Sentiment and Mental Health Effects of the COVID-19 Pandemic on UCLA Students

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Final Report

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Abstract

There has been a lot of ripple effect due to the Coronavirus, as schools, businesses and we as individuals have witnessed quite a bit of change over these last few months. Our group has decided to analyze the psychological impact this virus has had on us students. More specifically at an academic institution where some of the brightest students, who are generally motivated, from all over the world come to, in UCLA. With access to UCLA surveys given by various professors to their students' post pandemic, we were given the opportunity to explore the impact this pandemic has had on students' mental health.

The approach we took in order to analyze this was to attempt leveraging sentiment analysis, text mining skills and use some textual visualization techniques to explore the general feelings and thoughts expressed by the UCLA students prior to the pandemic as well as after the pandemic. By comparing students' responses to similar questions taken from pre pandemic and post pandemic surveys, we were able to identify a few important questions to explore. Our study aims to gage students' general feelings about life after this pandemic and to investigate if they are worse than prior to the pandemic, while also see if STEM majors, international students, and those with altered living arrangements express more negativity due to the pandemic. In addition, we also investigated student interaction between their peers and instructors, as we believe this is also affected due to the pandemic even with the given access to the Zoom platform.

We found that COVID-19 changed both the volume and type of negative emotions expressed by respondents, with a reorientation from academics related to mental health focused concerns. We further discovered that different demographic groups were relatively equally affected by the pandemic. However, we could not find a statistically significant connection between our quantitative sentiment analysis and our subjective interpretations of overall sentiment. As a result, this topic warrants further study with an expanded data-set for potential training of a sentiment model.

Final Data and Variables

Since we are exploring the impact this pandemic has had on students' mental health, we need to look at the responses both from the surveys of students before the pandemic and after the pandemic.

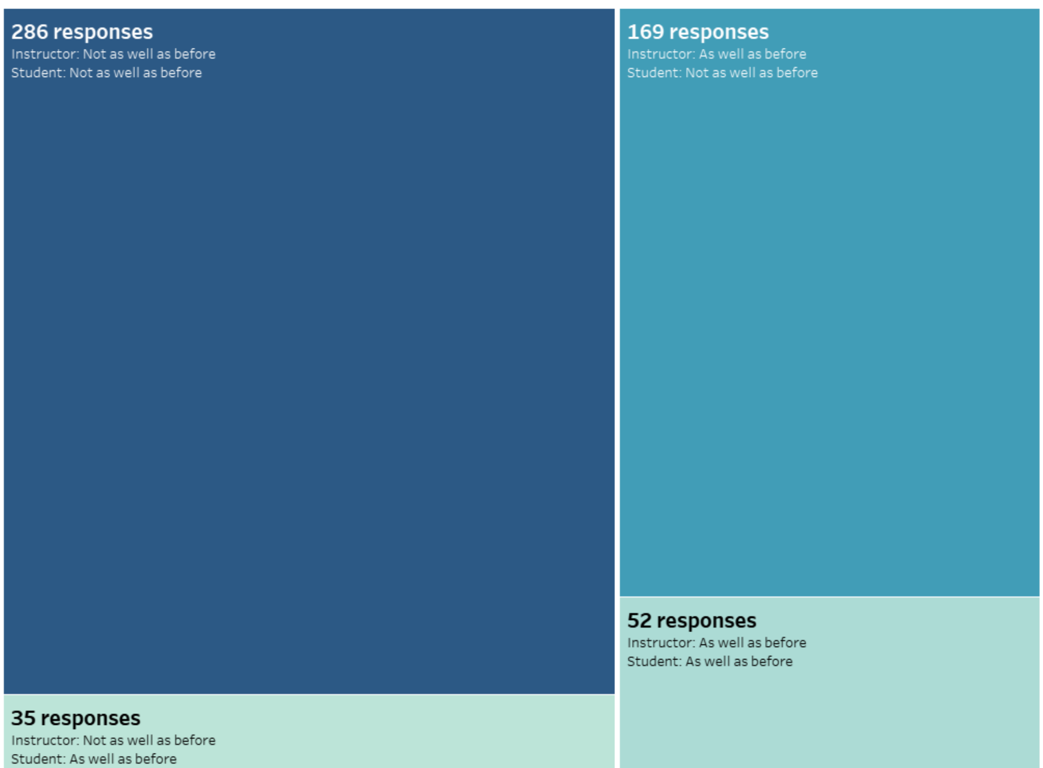
Our main sources of data came from three surveys collected by professors and given to their students, two that were distributed to students prior to the pandemic and one that was distributed post pandemic. The two pre-pandemic datasets contain 277 observations and 866 observations. Some of the pre-pandemic variables included students' academic background, academic state, sexual orientation, ethnic background, international state, sense of belonging, challenges they meet and ways to minimize those challenges. The post-pandemic dataset has 545 observations and 14 variables. Those variables gave information about students' living orientation, motivation, and interaction with professors and peers online. Some of the questions in the post pandemic survey also ask about students' concerns, sense of belonging, academics, social life, what students consider most important and positive effects, if any. The pre pandemic surveys, comparatively, asked more questions to their students, resulting in more variables. However, we tried to only pull text from questions we deemed similar to the ones asked in the post pandemic survey to get more of an accurate comparison. We also went through and read each free response question of the post pandemic survey to assign each student a value of "0" for negative sentiment and "1" for positive sentiment manually. Because we are mostly interested in the change of students' feelings, the variables we most used throughout this project for analysis included text and free response. We attempted to quantify the free response questions by summing up the number of types of words relating to sentiment which were used on the target questions for each student, resulting in a count of each type per line. The different sentiment types included Joy, Anger, Negative, and Positive. The other variables we took into account including living arrangements, motivation, along with other demographic entries, we processed as categorical variables and did some initial exploratory analysis on those.

