Analyzing COVID-19 Related Changes in Depression and Sentiment Analysis Online: a Study on American College Subreddits

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Abstract

Multiple studies have shown that a global pandemic can increase levels of stress and mental health-related issues in the general population. Among those affected are sub-groups who are particularly vulnerable to these increases in stress, and we focus on the college student demographic. Given that the extent of the impact of stress caused by the COVID-19 pandemic on college students in the United States has not been thoroughly quantified on a time-basis, we conducted an evaluation of depression using RoBERTa transformer-based learning to better understand the changes that occurred in the mental health of this sub-group during the COVID-19 pandemic as it progressed. In this paper, we seek to learn how the effects of COVID-19 on the mental health of college students are reflected on online communities by running an emotion classifier and a depression classifier on university subreddits of the titular platform Reddit. We show that although there are no statistically significant relationships, further improvements can be made to the study setup.

1 Introduction

University-specific online platforms, including subreddits, Facebook pages, and other social networks serve as discussion platforms for their corresponding students. These websites often allow students to speak honestly under the condition of anonymity, which is particularly useful when assessing sensitive topics such as mental health (Tsugawa et al., 2015), (Bagroy et al., 2017). During the COVID-19 pandemic, these communities served as a platform for many individuals, including students, to maintain communication with one another (Lisitsa et al., 2020) and discuss the varying policies that the US enacted as a response to the pandemic. Given the strengths of social media, we are interested in assessing the following question: how is the impact of COVID-19 on the mental health and emotional states of college students in America reflected in online communities? We hypothesize that analyzing the activity on these online communities, specifically school-specific subreddits, provides insight into the students' mental health and emotional states at a particular moment in time, given the homogeneity in such communities. Similarly, we predict that there will be a shift towards more expressions of depression, despair, hopelessness, and related feelings in these online communities at the onset of the pandemic during the Spring 2020 semester as a result of the spreading virus and the remote learning policies put in place by the universities. In addition, we hypothesize that there will be a more positive shift in the sentiments seen on these online platforms in the later months of the pandemic, namely Fall 2021, as a result of the universities reverting to attendance policies more similar to those prior to the start of the pandemic.

For this paper, we operationally define the change in mental health as the changes in the number of posts in the data set that can be labeled as depressed, as well as the changes in the sentiments of the online posts collected for this project. The two natural language processing classification models are used to label a text as depressive and identify the main sentiment associated with a post. Our depression model labels a text as either depressed or not, whereas the sentiment analysis model classifies each text as one of Ekman's six basic emotions (i.e. anger, disgust, fear, joy, sadness, surprise), in addition to a neutral class.

2 Background Work

The scale of the spread of COVID-19 has brought numerous challenges to emotional and mental health globally. Multiple studies have shown that a global pandemic such as the one caused by the Novel Coronavirus can increase levels of stress and mental health-related issues in the general population. College students are especially susceptible to these increases (Wang et al., 2020).

For many students, the pandemic added extra factors to the usual stressors which come with attending college, such as being away from home and family, financial, academic, and social stressors. Adding to all these existing factors the worry of becoming ill or having family members be sick with the novel coronavirus could greatly add to the overall stress levels of students and impact their mental health negatively. One large cross-sectional study done in China on 44,447 college students concluded that the risk of depression in students who had confirmed cases in their family of COVID-19 was three times higher than for the students without (Wang et al., 2020). Moreover, some subgroups of college students could be especially vulnerable to these changes in stress. One study from Polish universities found that there has been a significant increase in depression levels as the pandemic was progressing, but this was especially noticed among female students (Debowska et al., 2020). Similar trends were also observed in studies done on undergraduate students in the United States, where it was noticed that female, rural, low-income, and academically underperforming students were more vulnerable to COVID-19 related mental health issues (Lee et al., 2021). These empirical studies also suggest that the increase of stress in college students is a phenomenon observed across different continents.

