Analysis of Reactions on Social Media to U.S. University COVID Policies

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Abstract

The severity and novelty of the coronavirus pandemic (COVID-19) significantly disrupted the typical operations of universities in the United States, forcing universities to make hasty policy decisions. The lack of evidentiary support for the efficacy of various policies during a pandemic period resulted in arguably sub-optimal decision making, potentially exacerbating the effects of COVID-19 on student mental health and academic performance. This study uses data from comments on university Facebook posts to quantify and dissect public opinion toward university reopening policies during the 2020-2021 academic year through state-of-the-art sentiment analysis and topic modeling methodologies. This study's identification of differences in sentiment toward online, hybrid, and in-person reopening policies, as well as the potential forces which may be affecting these sentiment differences, offers universities a window into the impact and relative success of policy decisions as well as guidance in making the future policy decisions which most positively impact their student populations.

1. Introduction

Since the onset of the coronavirus pandemic in 2019, over 292.1 million cases and 5.4 million deaths have been reported worldwide [4], with 56.1 million of those cases and 826 thousand of those deaths being from the United States [3]. The near omnipresence of COVID-19 has made its impact on nearly all societal sectors extremely significant. The educational sector, in particular, has experienced high levels of pandemic-induced disruption, with university students being some of the most strongly impacted [13].[1] In the United States, over 25.7 million students across over 4.2

[1] The term "university" is used in this paper to refer to "an institution of higher learning providing facilities for teaching and research and authorized to grant academic degrees" [11]

thousand higher education institutions were affected by educational policy changes made during the initial coronavirus surge of March 2020 [3, 6]. Many universities abruptly evicted their students from university campuses and suspended in-person instruction in favor of virtual coursework conducted over platforms such as Zoom.[2]

During the 2020-2021 academic year, some universities continued providing instruction remotely, while others resumed in-person coursework or adopted hybrid instructional models [1]. Due to the unprecedented nature of the coronavirus pandemic, universities were forced to decide which instructional model (in-person, online, hybrid)[3] to adopt without much evidentiary support for such a model in a pandemic context. As a result of this lack of evidentiary support, university reopening policy decisions may have been suboptimal with respect to student well-being and academic success. Rates of anxiety and depression among college students increased significantly during the COVID-19 pandemic [16], while term grade point averages and other learning metrics declined [7]. Due to these significant implications of differing university reopening policies for university students, a large and particularly vulnerable population, this study aims to extract and examine reactions to such policy decisions. Specifically, the goal of this study is to extract the sentiment and polarity of public discourse surrounding differing U.S. university reopening policies during the 2020-2021 academic year, as well as determine the central topics of this discourse. Such an examination may provide a window into the impact and relative success of different policies and provide guidance to universities in making future policy decisions, namely adopting policies that most positively impact their student populations.

Many U.S. universities now have an established Facebook following [10] and increasingly turn to Facebook and other social media platforms as their primary modalities of communication with both university communities and the general populous [28]. As such, comments on university social media posts can provide a potential source for evaluating public opinion with respect to university reopening policy decisions. An example of a reopening-policy-related social media post and the

[2] https://zoom.us/

[3] The definitions of each of these learning models, adapted from Davidson College's Reopening Policy Study [1], are listed in the appendix

accompanying comments can be found in the appendix of this paper. Expanding on the higher-education-in-the-time-of-COVID related research of Vijayan and Figueira et al. [38, 19], this paper will use a corpus of comments made on coronavirus-related posts on university Facebook pages to perform both sentiment analysis (using the VADER sentiment model) and topic modeling (using Latent Dirichlet Allocation (LDA)). The calculated mean sentiment (aggregate public opinion) and standard deviation of sentiment (divisiveness of public opinion) reveal statistically significant differences between reactions to in-person, online, and hybrid reopening models as well as to COVID and non-COVID-related posts more generally. This paper then uses multiple regression to isolate the extent to which the reopening policies themselves influence that sentiment, but fails to find statistically significant results. Nonetheless, the high percentage of COVID and reopening-policy-related posts and high levels of polarity for comments on such posts reveals the significance of coronavirus-related policies for the U.S. higher education community. This prompts further research into the nuances of university reopening policy implications, so as to give universities a clearer insight as to the impact of their policies on university communities.

2. Approach, Problem Background, and Related Work

As this study aims to extract and examine reactions to such U.S. university reopening policies during the COVID-19 pandemic, a recent phenomenon, no related work exists that fully accomplishes this goal. As such, here I will survey a selection of studies that accomplish similar goals or ones from which this study draws methodology.

This study lies in the realm of natural language processing (NLP), specifically in the sentiment analysis and topic modeling sub-domains of NLP. Sentiment analysis, the process of determining whether data is positive, negative, or neutral, and topic modeling, a form of text-mining tool used to discover hidden semantic structures ("topics") in a body of text, are at the forefront of much present-day computer science research [18, 37]. As such, the techniques used to analyze data in this paper are particularly robust.

This study also uses data from social media, specifically comments on coronavirus-related posts made on U.S. university Facebook pages, as the corpus on which to perform topic modeling and sentiment analysis. Due to the prominence of social media platforms in the modern era, such platforms can serve as bountiful corpora in studies aimed at the gauging of public sentiment. Thus, along a similar vein as much previous research, this paper will use sentiment expressed in comments on Facebook posts to approximate public opinion and extract prominent comment topics [12, 17]. As Facebook is less commonly used than other social media platforms, such as Twitter (likely due to the difficulties of extracting Facebook data, detailed later in this paper), this study offers a unique perspective into public opinion toward COVID-19's impact on higher education in the U.S.

There are several related works that have utilized social media to better understand public opinion regarding the coronavirus pandemic. In 2021, Figueira et al. examined sentiment data related to COVID policies (i.e.: shelter-in-place orders, fall school reopening guidelines, face mask guidelines) extracted from Twitter, Facebook, and Reddit. They found that mask policies had a more positive public opinion toward them than shelter-in-place and fall school reopening policies. The presence of less positive sentiment towards school reopening policies in the aggregate motivates a more nuanced examination of in-person versus online versus hybrid reopening policies, which may perhaps have varying sentiments toward them. Such variations are key to accomplishing this paper's goal, namely that finding statistically significant differences between reopening policies (or a lack thereof) would enable universities to take more informed action when deciding between such policies in the future. Importantly, the Figueira et al. study established that there exist statistically significant differences in policy-related sentiment across states and used COVID-19 case and death data to contextualize these differences [19]. As COVID case and death rates vary significantly regions and such variations may impact public opinion toward reopening policies, this paper aims to similarly examine interregional[4] reactions to university policies and analyze the relationship of these reactions to regional COVID-19 case and death data.

A 2021 study conducted by Ranjit Vijayan of the United Arab Emirates University used topic modeling to understand the impact of the coronavirus pandemic on teaching and learning. His study

[4]This paper will use the Census Bureau's Divisions of the United States as its regions [2]

established that the largest proportion of research publications related to the keywords "teaching COVID-19" (28.2%) dealt with the challenges faced by higher education institutions, primarily U.S. universities. Such a finding validates the importance of this study, in that the impact of the coronavirus pandemic on U.S. universities is clearly at the forefront of modern research. To identify key themes surrounding COVID-19's impact on education, the Vijayan study used a frequently used form of topic modeling known as Latent Dirichlet Allocation (LDA), a Bayesian Inference Model that attempts to discover the set of topics most likely to have generated the given corpus [14]. Due to the robust nature of LDA and its frequency of use in NLP research, this study will similarly use LDA to learn topics surrounding COVID-19's impact on education. A key distinction between this study and the Vijayan study is the corpus on which LDA is performed, comments on university Facebook pages and education-related literature (respectively). The use of Facebook comments in this study offers a unique window into the general public opinion surrounding COVID-19 and education, whereas the Vijayan study focuses solely on the perspective of academics, which may not be as informative to universities in making policy decisions. The Vijayan study also found that a major theme in academic literature surrounding the pandemic was the manner in which universities delivered course content during the pandemic, which is the focus of this study and further validates its significance [38].