Because we are interested in the change in mental health, we mainly focus on the variables that can show and affect students' sense of belonging and stress. Thus, the variables demonstrating students' sense of belonging and stress are considered as response variables, while other variables like Stem Major, Student & Instructor Interaction Scores, and Living Arrangements, that might affect the sentiment of students would be regarded as independent variables.

Table: Sample of Post-Pandemic data

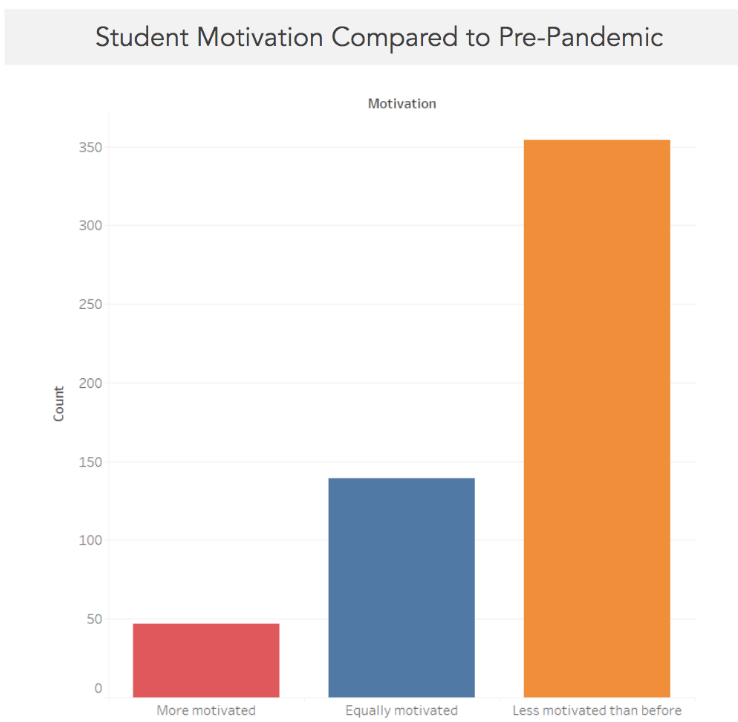
Timestamp	2020/04/19 5:19:21 PM MDT
Your major:	STEM
Are you an international student?	No
Your living arrangement during this pandemic	In my apartment
Does your living arrangement …?	No
How motivated are you…?	Less motivated than before?
How well are you able to interact with your classmates…?	2
How well are you able to interact with your instructors..?	1
Describe your sense of belonging to UCLA...	Very stressed all the time with regard to school work because of the lack of motivation. And having constant stress makes it even harder to stay motivated so it's just positive feedback loop.
What are the concerns do you have…?	How long will it last? Will I pass all my classes and graduate? How are grades going to be given at the end of the quarter?
….	…