COVID-19 induced changes in mental health in college students have been investigated in the US as well, but literature on the subject is still limited. Three large surveys conducted in the United States showed that the mental health of students has been worsening during the COVID-19 pandemic. One survey conducted by Active Minds, a nonprofit organization that works in the mental health domain in April 2020 concluded that 80% of college students reported that COVID-19 negatively affected their mental health (Horn and Ferrell, 2020). Another survey that collected data from May to early June 2020 found that 85% of students felt increased anxiety and stress during the pandemic, and only 21% looked for help from a professional (Timely MD, 2020). Lastly, according to a third survey conducted by the Healthy Minds Network survey in 2020, it was revealed that depression rates in college students increased by 5.2% compared to the previous pre-pandemic year (Healthy Minds Network, 2019) (Healthy Minds Network, 2020).

These previously mentioned studies relied on questionnaires to assess the mental state of college students, which inherently are unable to display mental health climate in a vacuum. Furthermore, the studies were cross-sectional and did not capture students' emotional states as the pandemic continued to progress. To see a fuller picture of the mental health of the subjects, different methods than just online questionnaires could be used. For instance, one study done by Huckins et al. investigated the mental health of 217 Dartmouth College undergraduates in the Winter term of 2020 using a combined method of data collection: self-reported ecological momentary assessments of the Patient Health Questionnaire-4 as well recorded data on behaviors such as locations visited, distance traveled, duration of phone usage, the number of phones unlocks, sleeping patterns and sedentary times through a phone sensing app (Huckins et al., 2020). The longitudinal study was running for 2 years when the pandemic started, which helped answer the questions of how the COVID-19 pandemic influenced the mental health of the subjects when compared to the previously established baseline. The study concluded that in the Winter 2020 term, the subjects were more sedentary, anxious and depressed than in the previous year, which can be attributed to the fluctuations of the COVID-19 news reporting (Huckins et al., 2020). Furthermore, the self-reported symptoms of anxiety and depression spiked noticeably in week 10 of that term when the newly widespread COVID-19 related policy was implemented in the college and nationwide and then continued to be high at all times until the end of the term (Huckins et al., 2020).

For the method of study, we collected data from college subreddits which met the criteria of having at least 10,000 members and being from colleges in the United States. Literature on the subject of assessing mental health on online platforms shows promising results when Reddit is used as a data source. Studies that used natural language processing and machine learning models successfully identified depression with high confidence in texts online by using Reddit posts as the data source (Tadesse et al., 2019). In addition to other studies which showed promising results when using Reddit, the platform seemed like an effective mental health lens compared to other social media websites, since it offers the benefit of anonymity and availability (Pirina and Çöltekin, 2018). Due to the aforementioned success of Reddit used in prior work, we decided to use Reddit to obtain data.

3 Data Collection

3.1 Web Scraping

A Python scraping script was created to extract data from subreddits for universities in the United States. We chose the following de-facto subreddits for 20 schools: Columbia, Cornell, NYU, Northwestern, UC Santa Cruz, UPenn, Berkeley, UC Irvine, UC Davis, UCLA, UC San Diego, Stanford, Ohio State, University of Central Florida, Georgia Tech, Rutgers, Penn State, University of Michigan, UNC Chapel Hill, and Northeastern. These universities were chosen since they all had well over 10,000 members, which would extract the most data since these subreddits would most likely have more posts. In addition, these universities had different characteristics, such as being an Ivy League school, state school, being in an urban, suburban, or rural environment, which would make the pool of schools more diverse.