Delving into a discussion of works unrelated to education during COVID-19 that this study nonetheless adopts methodology from, the first study examined is Pletea et al.'s "Sentiment Analysis of Security Discussions on GitHub" [29]. Though much work in topic identification utilizes a clustering-based approach (clustering the corpus into groups of entities and then identifying which cluster can be associated with a designated topic), Pletea et al. successfully use a keywords-based approach (constructing a list of relevant keywords) to find data points in their corpus related to their topic of study (application security). This paper will also use keyword-based data filtering to find coronavirus pandemic-related posts from its Facebook corpus, using domain literature and stemming to further refine keywords. Borg et al.'s 2020 study on investigating sentiment in customer support for a large Swedish telecom corporation heavily utilized the VADER sentiment model

[21] in its methodology and used mean sentiment as a notable statistic. From Borg et al.'s mean sentiment scores as measured by VADER, they were able to draw statically significant conclusions about their dataset and accurately predict sentiment on never-before-seen data [15]. Due to the robust nature of VADER and the relevance of mean sentiment as a measure of public opinion, this paper similarly uses the VADER model and mean sentiment statistic to draw conclusions regarding its data. Wang et al.'s 2021 study of the sentiment analysis of rumor spread during the COVID-19 pandemic used linear regression to examine the relationship between rumor spread and sentiment data. Through their examination, they found a causal interrelation between negative sentiment and rumor spread [39]. Along a similar vein, this paper will use linear regression (a highly popular statistical research methodology) to analyze relationships between sentiment data and other factors (specifically, COVID cases, deaths, and university reopening policies during the 2020-2021 academic year).

3. Implementation

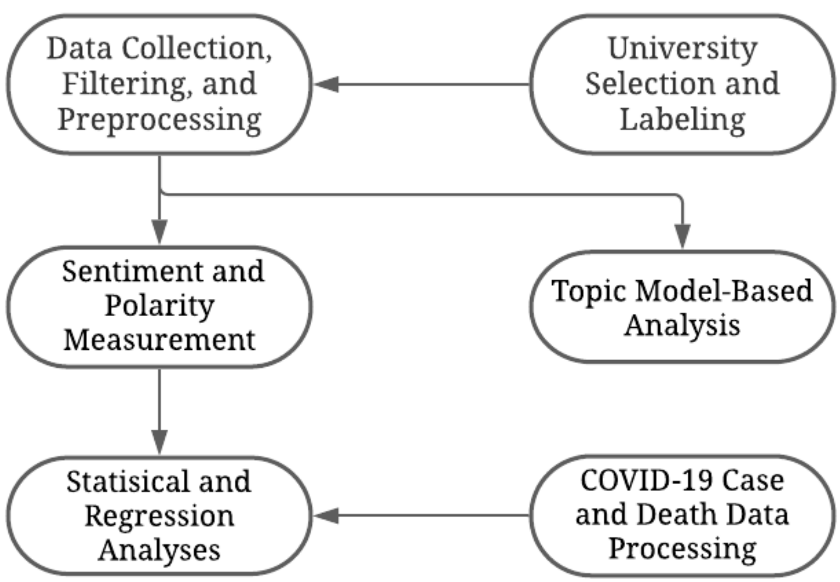

Figure 1: Flow chart detailing key implementation steps.

3.1. University Selection and Labeling

This study focuses on five universities from each of the nine U.S. Census Bureau Divisions. A relatively high volume of universities was selected so as to provide a robust corpus for analysis. In addition, universities were selected primarily on the basis of their social media following, as it is reasonable to assume universities with a larger social media following have higher engagement levels on their posts, thus further amplifying this study's corpus [10]. A secondary criterion used to select universities was their reopening policy, so as to ensure an approximately even distribution of universities across the three policy types. It is important to note that, as of April 27, 2021, there were 1,452 regionally accredited universities in the U.S offering four-year undergraduate degree programs [8]. Due to the inefficiencies of scraping Facebook, scraping data from more universities than the ones scraped from in the study would be infeasible to do in a reasonable time frame. Hence this study implicitly assumes that the selected universities are representative of the general U.S. university population. This may not necessarily be the case, but is a reasonable assumption to make given that universities of varying characteristics (i.e.: public and private, small and large student population, urban and rural location, etc.) were chosen. The U.S. Census Divisions were chosen as university groupings so as to readily enable statistical analysis of divisional sentiment and polarity data in the context of COVID-19 case and death data, which can be feasibly aggregated by division. Universities were then manually labeled with their reopening policies for the fall and spring semesters of the 2020-2021 academic year,[5] as well as with their Facebook profile names (to enable data scraping). The labeled university list is available in the appendix of this paper.

3.2. Data Collection, Filtering, and Preprocessing

The data used for this study were collected through the running of a web scraping algorithm on the Facebook pages of the above-mentioned, preselected U.S. universities. The Facebook scraper implemented in this study utilizes the Python "facebook-scraper" package[6] and operates by using universities' profile names to fetch pages of posts and post comments and then append fetched

[5] Policy data was obtained from Davidson College's Reopening Policy Study [1]

[6] https://github.com/kevinzg/facebook-scraper

data (including the time a given post was published) to a CSV file. Other social media platforms, specifically Instagram and Twitter, were considered as potential data sources for this study but were ultimately discarded due to platform-specific limitations. Instagram blocked scraping, returning the HTTP 429 "Too Many Requests" response status code after fewer than 100 posts were scraped and Twitter's API did not allow efficient access to tweet replies (the focus of this study), hence Facebook was selected as the social media data source for this study. It is important to note that Facebook, similarly to Instagram, also heavily blocked scraping, hence this study was not able to analyze the quantity of data initially intended. This limitation is further discussed in section 5 of this report. The unfiltered dataset contains 28,749 posts and 397,948 post comments.[7]

As this study concerns reopening policies for the 2020-2021 academic year, the data was filtered to only include posts made from July 1st, 2020 to June 30th, 2021.[8] Though university instruction typically does not begin until August or September, July was included in this paper's definition of an academic year as universities typically publish policy-related announcements significantly prior to the official academic year start date so as to give students ample time to adapt to them. For example, should a school adopt an online reopening policy, that school would need to notify students sufficiently early to ensure they have the technology necessary to complete remote coursework.

This study used a keywords-based approach to identify posts relevant to the coronavirus pandemic and university reopening policies. To construct a "COVID-19 dictionary" of relevant keywords, a literature review was conducted to determine the terminology most relevant to the coronavirus pandemic and reopening policies [9, 5, 26]. These words were then stemmed (reduced to their roots) and subsequently transformed into their relevant forms in an attempt to maximize relevant post capture. As an example, the words "vaccine," "vaccination," "vaccinated," and "vaccination" are all present in the dictionary. The entirety of the dictionary is located in this paper's appendix. Two versions of the assembled dictionary were then used to separately filter the Facebook data. Namely, a dictionary that contained terms generally related to the coronavirus pandemic and a dictionary

[7] The entirety of the unfiltered dataset, as well as all of the code used in this project, is available at https://github.com/mayaRozenshteyn/fall21-iw

[8] The fall semester dataset includes posts from July 1st, 2020 to December 31st, 2020, and the spring semester dataset includes posts from January 1st, 2021 to June 30th, 2021

that contained terms related specifically to reopening policies were used. The general dictionary enabled filtering for a larger dataset, from which more statistically significant conclusions could be drawn, while the reopening dictionary produced a more targeted examination of reactions to reopening policies, albeit with a smaller dataset.