Figure 1: Student Interaction with Other Students and their Instructors



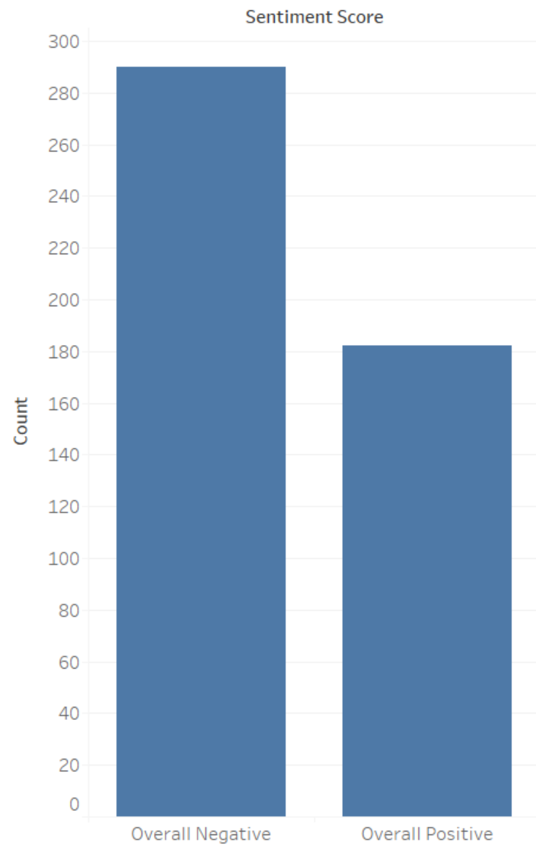
When we look at our post pandemic survey under the questions asking if students are able to interact with their professors and their peers as well as before or not as well as before, we can clearly see that interaction for students has become worse during the pandemic. Over 50% of students reported in the survey that they are not able to interact as well as prior to the pandemic with their instructors and peers, although we have access to the Zoom platform.

Figure 2: Student Motivation Compared to Pre-Pandemic



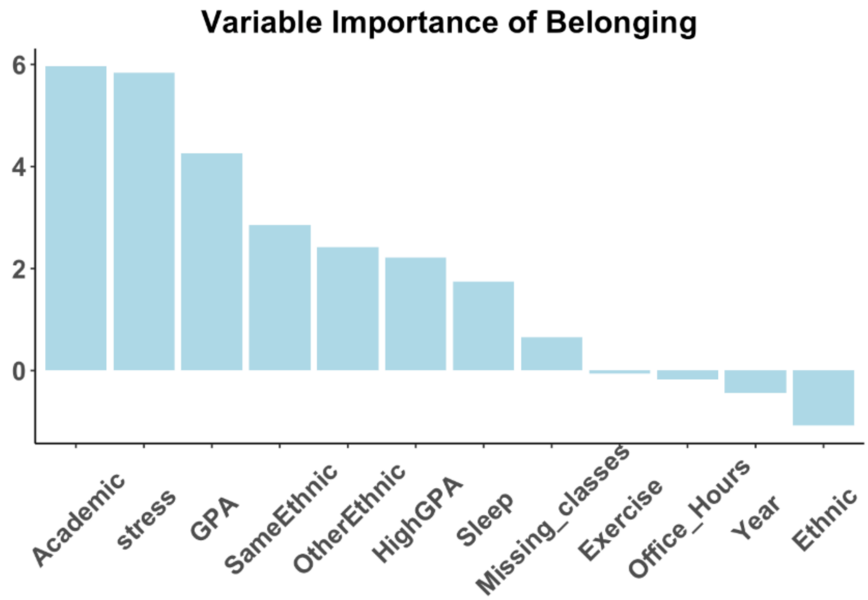
For this question students are asked how motivated they are feeling during this pandemic compared to before the pandemic. We can see that a vast majority of students are feeling less motivated than prior to the pandemic. This is likely rooted from being away from campus, all their peers, and maybe has to do with the students' reduced interaction with others as well.

Figure 3: Manual Sentiment Scores



After going through and reading the post pandemic responses manually, we were able to assign each survey entry a score of 0 for overall negative responses or 1 for overall positive responses. As we can see in this plot, there are many more students who are answering the questions in the post pandemic survey in a negative light. While we do have some students who are trying to stay positive throughout these circumstances, a majority of them responded to these questions negatively. These scores are fairly accurate as well because of the manually coded results by our group.