3.2 Establishing Markers

Five time periods were established where each had critical moments in the COVID-19 pandemic. The periods were each a semester-long. The markers were the Fall 2019 semester, the Spring 2020 semester, the Fall 2020 semester, the Spring 2021 semester, and the Fall 2021 semester. The fall semesters had a time period of September 1 to December 31 while the spring semester had a time period of January 15 to May 18. The Fall 2019 marker was used as a control since there were no COVID-19 cases at that time in the United States. The Spring 2020 marker was when all the universities sent their students back home and announced that the rest of the semester would be taught online. Fall 2020 represented a fully online model for most universities. Spring 2021 was when the vaccines were released and some universities allowed students to come back while other universities still had classes online. Fall 2021 was when the majority of universities conducted classes back in person. The datetime library in Python was utilized to represent these markers. There were 10 markers in total and split into two arrays: five representing the start of the semester and five representing the end of the semester. An array of the five semesters and the twenty subreddits were also created.

3.3 Using Pushshift

The PMAW wrapper for the Pushshift API was utilized to scrape subreddit data with the time markers described in the previous section as parameters. PMAW was chosen due to its ability to scrape in a multi-threaded manner, unlike other Pushshift wrappers such as PSAW and PRAW. We scraped 1,000 posts from each of the designated time periods for each school, giving a total of 20,000 posts per time frame and 100,000 posts overall.

3.4 Tabulating the Data

The pandas library was used to generate a dataframe of the posts that were retrieved from the Pushshift API. The dataframe originally contained 32 columns, most of which were not relevant, so we cleaned the dataframe by extracting the 'title', 'selftext', 'created _utc', 'score', and 'total _awards _received' columns. The tabulated dataset was then exported as CSV files by using the to _csv module of the pandas library and was named by each subreddit and semester.

3.5 Data Pre-Processing

Since we are interested in how depression levels and emotions change across each semester for American college students overall rather than specific universities, we combined the data from each university subreddit by semester. To ensure that specific subreddits cannot be identified, we randomized the aggregated dataset. Since the data we input into the classification models is text, we cleaned the selftext (i.e. the body of the post) and title fields of the dataset by removing unparsable or empty inputs. Given that focus was not on a specific university, we felt that even if removing malformed input ended up removing more from one subreddit, it would not greatly impact the overall results. Furthermore, this step was carried out after shuffling the data, so it is unlikely that we particularly impacted only a few schools. Since we had sufficient data, we believe it was appropriate to remove these unusable inputs. In addition, there are cases where the title can be the entire post, so we did not remove rows where the text was empty but the title was not. We then combined the title and selftext columns into a new column. After the data was preprocessed, we tokenized the data using the pretrained tokenizer used by our models, which included padding and truncating inputs to be of acceptable length.