As social media data contain significant noise (i.e.: spam comments, URLs, etc.) which may convolute this paper's findings, the dataset was cleaned prior to analysis. Much of this study's data prepossessing was completed using Python's premier open-source NLP library called the Natural Language Toolkit (NLTK).[9] The sentiment analysis tool used in this study (VADER)[10], detailed in section 3.3, works best when analysis is done at the sentence level, so the dataset comments were broken down into individual sentences using the sentence_tokenize function from the NLTK library. Comments were also stripped of URLs and tags (mentions of other Facebook users). As VADER is designed for social media sentiment analysis and can process emojis and other social-media-specific content, no further processing was necessary to utilize the VADER model. For the topic model, however, standard natural language preprocessing was necessary for optimal model performance. Specifically, through the use of NLTK, non-ASCII characters (i.e.: À, µ, etc.), punctuation, stop-words, and non-English comments were removed. Finally, NLTK was used to lemmatize the data, transforming words to their roots.

3.3. Sentiment and Polarity Measurement

This study utilized the Valence Aware Dictionary and sEntiment Reasoner (VADER), a highly popular open-source sentiment analysis tool specifically developed to measure sentiments expressed in social media, to quantify the sentiment of Facebook comments (i.e.: whether a comment is generally positive, neutral, or negative). Amongst other data, for each Facebook, post VADER returns a compound sentiment score, which is most commonly used for sentiment analysis by most researchers. The compound sentiment score is a weighted sentiment composite score normalized to lie between -1 (most extreme negative) and +1 (most extreme positive). It offers a uni-dimensional

[9] https://www.nltk.org/
[10] https://github.com/cjhutto/vaderSentiment

measure of sentiment for a given sentence, with a score strictly less than -0.05 indicating a negative comment, a score strictly above 0.05 indicating a negative comment, and a score weakly between 0.05 and 0.05 indicating a neutral comment [21]. These sentiment scores are used heavily in the statistical and regression analyses detailed in section 3.5. As above-mentioned, VADER utilizes content that is usually removed in NLP research through preprocessing (i.e.: emojis, punctuation, etc.) to extract sentiment information cues such as punctuation and emojis, so only the removal of URLs and user tags was necessary before running VADER on Facebook data.

3.4. COVID-19 Case and Death Data Processing

As many researchers have done previously, this study aims to contextualize its findings using coronavirus case and death data [26, 19]. Analyzing sentiment findings through the lens of the contemporaneous pandemic state may enable a more find-grained and revealing insight into the factors driving public sentiment toward varying reopening policies. The COVID case and death data used in this study is official government data made publicly available by `usafacts.org`. To clean the dataset, I removed data not allocated to a particular state, grouped data by Census Division, and filtered the data to only span the 2020-2021 academic year (July 1st, 2020 to June 30th, 2021). I subsequently used publicly available population data to compute the percentage of the population in each Census Division who contracted or passed away from COVID-19 during each of the fall and spring semesters of the 2020-2021 academic year. Such percentages are used heavily in the statistical analyses of the subsequent section and can be found in the appendix of this paper.

3.5. Statistical and Regression Analyses

To solidify the significance of the coronavirus pandemic in the context of the U.S. higher education system, this study first aimed to determine the percentage of posts that are coronavirus and reopening policy-related. This can be done relatively simply, namely by using the COVID and reopening policy dictionaries to filter out relevant posts and subsequently dividing the number of relevant posts by the total number of posts.

After measuring the VADER sentiment scores for the Facebook comment dataset, this study used these scores to calculate sentiment, polarity, and divisiveness-related statistics along a multitude of dimensions. Specifically, the dataset was subdivided in the following manner:

- COVID-19 and reopening policy-related posts for all universities were compared university Facebook posts as a whole to provide context to more nuanced data examination.
- All posts belonging to universities with a specific learning policy for a given semester (i.e.: Fall 2020 or Spring 2021), which can be either online, hybrid, or in-person.[11]
- All posts belonging to universities in a specific region for a given semester.

For example, one generated subset of posts (and corresponding post comments) was those made during the fall 2020 semester by all of the universities that had a hybrid learning policy for that semester.

Two statistics were calculated for each of the above-mentioned subdivisions of the dataset. The first of these statistics was the subset's mean sentiment, calculated by taking the arithmetic mean of the VADER sentiment scores for each comment in the sub-dataset. This statistic can be interpreted as a measure of the comments' aggregate sentiment (i.e.: the average opinion toward a particular reopening policy). When calculating the mean sentiment, this study first calculates the mean sentiment for each individual university in the subset, and then averages those means, so as to not over-inflate the importance of universities with higher levels of engagement on their Facebook pages. The second such statistic is the subset's standard deviation of sentiment, a measure of the amount of dispersion of comment sentiment scores. A higher standard deviation of sentiment scores corresponds to higher levels of polarity between comments. The presence of coherent or divisive sentiments can be an equally if not more useful gauge of the public's opinion toward a particular reopening policy. For example, low divisiveness may indicate that there is great consensus among the public's viewpoint toward a particular reopening policy, giving greater weight to the mean.

To evaluate the statistical significance of the measured sentiment statistics, I first attempted to use an independent sample t-test, a robust test of statistically significant difference between the means in two independent populations [20]. However, a prerequisite for T-Test accuracy is a

[11] It is important to note that the 2020-2021 academic year cannot be examined in the aggregate, as some universities had different policies for the fall and spring semesters.

normal distribution of the data on which the test is being run. After running the Shapiro–Wilk test for normality on each of the subdivided corpora's VADER sentiment, however, I found that the sentiment data was not normally distributed ($p << 0.05$, where the null hypothesis is that the data is normally distributed) [33]. As such, this study evaluates the statistical significance of its findings using Mann-Whitney U tests. The Mann-Whitney U test is the non-parametric (i.e.: does not rely on a particular data distribution) alternative test to the independent sample t-test. The test is similarly used, however, to detect statically significant differences between two independent data sets. The test is frequently used in research and is as follows:

$$U_1 = n_1 n_2 + \frac{n_1(n_1+1)}{2} - R_1$$

where n_1 is size of sample one, n_2 is size of sample two, and R_1 is the sum of ranks in sample one [27]. The null hypothesis for this test is that the distributions of two data sets are identical.

To analyze to what extent university reopening policies influenced the sentiment of comments on COVID-related posts (as opposed to other factors such as COVID cases and deaths), I performed multiple regression using Python's statsmodels library [32]. For the purposes of regression analysis, I considered all universities as individual data points, regardless of their reopening policies. In addition, each university was represented by two data points, one for the fall 2020 semester and another for the spring 2021 semester. Specifically, I ran four regressions, two in which the dependent variable was mean comment sentiment and another two in which the dependent variable was the standard deviation of comment sentiment. The independent variables in the regressions were the reopening policy type of a particular university and either the percentage of the population in the Census Division in which a particular university is located who were reported to have contracted COVID (COVID cases) or the percentage of the population in the Census Division in which a particular university is located who were reported to have died of COVID (COVID deaths). I could not include cases and deaths in the same regression as, when I attempted to do so, I found that they were highly multicollinear (the condition number of the regression was significantly greater than 30, which is considered to be the multicollinearity threshold [24]).