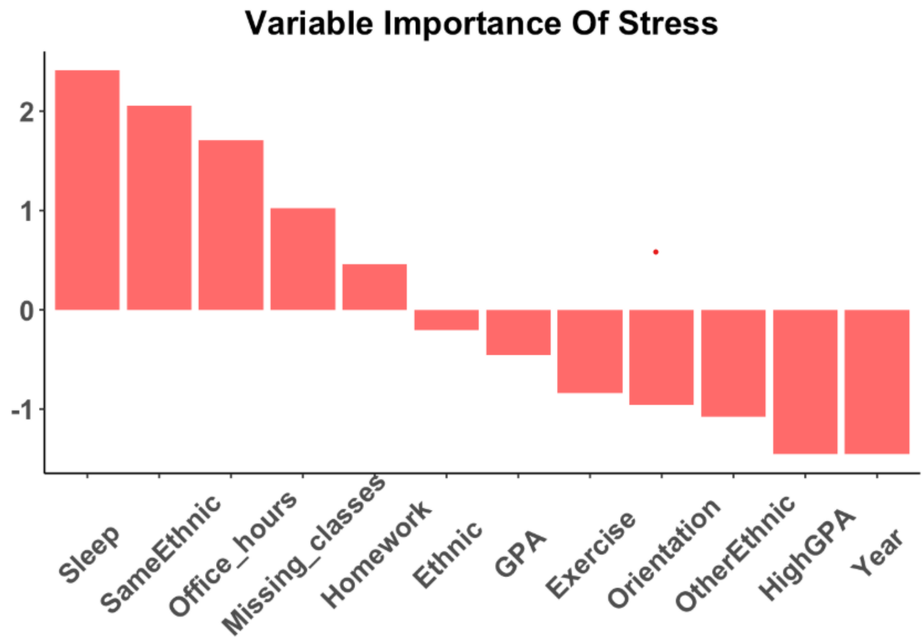
Figure 4: Plot of Variable Importance of Belonging Pre-Pandemic



*These variables were calculated as raw scores of 0-100 based on the free response questions asked in the pre pandemic survey. They were calculated by a prior Stats 141SL group and NOT by our group. We are only performing exploratory analysis on the variables.

In Figure 4, we are looking at variable importance of the belonging category which is defined as "an indicator for sense of belonging." Variable importance is helpful because it shows us which variables do the best at predicting Belonging and it is obtained from using the RandomForest method. Here we see important variables as "Academic", "Stress", "SameEthnic", and "OtherEthnic." The "Academic" variable is defined as an indicator for confidence of academic performance and "SameEthnic" along with "OtherEthnic" are defined as having friends from the same ethnic background and or other ethnic backgrounds. We see the main indicators of Belonging prior to the pandemic are these three variables, where clearly all have to do with academia and social life.

Figure 5: Plot of Variable Importance of Stress Pre-Pandemic



*These variables were calculated as raw scores of 0-100 based on the free response questions asked in the pre pandemic survey. They were calculated by a prior Stats 141SL group and NOT by our group. We are only performing exploratory analysis on the variables.

In Figure 5, we are looking at which variables are the most important predictors of the variable Stress. We see from this plot that getting enough sleep, having friends, and attending office hours are some of the variables that most contributed to stress prior to the pandemic. We see from both Variable Importance Plots that having friends are a key contributor to both Belonging and Stress prior to the pandemic. Later in the report, we will look at some of these variables post pandemic in Word Networks to determine what language is being used in conjunction with stress and social life.

Explanation of Methods

At the document level, we classified whether the students' views express positive or negative emotions. The sentences to identify each sentence indicates positive or negative. The entities/connection level, instead of the language structure, but rather to pay direct attention to the comments themselves. It is based on the idea that the perspective of emotions (positive or negative). The document classification of emotions is through the monitoring of machine learning methods on a survey of mental health of UCLA students. It is believed that the word-by-word dependency tree is the emotional polarity classification characteristics.