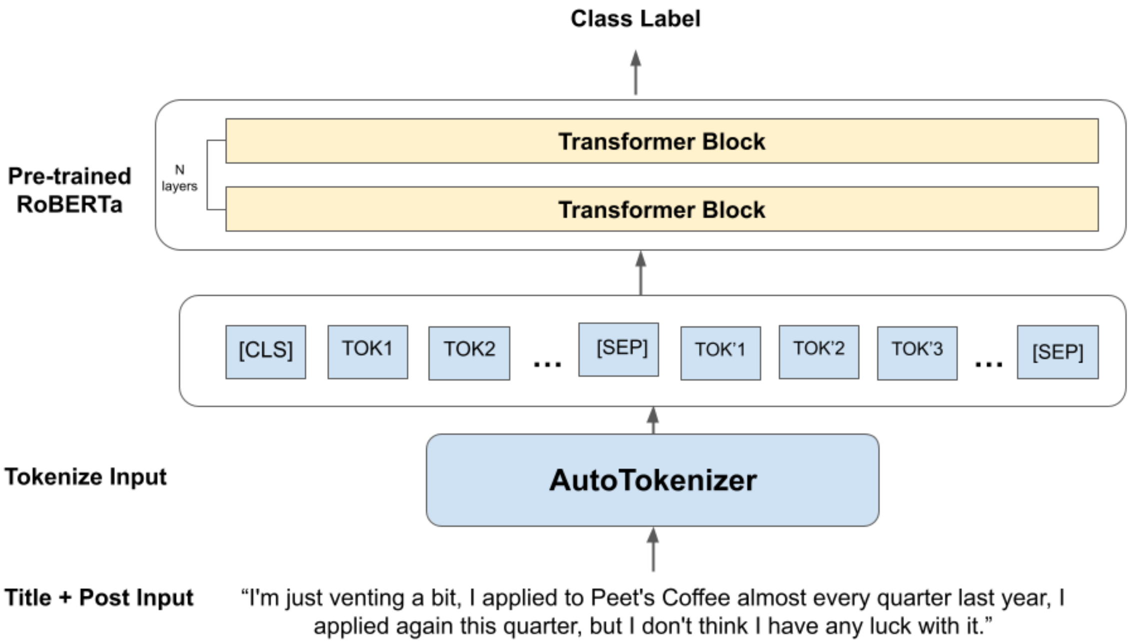

Figure 1: An example of a sample input that is tokenized, with [sep] tokens to indicate each sentence. The tokens are fed into the RoBERTa model, which has n layers depending on whether it is a distilled or base version. The RoBERTa model ends with a softmax layer to transform predictions into a score.

3.6 Classification Models

We utilize two pre-trained RoBERTa classification models to label our data. RoBERTa is an open-source, optimized version of BERT, a transformer-based machine learning technique for natural language processing (Devlin et al., 2018). BERT's architecture consists of n layers of encoder-decoders that utilize multi-attention heads introduced by Vasawni et al. (2017). This allows the model to learn the bidirectional representation of the input sequence rather than a linear representation, as is the case for recurrent neural networks. The first model (Hartmann, 2022) is a multi-classification model that predicts seven emotions: anger, disgust, fear, joy, neutral, sadness, and surprise. It is a fine-tuned checkpoint of a distilled RoBERTa model with 6-layers, 768-hidden, 12-heads, and 82M parameters. The emotion classifier's evaluation accuracy is 67% and it was trained on a variety of texts, including texts from Twitter, Reddit, student self-reports, and utterances from TV dialogues.

The second model (Shreya, 2022) is used to classify depression and is a fine-tuned version of the RoBERTa base model, which is comprised of 12-layers, 768-hidden, 12-heads, 125M parameters. The model was trained on a labeled depression dataset consisting of text data scraped from the internet. The model classifies a given text input as either label 0 (non-depressive) or label 1 (depressive) with an accuracy of 97.45% and a loss of 13.85%.

4 Results

The RoBERTa model identified the overall emotion scores for each semester as described in the table shown in Figure 2. When running the chi-square test between semesters and overall emotion, the emotion classifier resulted in:

$$\chi^2(24) = 0.01, p = n.s.$$

A bar plot of the percentage distribution of emotions for each time marker shows that the majority of posts were classified by the RoBERTa emotion classification model as "neutral", with "surprise" as a distant second. Emotions also tend to stay consistent across semesters (Figure 3).

	Anger	Disgust	Fear	Joy	Sadness	Surprise
Fall 2019	0.04	0.027	0.065	0.064	0.079	0.13
Spring 2020	0.031	0.025	0.07	0.065	0.07	0.13
Fall 2020	0.033	0.026	0.071	0.056	0.08	0.13
Spring 2021	0.026	0.02	0.07	0.065	0.073	0.13
Fall 2021	0.028	0.023	0.061	0.06	0.073	0.12

Figure 2: A table showing results of the emotion classifier. Negative emotions experience minor increases during Spring 2020 and Fall 2020. Surprise is consistently the largest label.