As reopening policy type is a categorical variable, while the percentages of COVID cases and deaths in a particular region are continuous variables, I decided to use least squares regression, as it allows for the interspersal of categorical and continuous predictors [35]. To do enable such interspersal, I created "dummy variables" for the reopening policy predictor. A dummy variable is a numerical indicator variable (can take on a value of 0 or 1) that represents categorical data and allows typically non-numerical variables to be included in regression analysis. For the regressions in this study, we can define three dummy variables, R_1 , R_2, and R_3. For each university, $R_i = 1$ if the university has the ith reopening policy (we can arbitrarily define online = 1, hybrid = 2, in-person =3), otherwise $R_i = 0$. We thus have a regression model of the form:

$$Y = \alpha_0 + \alpha_1 X_1 + \beta_1 R_1 + \beta_2 R_2 + \beta_3 R_3 + \mu$$

where X is the value of the continuous variable (either COVID cases or deaths), the α's and β's are the coefficients that will be estimated through the regression, and μ is a normally distributed, uncorrelated noise term. However, if one of the R_i's or X was a linear transformation of one or more of the other R_i's or X, that R_i or X would not add any additional information about Y and thus there would be an infinite number of ways of assigning values to the β's or α's. The dummy variables thus pose a difficulty in that the value of all of the R_i's is known from knowledge of all but one of them. For example, if $R_1 = 0$ and $R_2 = 1$, we know $R_3 = 0$ since a university can't have both a hybrid and in-person learning policy for the same semester. We can solve this issue by setting one of the β_i's to 0, effectively dropping one of the R_i's from the equation. Arbitrarily selecting R_3 without loss of generality, we get a regression model of the form:

$$Y = \alpha_0 + \alpha_1 X_1 + \beta_1 R_1 + \beta_2 R_2 + \mu$$

3.6. Topic Model-Based Analysis

In order to gain a more nuanced, topic-centered understanding of public opinion toward reopening policies, this study applies a topic model-based analysis to the comment dataset. Specifically, to understand the topics frequently commented on in the preprocessed Facebook corpus, I chose to use a Latent Dirichlet Allocation (LDA) model, a state-of-the-art generative probabilistic model commonly used in NLP research [14].

LDA uses a "bag of words approach," namely assuming each Facebook comment (document) consists of a combination of topics, and each topic consists of a combination of words. It then approximates probability distributions of topics in a given document and of words in a given topic. The model assumes that the topics are generated before documents and the generative process [12] is as follows (for a collection of M documents, where each document d is composed of N_d words):

- For each topic t, select a multinomial distribution ϕ_t whose hyper-parameter β follows the Dirichlet distribution (distribution of words over a topic).
- For each document d, select a multinomial distribution θ_t whose hyper-parameter α follows the Dirichlet distribution (distribution of topics over a document).
- For each word w_n in document d,
  - Choose a topic z_n from θ_d
  - Choose a word w_n from ϕ_{zn}
- Find the set of topics most likely to have generated the collection of documents.

The algorithm uses collapsed Gibbs Sampling to repeat the above generative process until word assignments to a topic reach a steady state (consistent per-document topic distribution ϕ_t and per-word topic distribution θ_t). The corpus probability is expressed as follows:

$$p(D \mid \alpha, \beta) = \prod_{d=1}^{M} \int p(\theta_d \mid \alpha) \times \left(\prod_{n=1}^{N_d} \sum_{z_{dn}} p(z_{dn} \mid \theta_d) p(w_{dn} \mid z_{dn}, \beta) \right) d\theta_d$$

The corpus used for LDA in this paper is the spring 2021 semester comments corpus, as topic distribution is likely to evolve over time and the spring semester is closer to the present day. LDA requires that the number of topics that exist in a corpus of text is pre-specified. Topic modeling literature indicates that maximizing a coherence metric leads to better human interpretability of topics output by LDA [31]. Thus, I ran LDA for different numbers of topics on the spring 2021 corpus and found that for online, hybrid, and in-person policy types, using 5, 12, and 16 topics respectively had the highest coherence (0.49, 0.45, 0.42).

4. Results and Evaluation

4.1. Sentiment Statistics

The percentage of posts that are coronavirus and reopening policy-related are shown in Tables 1 and 2, respectively. These percentages translate into quantities of comments (listed in parentheses in Tables 1 and 2) which are large enough in order to derive relevant conclusions for the Facebook dataset in the case where the more broad COVID dictionary was used for post filtering. In the case of the much narrower reopening policy dictionary, the resulting corpus size is not large enough to produce statistically significant results, so subsequent results will focus on datasets procured by filtering with the broader COVID dictionary (which notably includes all of the terms in the reopening policy dictionary, so reopening policy-specific posts are still reflected in the dataset). Notably, across all policy types, over a quarter of all university Facebook posts were in some manner related to the coronavirus pandemic. Such a statically large percentage validates the significance of this study by indicating that the pandemic is of high relevance to the U.S. university community. In addition, across all policy types, the percentage of pandemic-related posts decreased from the fall to the spring semester. This may reflect the general down-tick in U.S. coronavirus cases from the fall to the spring semester (16,756,968 cases compared to 12,617,442 cases, respectively).

	Fall - Coronavirus	**Spring - Coronavirus**	**Fall - Reopening**	**Spring - Reopening**
Online	27.88% (6,680)	23.41% (14,260)	2.16% (695)	1.22% (627)
Hybrid	28.85% (11,998)	17.85% (6,948)	1.89% (780)	0.95% (267)
In-Person	28.82% (12,106)	17.34% (6,337)	1.17% (1,062)	1.074% (385)

Table 1: Identification of coronavirus (left) and reopening policy-related (right) posts.

The differences between the mean sentiment for comments on non-coronavirus-related posts and coronavirus-related posts are illustrated in Figure 2 below.

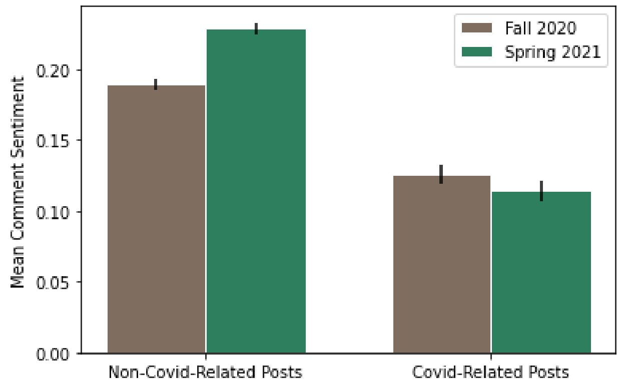

Figure 2: Mean sentiment of comments on COVID and non-COVID related University Facebook posts. Error bars represent the confidence intervals for the means.

One can observe that, for both the fall and spring semesters, comments on COVID-related posts on average have a less positive sentiment than comments on COVID-related posts. To evaluate the statistical significance of this finding, the Mann-Whitney U test was run on the VADER sentiment scores for the non-coronavirus-related post comments (sample one) and the coronavirus-related post comments (sample two). For the fall semester, $p = 9.91 * 10^{-196} < 0.05$, and for the spring semester the p-value was so small that that it was represented as $0.0 < 0.05$. Thus, the null hypothesis can be rejected and the sentiment findings are statistically significant. This validates the significance of this study and future related work in that the general public seems to be reacting differently to COVID-related posts vs non-COVID-related posts, so the details of this reaction may be worth pursuing (to mitigate the less positive reaction to COVID posts, for example). When evaluating the standard deviation of comments on non-coronavirus-related posts and coronavirus-related posts, this study found statistically similar values across both semesters and both post categories (0.38 ± 0.01), indicating similar levels of polarity across all university posts. When examining all the aggregated comment sentiment scores for both post categories, one can indeed observe a large cluster of sentiment scores around 0.0 (neutral sentiment; with a "tail" extending in the negative direction) and another medium-sized, approximately Gaussian cluster of scores clustered toward the positive end of the sentiment spectrum (about 0.6). This multi-modal distribution of sentiment was in fact present in all subdivisions of the dataset, the plots for which can be found in the appendix of this paper.