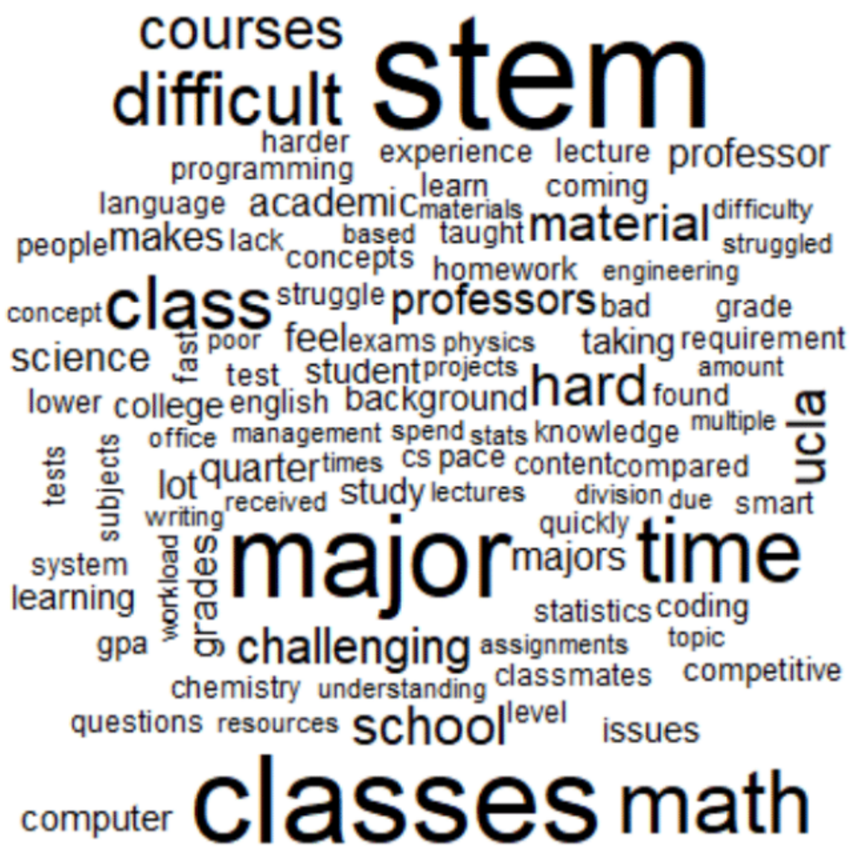
On the contrary, the project is done by determining the polarity of the unknown word with a manual selection of the relationship between the seed of the polarity of the unknown word is classified as either positive or negative. Also, at the sentence level, we provided text mining methods for detecting embedded English sentences in a single event. The approach is based on the theme of the survey and object interactions between common probability distribution.

Additionally, in order to perform quantitative analysis on our data set, we took to count the number words that were categorized under 'joy', 'anger', 'positive', and 'negative' by open source sentiment dictionaries. To find the raw counts we simply filtered for words matching these categories and added them to the data-set using standard data transformation tools.