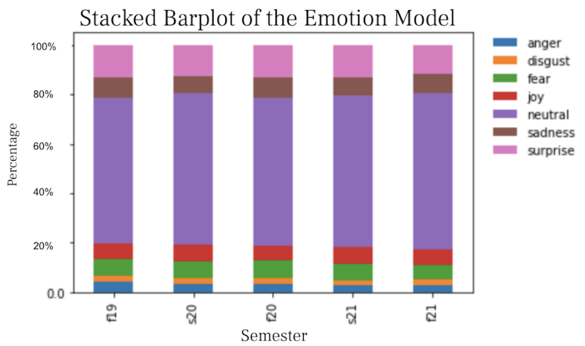

Figure 3: A stacked bar chart of the results of the emotion classifier. This illustrates how small the changes in emotions between semesters are, and that the neutral class is the overwhelming majority.

Due to the skew in data labeled as "neutral," we also ran a chi-square test after removing the "neutral" label. The results were similar:

$$\chi^2(20) = 0.02, p = n.s.$$

4.1 Depression Classifier

After running the depression classifier on the data from the twenty schools across five semesters, the depression scores for each semester ranged from 0.52 to 0.62, representing probabilities. Fall 2019 had a score of 0.58, Spring 2020 had a score of 0.6, Fall 2020 had a score of 0.62, Spring 2021 had a score of 0.59, and Fall 2021 had a score of 0.52. The depression classifier also returns scores for "not depressed", and that label had values ranging from 0.38 to 0.48. When running the chi-square test between semesters and scores of depression, the depression classifier resulted in:

$$\chi^2(4) = 0.02, p = n.s.$$

Although the chi-square test revealed that there is no statistically significant association between the semester in which a specific post was made and the score given by the depression classifier, a heat map generated from the contingency table (Figure 5) revealed slight variations in scores across semesters. The semester with the posts that were the most depressed was Fall 2020 and the semester with the posts that were the least depressed was Fall 2021.

5 Discussion

5.1 Emotion Classifier

The emotion classifier did not lead to any statistically significant results, therefore leading us to reject the null hypothesis. However, there were still insights that could be noticed from the results. As seen in Figure 3, the overwhelming emotion identified by the model was the 'neutral' one. This observation led us to believe that the lack of significant results could potentially be attributed to a lack of relevant data for the scope of the project, as opposed to the unsuitability of the model used. In addition to this insight, later on in this paper when the depression model is discussed more in depth, it is clear that the results from the depression model are in agreement with the emotion model, therefore providing further evidence that the data is not ideal for the scope of the project. In order to better analyze the insights in the labeled overall emotions associated with each semester, the emotion 'neutral' was removed and a heat map was created to better visualize the results (Figure 4).

From this, it is clear that 'surprise' was the most common emotion throughout all semesters chosen, which we found to not support our initial hypotheses.

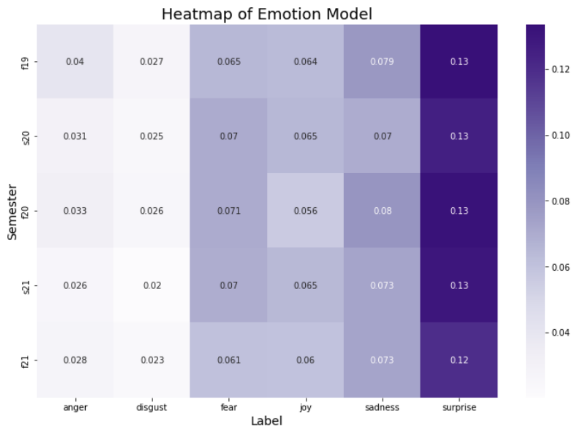

Figure 4: A heat map of the results of the emotion model without the neutral class to easily compare the most prominent emotions. Fear, joy, and sadness have a similar range of values, as do anger and disgust.