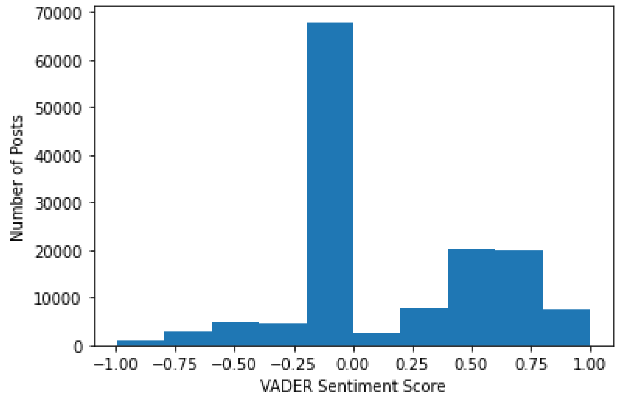

Figure 3: Sentiment for non-COVID posts.

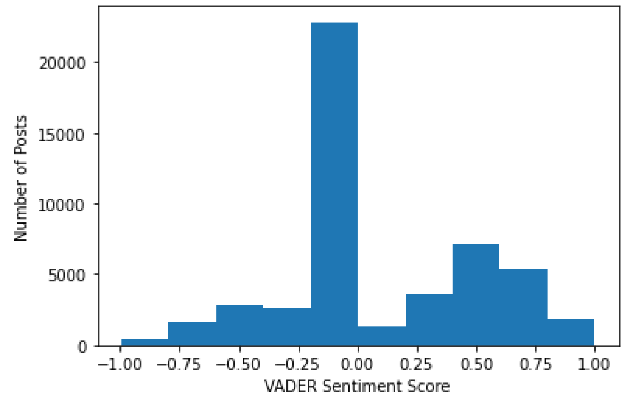

Figure 4: Sentiment for COVID posts.

The differences between the mean sentiment for comments on coronavirus-related posts for schools with online, hybrid, and in-person policies during both the fall and spring semesters of the 2020-2021 academic year are illustrated in Figure 5 below. Mann-Whitney U tests were run on all pairs of policy types for both semesters, the results of which are summarized in Table 2 below.

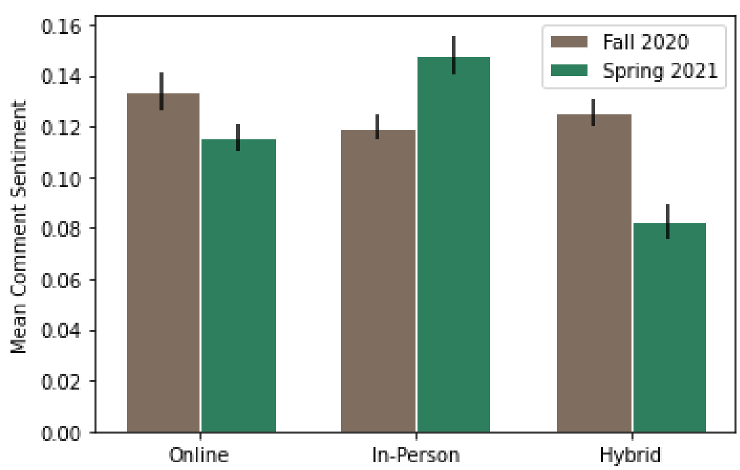

Figure 5: Mean sentiment of comments on COVID-related posts for universities with differing re-opening policy types. Error bars represent the confidence intervals for the means.

As all of the p-values are less than 0.05, we find that the sentiment score distributions of the data sets for schools with different reopening policies are not identical. Thus, different reopening policies may have differing public opinions toward them. However, the mean sentiment data is only

	Fall 2020	Spring 2021
Online + Hybrid	0.0293704	4.517611e-15
Online + In-Person	0.0005396	1.052928e-08
In-Person + Hybrid	0.0494783	1.766420e-32

Table 2: p-values for Mann-Whitney U tests for different-policied universities.

moderately revealing, with Figure 5 illustrating a slightly more positive sentiment toward online universities in the fall and in-person universities in the spring. In addition, sentiment on online and hybrid university post comments decreased from the fall to the spring semester, while sentiment on in-person post comments increased. These trends may reflect the downturn in COVID cases in the spring semester compared to the fall semester (i.e.: it's arguably safer to attend courses in-person when there are fewer COVID cases) or growing fatigue regarding online and hybrid learning during the spring semester. Further studies (potentially with a larger corpus) should be conducted to validate these findings, however, as the means for all policy types were relatively close to one another (some overlap in confidence intervals). We find similar findings with sentiment standard deviation as we found when examining non-COVID versus COVID-posts above (0.38 ± 0.01), with the exception of online-policied universities during the spring semester, which had a standard deviation of 0.41. This greater divisiveness of sentiment may reflect the larger trend toward increased polarization in the United States [23].

4.2. Regression Results

The results of running the linear regressions detailed in section 3.5 are listed in Table 3 below. The estimated coefficient of a covariate represents its average effect on the linear predictor, while the p-value for each covariate is the value of the t-statistic for testing if the corresponding coefficient is different from 0. The relative importance measures how much a covariate's inclusion in a regression model adds to the estimated model's R^2 value. These statistics were gathered using Python's statsmodels and pingouin libraries [32, 36]. The "Online" and "In Person" independent variables are the "dummy variables" described in section 4.5 ("Hybrid" is omitted due to the redundancy of dummy variables). When examining the results in Table 3, one can see a notable lack of any covariate having a statistically significant effect on the dependent variable for any of the regression (all p-values > 0.5). The lack of any significant results for regressions likely stems from the fact that all universities in the same region were represented by the same COVID case and death data, despite having different sentiment statistics. As a result, cases and deaths are not truly continuous covariates, making it difficult for regressions to determine their impact on the dependent variable. Notably, however, the relative importance of cases and deaths is significantly larger than that of the policy-related variables in the predicting mean sentiment, so potentially variations in reopening policies do not have a significant impact on sentiment and such variations can be better explained by variations in COVID cases and deaths. The relative importance of policies in predicting standard deviation of sentiment was much higher, however, so perhaps reopening policies may influence the divisiveness of public opinion. These findings should be taken with a grain of salt, however, as the R^2 values for the performed regression were quite low (0.034, 0.046, 0.071, 0.096, for each row of Table 3, respectively), so the linear model was generally unable to explain sentiment statistics.

Cont. Var., Stat	**Indep Vars.**	**Est. Coeff.**	p**-value**	**% Rel. Imp.**
Cases, Mean	Cases	-0.008845	0.112	91.298
	Online	0.004774	0.814	7.304
	In-Person	0.004785	0.819	1.398
Deaths, Mean	Deaths	-0.940754	0.058	90.550
	Online	0.000320	0.988	5.099
	In-Person	0.0115010	0.589	4.351
Cases, Std. Dev.	Cases	0.000218	0.901	2.0371
	Online	0.007217	0.263	45.051
	In-Person	-0.008826	0.184	52.912
Deaths, Std. Dev.	Deaths	-0.2415	0.120	46.110
	Online	0.0041	0.531	24.025
	In-Person	-0.0065	0.334	29.864

Table 3: Estimated coefficients, their p-values, and relative importance values of each covariate in four selected regressions.