Sentiment Analysis

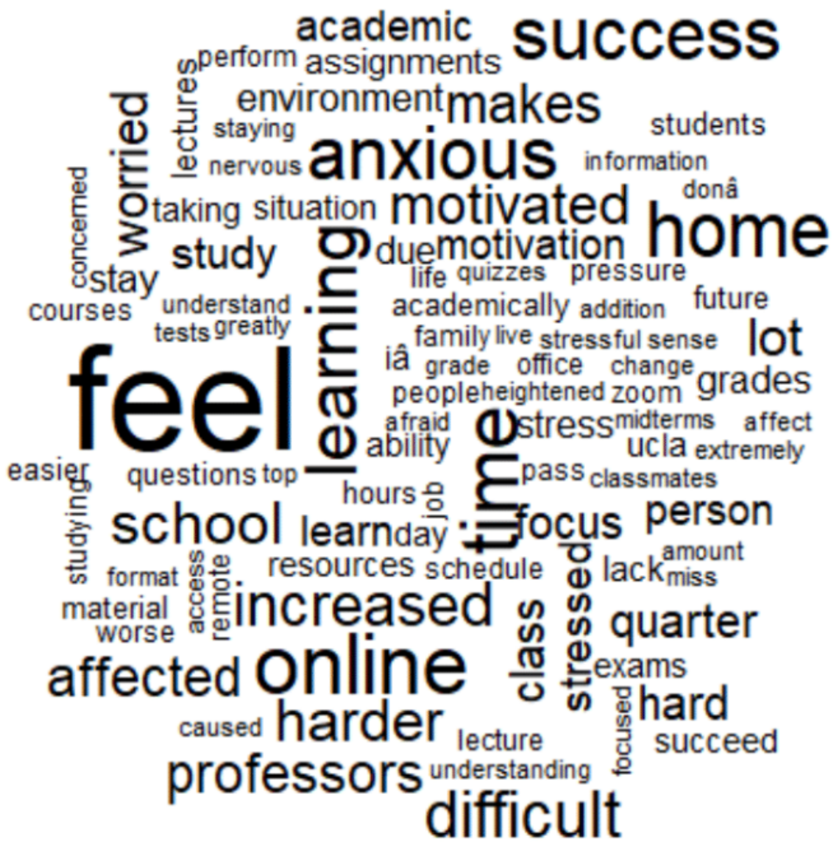
Word Clouds

Figure 6: Pre- Pandemic Stress Related Questions



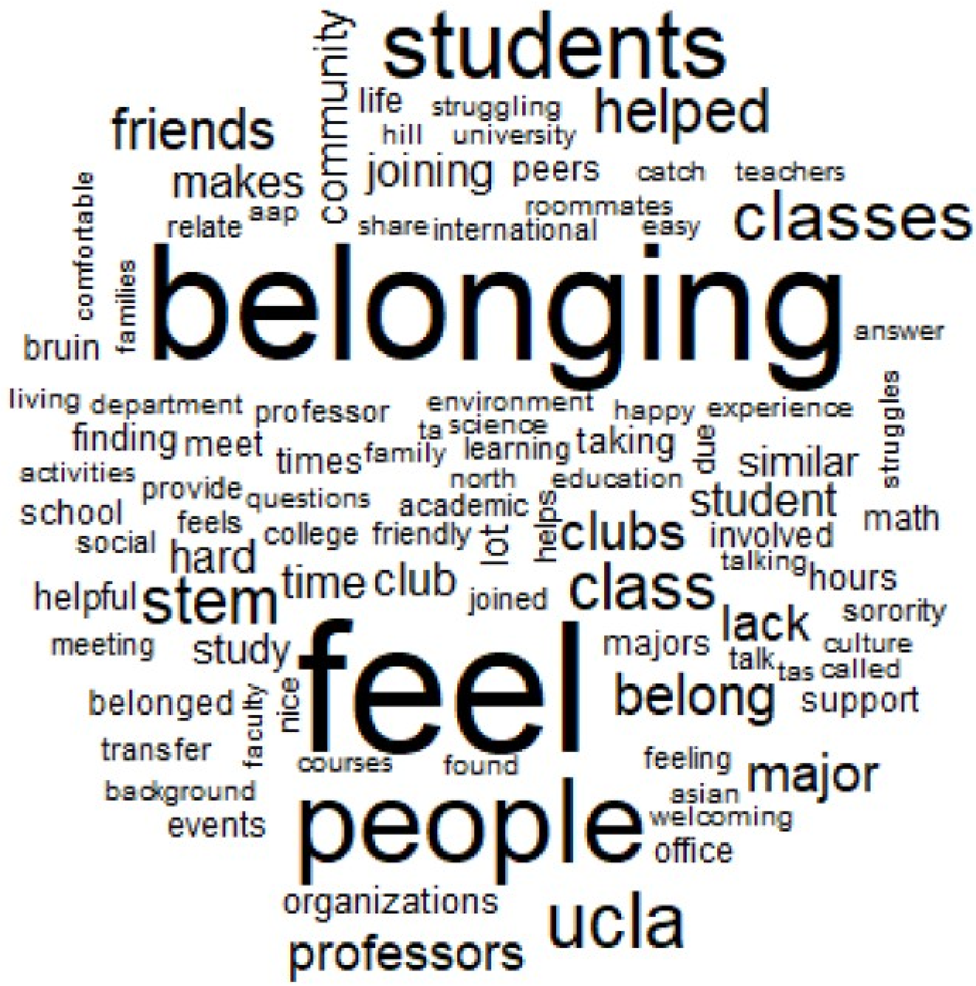
Before the pandemic occurred, much of student stress was around classes, particularly in regards to the difficulty in STEM classes. This is reflected as most of the words used are class related and about the challenge, difficulty, or rigor of an academic environment. Some of these important words which were used most frequently include “difficult”, “challenging” and “hard.”

Figure 7: Post - Pandemic Stress Related Questions



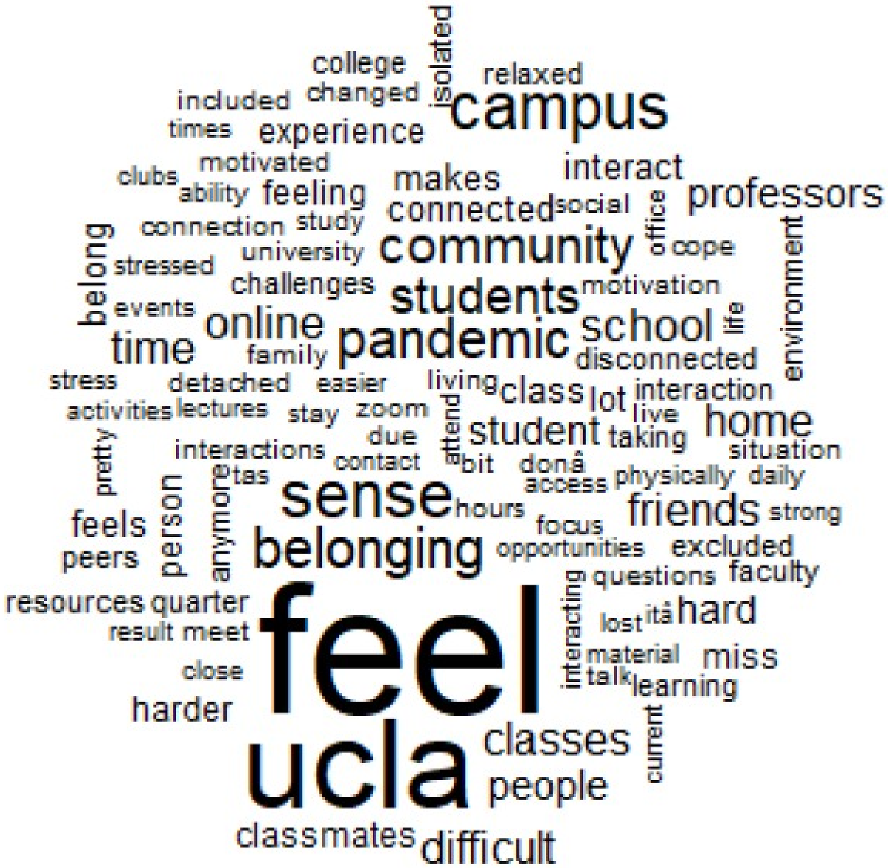
Post-pandemic, students express their stress through the difficulty transitioning to online classes as well as a more general anxiety about the future and success. This is in contrast to pre-pandemic students, where words were more exclusively academic and class related. Post-pandemic we see a shift with a relatively lower frequency of academic words and more words about more general terms such as “motivation”, “anxiety”, and “time”.