The semester that had the highest scores for negative emotions, such as fear and anger, was Fall 2020, when a lot of colleges changed their policies to either continue to conduct courses online or welcome a part of the student body back to campuses but with a new set of restrictions and rules. Since the vaccines were not available at that point in time, there might have been more stress caused by the COVID-19 pandemic as opposed to the later semesters. The fear score from Fall 2020 is however very close to the fear scores from Spring 2020 and Spring 2021. In the control semester (Fall 2019), the fear score is smaller, but this decrease is also seen in the fear score for the semester Fall 2021. These two insights could indicate that the elevated fear online coincided with the semesters with the most uncertainty and restrictions related to COVID-19. Fall 2021 was the semester when a lot of universities tried to maximize the return to normalcy on campuses and classrooms. This could be reflected in the lower score of fear for the semester of Fall 2021.

Due to the fact that there was not any correlation found between semesters and emotions, it is not clear what the relationship between each semester and sentiment online for college subreddits is. No relationship was found in the data that would indicate that any emotion was significantly getting worse as the semesters progressed throughout the pandemic. As discussed later in the Conclusion section, a different approach to data collection and/or the models used would need to better assess emotional states across crises such as a global pandemic.

5.2 Depression Classifier

Though the depression classifier led us to reject the null hypothesis and say that there is no association between the semester when the post was made and how depressed the post is, there are still interesting variations in the heat map that should be taken note of. For instance, Fall 2020 had the highest depression score and was also the first full semester of virtual learning. This may be a result of increased despair as a result of an entire semester being online and the continued persistence of the spread of the virus.

This also aligns with the prior work found that college students are part of a group more vulnerable to the stress caused by the pandemic (Wang et al., 2020). Although the pandemic started during the Spring 2020 semester, the virtual learning policies were enacted approximately halfway in between. Consequently, the depression classifier may not have had a higher score for the Spring 2020 semester because the earlier posts made during in-person learning were combined with the later posts made during virtual learning. In addition, Fall 2021 had the lowest depression score and was the first full semester of in-person learning. This decrease in despair may be a result of a return to normalcy or at least a return to policies more similar to prior to the start of the pandemic. This leads us to believe that there may be a correlation between university attendance policies and depression in students that is reflected online, seeing as how the extreme ranges in depression scores also correspond to semesters on the extreme ends of attendance policies. In addition, the stacked bar plot showing the depression scores for each semester shows an increase in depression during the starting months and there is a slight decrease in depression scores in the later months of the pandemic.

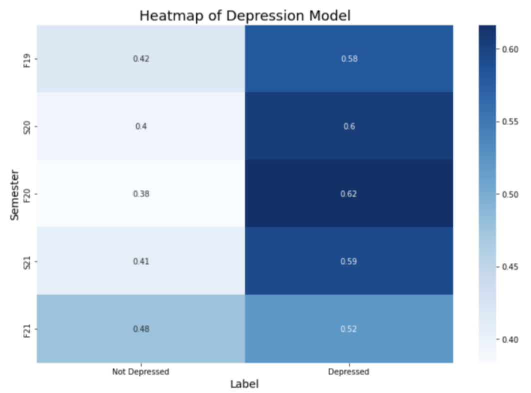

Figure 5: A heat map of the results of the depression model to assess the most prominent semesters.

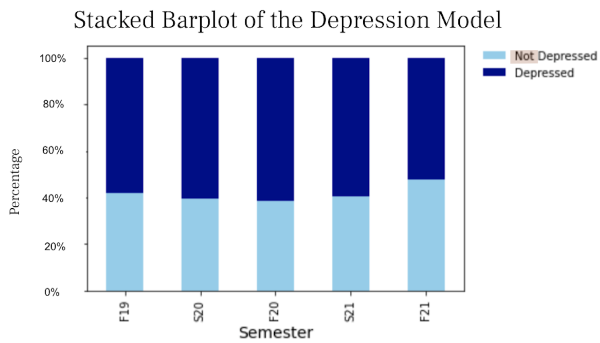

Figure 6: A stacked bar chart of the results for the depression model to better understand percent changes across semesters.