4.3. Topic-Modeling Results

The three most salient topics for comments on posts of schools of each policy type during the spring 2021 semester are listed in Figure 6 below. The most salient topics for online universities seemed to be vaccination policies and the university community at large (parents, staff, etc.). Vaccination policies seemed to be one of the most salient topics for in-person and hybrid universities as well, which is reasonable given that the spring 2020 semester was when COVID-19 vaccinations became available to the general public. Perhaps universities should ensure their study body and larger community has adequate access to future vaccinations and boosters (potentially holding vaccination clinics on campus, etc.) prior to mandating an in-person learning policy. For in-person universities, aspects of campus life such as food and housing also seemed particularly salient. For hybrid universities, graduation was the most salient topic, perhaps because the community was unsure if the ceremony would be held remotely or on-campus given the duality of hybrid models. The topic coherence values for the LDA analyses listed in section 3.6 (0.49, 0.45, 0.42) are typical for topic modeling studies done on social media. In general, it is difficult to predict a baseline coherence metric for a previously unstudied corpus [34]. However, the Python Gensim library used to perform LDA in this study is frequently used in academic topic modeling, and thus the topics predicted are likely relatively accurate for the spring semester corpus [30].

	Topic 1	Topic 2	Topic 3
0	vaccine	school	thank
1	covid	congratulation	work
2	mask	parent	help
3	virus	proud	student
4	choice	life	field
5	vaccination	thing	share
6	test	love	neighborhood
7	shot	student	staff
8	vaccinate	university	year
9	boiler	family	class

	Topic 1	Topic 2	Topic 3
0	vaccine	student	student
1	covid	vaccine	power
2	choice	love	food
3	virus	staff	university
4	pfizer	mandate	dorm
5	study	risk	hall
6	body	college	campus
7	immunity	require	kid
8	case	term	plan
9	report	effect	money

	Topic 1	Topic 2	Topic 3
0	graduation	vaccine	student
1	parent	vaccinate	campus
2	student	age	child
3	ceremony	shot	staff
4	family	immunity	trial
5	stadium	patient	choice
6	graduate	vaer	summer
7	commencement	rate	life
8	faculty	university	college
9	attend	covid	teach

Figure 6: Three most salient topics for comments on online (left), in-person (center), and hybrid (university) Facebook pages made during the spring 2021 semester.

5. Conclusion, Limitations, Future Work

The COVID-keyword-based filtering approach used to isolate pandemic-related posts in this study indicates a high prevalence of pandemic and reopening-policy-related posts on university Facebook pages, which is consistent with background literature in that it is indicative of the large impact of the coronavirus pandemic on the U.S. higher education system. The calculated mean sentiment statistics indicate the presence of a statistically significant difference in sentiment between coronavirus-related and non-coronavirus-related university Facebook posts, as well as between schools with different reopening policy types. Potentially, in-person policies are viewed most favorably during times where COVID cases are on the decline, while online policies are viewed most favorably during times where COVID cases are on the rise. In addition, high standard deviations of sentiment across all semesters and policy types indicate high divisiveness of sentiment toward university reopening policies. Coronavirus cases and deaths may hold more predictive power with respect to the aggregate public opinion toward university reopening policies than does the policy itself. However, reopening policies may be a more effective predictor of the divisiveness of sentiment. In addition, vaccination seems to be a key topic of interest regardless of university policy. Future work can be done to match each post comment to a topic (as output by the LDA topic model), enabling the sentiment associated with each topic for a given policy type to be studied. For example, though vaccinations were relevant across universities, perhaps they were viewed with a more negative sentiment at in-person universities than remote or hybrid universities.

The main limitation of this study was the limited quantity of its corpus. Scraping data from Facebook is extremely inefficient (likely why most social-media-based NLP studies use a Twitter corpus), with only small quantities of data (fewer than 100 posts) able to be scraped at a time before scraping requests are denied by Facebook. In addition, the process of scraping each set of about 100 posts takes approximately one hour. As such, the corpus for this study was limited to 45 universities, which is much smaller than the total number of universities in the U.S. (approximately 1,500). So, its findings may not be particularly generalizable (the optimum sample size for the U.S. university population would be close to 230 [25]). Future work, then, should either attempt to increase the size of the Facebook corpus by conducting further scraping, or select a comparable corpus (i.e.: university Twitter posts) from which the data collection process is more straightforward. In addition, it may be worthwhile to look at student-specific sentiment (as students are most affected by university reopening policies), so future work could use university forums (i.e.: Reddit, surveys, etc.) as its corpus. With a larger dataset, the COVID-dictionary could also be narrowed to only include reopening-policy-specific terms rather than COVID-related terms in general (as when this study tried to do so, only a few thousand comments were extracted). The use of such a more narrow dictionary would enable conclusions to be more accurate in quantifying public opinion toward reopening policies in particular rather than all university-COVID-related announcements.

Another limitation of this study was the lack of truly continuous case and death data in the linear regression, which is largely due to the above-mentioned corpus quantity limitation. With a larger corpus, the dependent variable for the regression could be the sentiment of a particular comment (rather than the mean comment sentiment), and the independent variables could be the COVID cases or deaths in the state in which a University is located during the week the comment was posted (as well as the university policy, as previously mentioned). Such a dataset would match comment sentiment much more closely to contemporaneous COVID data and would offer significantly more data points as regression input. Other kinds of regression models may also be more appropriate for the structure of the dataset and should be explored in future work. A time-series-based regression could be run to account for the lagged impact of cases and death on public opinion, and a logistic regression model may be particularly informative due to the presence of categorical policy values.

This study was also limited by the presence of spam comments. Preprocessing was able to remove some spam comments, such as those with URLs and those not written in English, however, it cannot remove comments on the basis of irrelevancy to posts. As such, future work should consider creating a Machine-Learning-based spam-comment-filter, such as the one described in Java and Akshay's "Modeling Influence, Opinions and Structure in Social Media Research" [22]. Such a filter may help reduce noise in the corpus and increase the accuracy of sentiment measurements as reflections of public opinion toward reopening policies.

As the coronavirus pandemic has significantly impacted the operations of U.S. universities, with detrimental effects on student mental health and academic performance, it is my hope that future work in this research domain is pursued, so as to enable universities to make the optimum policy decisions in order to best mitigate the pandemic's catastrophic consequences on their communities.