Figure 8: Pre-Pandemic for Sense of Belonging Questions



Prior to the pandemic, students place their sense of belonging to their fellow students, classes, major, and organizations. Words typically used involved student organizations and regular social activities that occur through campus life. Some instances of words that were most frequently used to show this were “students”, “people”, “clubs”, “community” and “friends”.

Figure 9: Post-Pandemic for Sense of Belonging Questions



Post-pandemic, students particularly emphasize their lack of connection and the sense of distance caused by the pandemic. Given the situation, we see a clear shift from overall positive to negative perspectives through the pandemic. Clearly negative terms like, “miss”, “challenges”, “harder”, “cope”, “isolation” and “detached” appear, where in pre-pandemic data they were not present at all.

Sentiment Word Counts

Figure 10: Pre-Pandemic Word Counts for “Negative” Sentiment

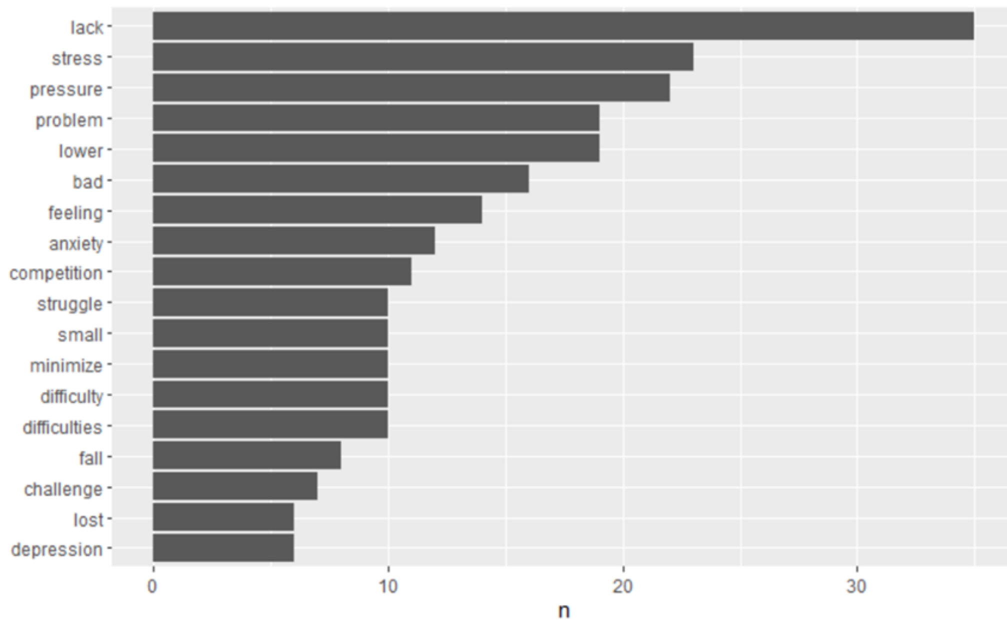
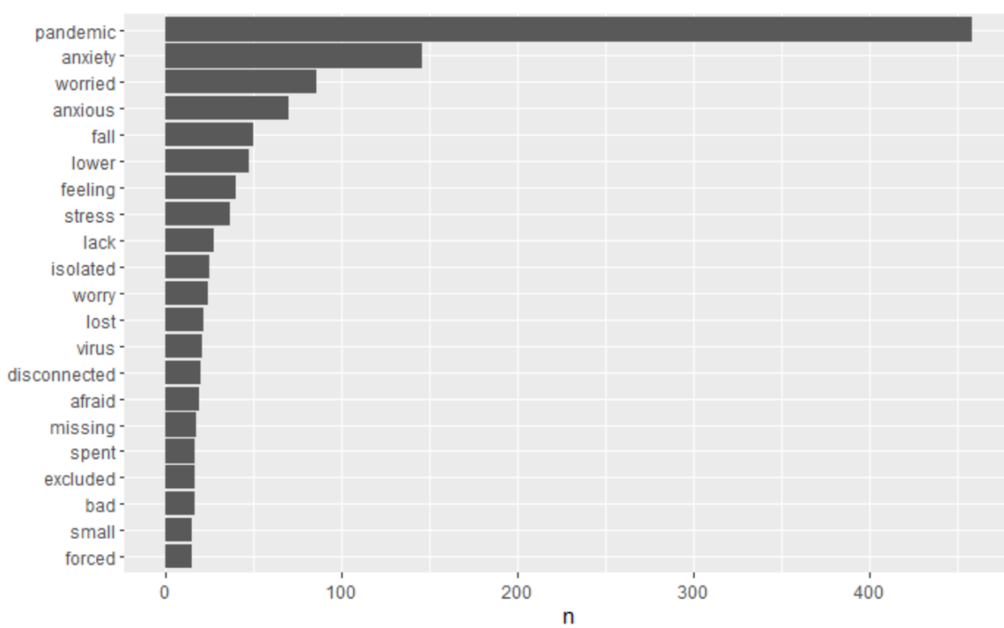