5.3 Similarities in Results Between the Two Classifiers

Although both models were chosen for their differing perspectives on mental health on the subreddits, there are some similarities in the results they produced. For instance, as aforementioned, the emotion classifier results showed that Fall 2020 had the highest scores for negative emotions. Similarly, the depression classifier showed that posts from Fall 2020 had the highest depression score. This leads us to believe that Fall 2020 indeed had the biggest negative impact on college students' mental health as a result of being the first fully virtual semester and the implications that came with it. In addition, the emotion classifier showed an increase and then decrease in fear throughout the pandemic. Similarly, the depression classifier showed an increase and then a decrease in depression throughout the pandemic. Both of these lead us to believe that COVID-19 had a negative impact on students' mental states at the start of the pandemic, but then there were improvements seen in the later months. Although running chi-square tests on both of the classifiers revealed no significant associations, these similarities show that the online communities may have potential to show fluctuations representative of students' mental health, which led us to explore the limitations of our study. We believe that a closer a look into the limitations of the methodlogy of our study and dataset provides a more holistic view of why the hypothesis was not sufficiently supported.

5.4 Limitations

Firstly, Reddit is not necessarily representative of the whole student body nor it is usually used as a medium for venting for college students. This is illustrated by the large proportion of posts labeled as neutral by the emotion classifier. Although there are posts that contain venting, the proportion is much lower than that of a Facebook group whose main use is for venting. Even though Reddit may not have been the best platform to use for analyzing this question, the college Facebook groups whose main purpose is for users to vent anonymously usually only accept members who go to the university. Thus, it would have been difficult to access these platforms and scrape the data from them ethically. In addition, if we were to use these platforms made for venting, this might bias the data since there would be more negative sentiment posts present and this may not represent the student body accurately.

In terms of our dataset, we were unable to scrape a larger dataset due to limited resources. In addition, the range of each time period is fairly large (i.e. 3 months), which affects the quality of data received. Due to the fact that the Pushshift API was not given specific keyword queries, it randomly scrapes posts from within the designated time frame, which means that the content may not be the most representative of a given semester. In other words, our data could have been biased since it was only a small sample from a very large amount of data available for a given time period. We discuss how to address this limitation in the Future Works section.

There are a few limitations in the portion of our study using the depression classifier. For instance, there is not a great variation detected among the scores. In addition, some of the posts did not include wording that may be directly associated with depression, so it may have come across as ambiguous to the depression classifier. In addition, as previously stated, the posts during the Spring 2020 semester were not divided between prior to the start of the pandemic and during the pandemic and this may have resulted in a decrease in the expected score during that time period.

In order to maintain consistency with the depression classifier, the overall label was used for the emotion classifier. However, given that there are seven output labels for the emotion classifier, using only one label is not necessarily accurate. Some emotions are often associated with the other, such as anger and sadness, or joy and surprise. There are cases where the sadness score and anger score are quite similar, but only one emotion is outputted. Thus, the emotion classifier is unable to capture the nuanced emotions present in our dataset. A more accurate way to use the model would be to examine the scores of each emotion and check if there is a small difference between the top two or three emotions. If that is the case, we could output multiple labels, which better reflect the emotion of a post.

In addition, since our time periods were each a semester long and did not capture the time markers during the COVID-19 pandemic on a more nuanced scale, there are additional details that neither of the two classifiers would have distinguished between. For instance, the attendance policies of the various universities varied during the pandemic. This variance can be attributed to a variety of reasons, like political affiliation and location. There has been research showing the relationship between policies enforced during the pandemic and the governor's political affiliation; for instance, Democrat governors enforced social distancing earlier than Republican governors (Adolph et al., 2021). The colleges we chose spanned 11 states (California, Florida, Georgia, Illinois, Massachusetts, Michigan, North Carolina, New Jersey, New York, Ohio, and Pennsylvania) that are spread out across the country. As a result, varying state-level mandates at different points of time prevented normalization in our data.

