements filled most of the posts under the topic of online learning. There are more ratio of people express their emotions about online learning, pandemic, and covid-19 during the first wave. However, during the second and third wave, more and more people start use social media as the best platform to post advertisements. These advertisements include

personal tutor, free computer language course, self-learning topic. We found that people start to get used to the new form of education. Since during pandemic, many people are faced with job loss and lack of financial resources, and conducting online courses seems to be a way to make profit.

6.   Conclusion

Before making conclusions from our findings, few limitations of this research must be raised. First, the data of this research only is a period during pandemic. We could not infer it can represent the people's attitude towards online learning for whole pandemic period. Second, this research only chooses 5000 sample posts from more than 1 million of total posts, so we may not conclude that it can represent the whole population who posts on twitter under the topic of online learning. Thirdly, the results of MDCOR shows large number of advertisements, we may miss opinion from other perspective of online learning other than advertisements.

In summary, this research can help to understand people's basic attitudes towards online learning are more positive. People shows more trust, anticipation, and joy under the online learning topic. Online learning is more accepted by everyone than we thought, and this new way of education may help more people even not in pandemic. At the same time, traditional classroom setting of education also needed, since we found people's attitude toward online learning change negatively between wave 2 and wave 3.

Moreover, online learning provides more opportunities to earn profit. Advertisements online are easier and less expensive. Online learning also lifts geographic barriers which allows more people to get engage in more resources.

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