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7. Appendix

7.1. University Reopening Policy Definitions

- Fully In-Person – Classes will exclusively be conducted in person
- Primarily In-Person – Classes will be mainly conducted in person with certain exceptions for online delivery
- Fully Online – Classes will only be conducted online
- Primarily Online – Classes will be taught primarily online with the exception of some courses
- Hybrid – Professors are allowed to decide how to teach their course on a rolling basis (e.g.: some weeks/days online, some weeks/days in person)

7.2. Example Reopening Policy Social Media Post

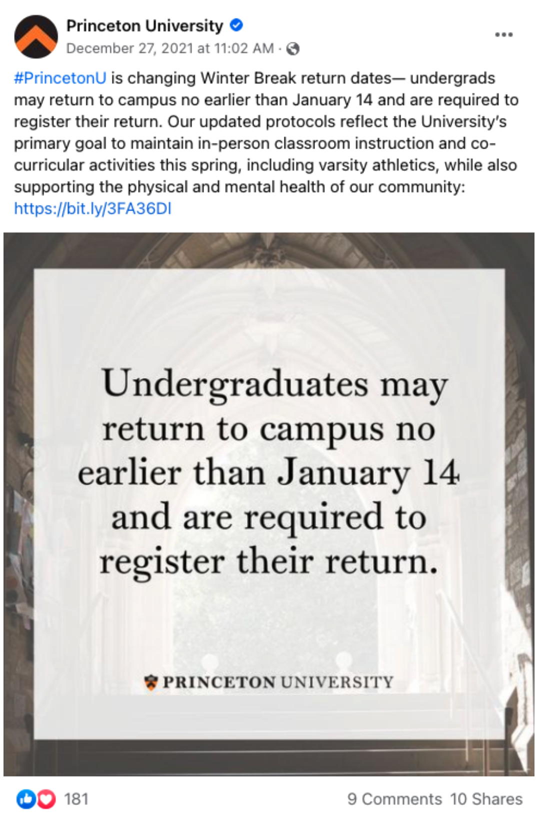

Figure 7: Princeton University Facebook post.

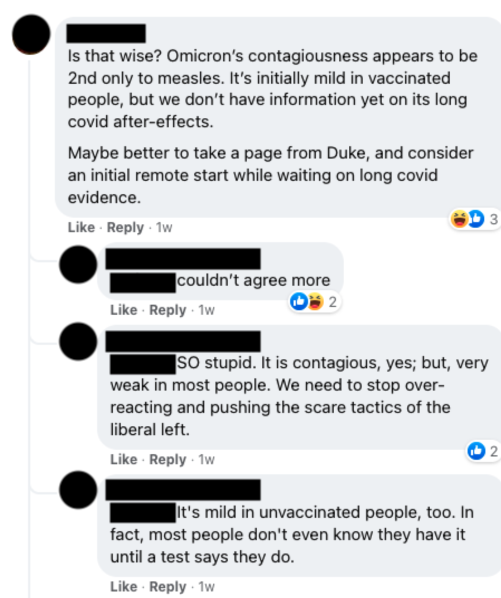

Figure 8: Polarized comments on the post.

7.3. Divisional University Lists

University	Policy Fall 2020	Policy Spring 2021	Profile Name
Harvard University	Primarily or Fully Online	Primarily or Fully Online	Harvard
Boston College	Primarily or Fully In Person	Hybrid	BostonCollege
Darmouth University	Primarily or Fully Online	Primarily or Fully Online	Dartmouth
University of Connecticut	Primarily or Fully Online	Hybrid	UConn
Massachussetts Institute of Technology	Primarily or Fully Online	Primarily or Fully Online	MITnews

Table 4: New England

University	Policy Fall 2020	Policy Spring 2021	Profile Name
Penn State University	Hybrid	Hybrid	pennstate
New York University	Hybrid	Primarily or Fully Online	NYU
University of Pennsylvania	Primarily or Fully Online	Primarily or Fully Online	UnivPennsylvania
Princeton University	Primarily or Fully Online	Primarily or Fully Online	PrincetonU
Rochester Institute of Technology	Primarily or Fully In Person	Primarily or Fully Online	RITfb

Table 5: Mid-Atlantic

University	Policy Fall 2020	Policy Spring 2021	Profile Name
University of Michigan, Ann Arbor	Hybrid	Hybrid	UniversityOfMichigan
University of Notre Dame	Primarily or Fully In Person	Primarily or Fully In Person	notredame
Michigan State University	Primarily or Fully Online	Primarily or Fully Online	spartans.msu
University of Illinois at Urbana-Champaign	Hybrid	Hybrid	illinois.edu
Purdue University at West Lafayette	Primarily or Fully In Person	Primarily or Fully Online	PurdueUniversity

Table 6: East North Central

University	Policy Fall 2020	Policy Spring 2021	Profile Name
Kansas State University	Primarily or Fully In Person	Primarily or Fully Online	KState
University of Iowa	Primarily or Fully In Person	Primarily or Fully In Person	universityofiowa
University of Kansas	Primarily or Fully In Person	Primarily or Fully In Person	KU
Iowa State University	Primarily or Fully In Person	Hybrid	IowaStateU
University of Minnesota-Twin Cities	Primarily or Fully Online	Hybrid	UofMN

Table 7: West North Central

University	Policy Fall 2020	Policy Spring 2021	Profile Name
Clemson University	Primarily or Fully Online	Primarily or Fully Online	clemsonuniv
University of Georgia	Primarily or Fully In Person	Primarily or Fully In Person	universityofga
Georgia Institute of Technology	Hybrid	Primarily or Fully In Person	georgiatech
Duke University	Hybrid	Hybrid	DukeUniv
Virginia Tech	Primarily or Fully In Person	Primarily or Fully In Person	virginiatech

Table 8: South Atlantic

University	Policy Fall 2020	Policy Spring 2021	Profile Name
The University of Alabama	Primarily or Fully In Person	Primarily or Fully In Person	universityofalabama
Auburn University	Hybrid	Primarily or Fully In Person	auburnu
The University of Tennessee, Knoxville	Hybrid	Hybrid	UTKnoxville
Mississippi State University	Hybrid	Primarily or Fully In Person	msstate
University of Mississippi	Hybrid	Primarily or Fully In Person	olemiss

Table 9: East South Central

University	Policy Fall 2020	Policy Spring 2021	Profile Name
The University of Texas at Austin	Hybrid	Primarily or Fully Online	UTAustinTX
The University of Oklahoma	Primarily or Fully In Person	Primarily or Fully In Person	uofoklahoma
Texas State University	Primarily or Fully In Person	Primarily or Fully In Person	txstateu
Texas A&M University	Primarily or Fully In Person	Hybrid	tamu
Baylor University	Hybrid	Primarily or Fully In Person	BaylorUniversity1845

Table 10: West South Central

University	Policy Fall 2020	Policy Spring 2021	Profile Name
Brigham Young University	Primarily or Fully In Person	Hybrid	BYU
Arizona State University	Hybrid	Hybrid	arizonastateuniversity
The University of Utah	Primarily or Fully Online	Primarily or Fully Online	universityofutah
University of Colorado Boulder	Hybrid	Primarily or Fully Online	cuboulder
The University of Arizona	Primarily or Fully Online	Primarily or Fully Online	uarizona

Table 11: Mountain

University	Policy Fall 2020	Policy Spring 2021	Profile Name
Stanford University	Primarily or Fully Online	Primarily or Fully Online	Stanford
University of California, San Diego	Primarily or Fully Online	Primarily or Fully Online	UCSanDiego
University of Washington	Primarily or Fully Online	Primarily or Fully Online	UofWA
University of California, Davis	Hybrid	Primarily or Fully Online	UCDavis
University of Oregon	Primarily or Fully Online	Primarily or Fully Online	universityoforegon