6 Conclusion

This paper evaluates whether COVID-19 related mental health changes in American college students are reflected online, specifically on Reddit. We characterized mental health changes as changes in emotional state and depression within Reddit posts across a semesterly basis. We identified these mental health changes in posts using two RoBERTa models and analyzed the correlation between each semester and the mental health in posts. However, our results from both models were not significant. Thus, we believe that the methodology of the experiment should be refined to address limitations in order to assess the research question in a more comprehensive manner.

6.1 Future Work

Given the identified limitations, we believe addressing them in the future would lead to more significant results. To better account for the randomness of the posts scraped using the Pushshift API, we will use more specific time periods or have sub-markers for each semester to have more fine grained posts according to COVID-19 events. For example, instead of solely having Spring 2021 as a time marker to represent the announcements of vaccines and a shift into more hybrid learning models, we could have sub-markers that represent the announcement of the Pfizer vaccine, the Moderna vaccine, and the Johnson & Johnson vaccine. The use of sub-markers or more specific time markers can give us more accurate results since it would show the sentiment regarding the announcement of the vaccines rather than some other arbitrary time in the spring semester. This would allow us to better account for and filter out time periods where negative emotions may be prevalent due to school-related events, such as midterms or finals.

Given that we looked at American college students overall, we could not fully explore the complexity of different categories of schools and the relationship between their characteristics and COVID-19. For example, a rural university may not have imposed strict COVID-19 restrictions due to its small population size and more open area compared to a primarily urban school. Thus, another way we plan to improve our analysis is by scraping data from more schools and comparing the results from each category. As mentioned before, our selection pool of universities had a wide range of characteristics such as being an Ivy League school, state school, in an urban area, or a suburban area. If we increase the number of schools, we can then run the models on each category of data and compare the results.

In addition, we would take into account the score of the posts that the Pushshift API retrieves. The score represents the number of up-votes that a given post receives. In the future, we can implement this score by weighing the posts that have a higher score more than the posts that have a lower score. A higher score indicates that more students agree with the sentiment present in that specific post.

We previously discussed how the emotion model fails to capture the nuanced emotions present in the data. In order to better address this limitation, we believe that combining our classification model with techniques such as word frequency analysis and topic modeling will make our results more accurate, as we can better understand which words are associated with specific emotions and depression. Furthermore, these techniques can help in adjusting keyword queries to retrieve posts that contain a large number of words rated as high term-frequency inverse document frequency (tf-idf). After performing algorithms that obtain the tf-idf for our dataset to extract relevant terms, we can feed them into Linguistic Inquiry and Word Count (LIWC). LIWC calculates the percentage of words that fall into a specific category such as grammatical, psychological, and other cognitive categories. LIWC has also been used to accurately identify emotions in language use and high language emotionality (Tausczik and Pennebaker, 2010) and assist in topic modeling for depression (Resnik et al., 2013), which enables us to collect Reddit data that is more catered to "venting." As previously mentioned in the limitations section, this may help us tailor our data to be more relevant to our research question but will also introduce biases into our data. However, it is worth exploring this method to ensure that our data is both relevant and ethically collected. Another method we can use to employ LIWC is to use the content of the posts as input instead of the high tf-idf terms to evaluate the percentage of posts that meet some predetermined threshold.

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7 Individual Contribution

Daria Manea contributed to data scraping, to creating the code that ran the data through the emotion classification RoBERTa model, to interpreting its results as well as to researching background literature.

Aditi Dam contributed to scraping Reddit data, creating the code that ran the data through the depression RoBERTa model, and running the chi-square tests on the depression analysis results, and interpreting results.

Janelle Ponnor contributed to data scraping, writing the code that ran the data through the depression classifier, running the chi-square tests on the depression analysis results, and interpreting results.

Jenny Cha contributed to creating the data scraping script, data scraping, data preprocessing, choosing models, creating the code that ran through the emotion classification RoBERTa model, and running chi-square tests on the emotion analysis results and interpreting its results.