Table 12: Pacific

7.4. COVID-19 Dictionary

6 feet apart	herd immunity	learning online	rapid test	vaccinate
6’ apart	hybrid classes	learning remotely	remote coursework	vaccinated
asymptomatic	hybrid instruction	lockdown	remote instruction	vaccination
community spread	hybrid learning	mask mandate	remote learning	vaccine
confirmed positive case	hybrid semester	mask required	remote semester	vax
confirmed positive cases	hybrid semester	masks required	remote teaching	vaxination
contact trace	hybrid teaching	nasal swab	return to learn	vaxine
contact traced	in person classes	online classes	return to the classroom	vaxx
contact tracing	in person courses	online courses	safety protocols	vaxxination
coronavirus	in person intruction	online instruction	SARS-CoV-2	vaxxine
COVID	in person learning	online learning	self-isolation	ventilator
COVID-19	in person school	online school	self-monitoring	virtual instruction
COVID19	in person semester	online semester	shelter-in-place	virtual learning
distance learning	in person teaching	online teaching	six feet apart	virtual semester
endemic	in-person classes	outbreak	social distance	work from home
epidemic	in-person courses	pandemic	social distancing	working at home
face covering	in-person intruction	physical distance	social isolation	working from home
face coverings	in-person learning	physical distancing	socially distanced	working remotely
facemask	in-person school	physically distanced	socially distant	zoom classes
facemasks	in-person semester	physically distancing	spit test	zoom coursework
flatten the curve	in-person teaching	PPE	symptomatic	zoom instruction
flattened the curve	learning at home	quarantine	teaching remotely	zoom learning
flattening the curve	learning from home	quarantining	transmission	zoom semester

Table 13: Dictionary of Terms used to Filter-Out Coronavirus-Related Posts

7.5. Reopening Policy Dictionary

distance learning	in person learning	in-person teaching	online semester	virtual learning
hybrid classes	in person school	learning at home	online teaching	virtual semester
hybrid instruction	in person semester	learning from home	remote coursework	work from home
hybrid learning	in person teaching	learning online	remote instruction	working at home
hybrid semester	in-person classes	learning remotely	remote learning	working from home
hybrid semester	in-person courses	online classes	remote semester	working remotely
hybrid teaching	in-person instruction	online courses	remote teaching	zoom classes
in person classes	in-person learning	online instruction	return to learn	zoom coursework
in person courses	in-person school	online learning	teaching remotely	zoom instruction
in person instruction	in-person semester	online school	virtual instruction	zoom learning

Table 14: Narrower Dictionary of Terms used to Filter-Out Reopening Policy-Related Posts

7.6. Sentiment Distributions Based on Policy and Semester

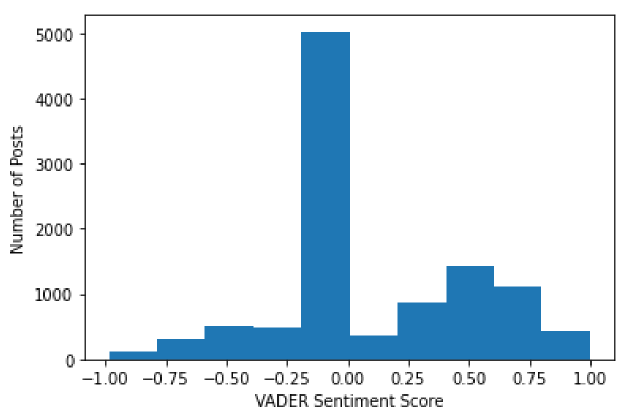

Figure 9: Online Policy, Fall 2020.

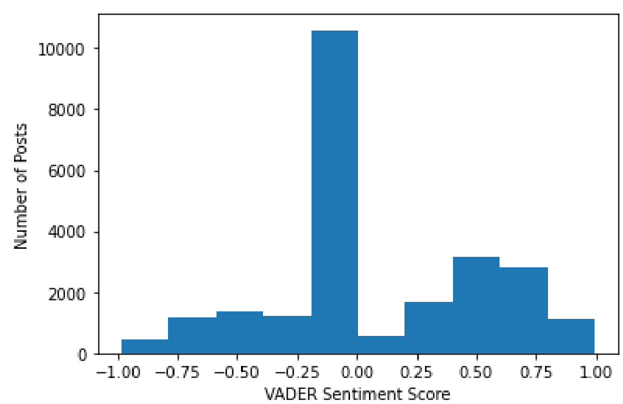

Figure 10: Online Policy, Spring 2021.

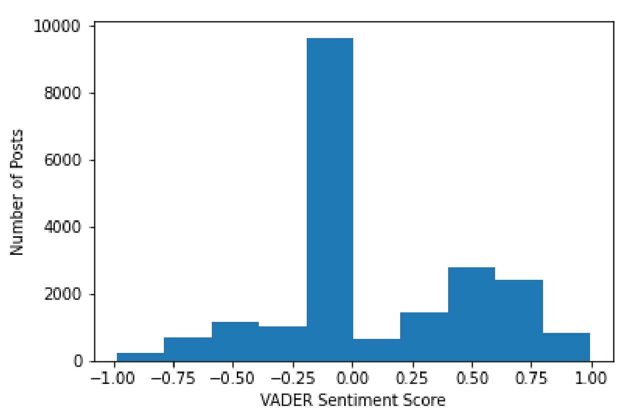

Figure 11: Hybrid Policy, Fall 2020.

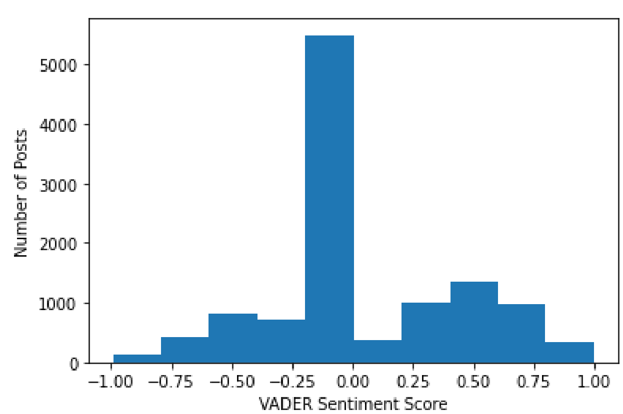

Figure 12: Hybrid Policy, Spring 2021.

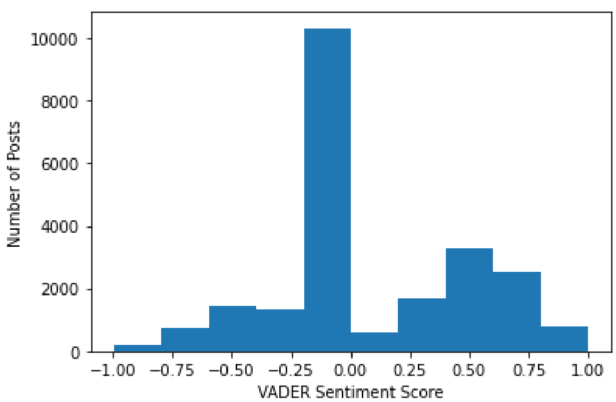

Figure 13: In-Person Policy, Fall 2020.

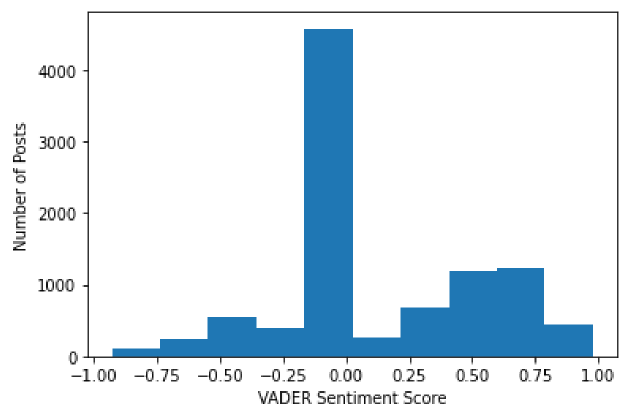

Figure 14: In-Person Policy, Spring 2021.