Figure 11: Post-Pandemic Word Counts for “Negative Sentiment”



From the negative words that appear, we see there is a shift in the volume and type of negative words being used pre and post pandemic. Pre-pandemic we see terms relating to stress, pressure, and competition, illustrating that most negative thoughts surround academic topics and performance in the classroom. In comparison, post-pandemic, we see words relating to the “pandemic” and general “anxiety” or “worry” overtake academic related words like “stress”. Students have started to rearrange their worries, as factors outside of academic performance and focus more on the unknown of the pandemic have started to overtake their thoughts. This illustrates a shift in the drivers of negative feelings through the pandemic.

Figure 12: Pre-Pandemic Word Counts for “Joy” Sentiment

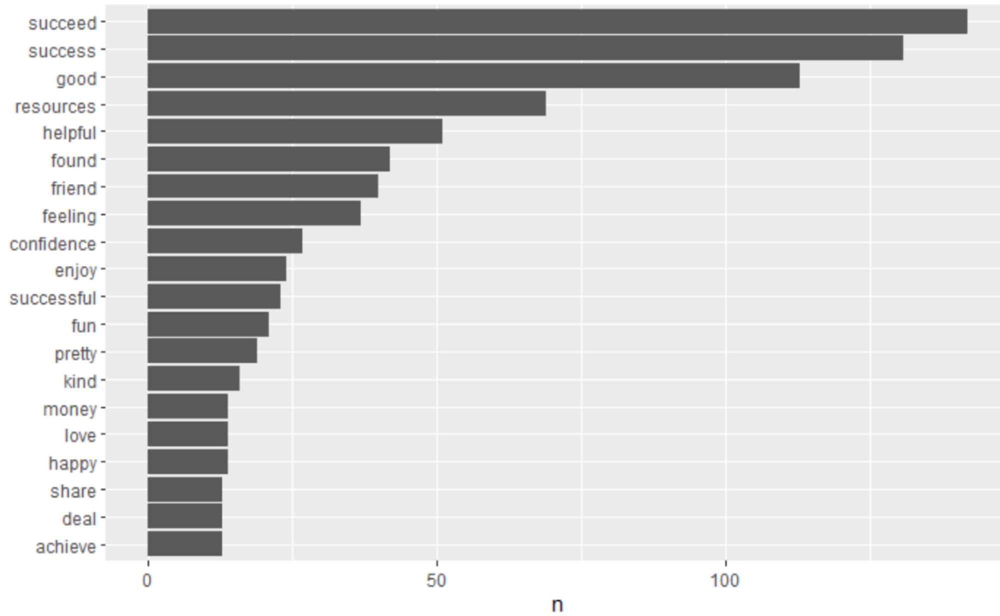
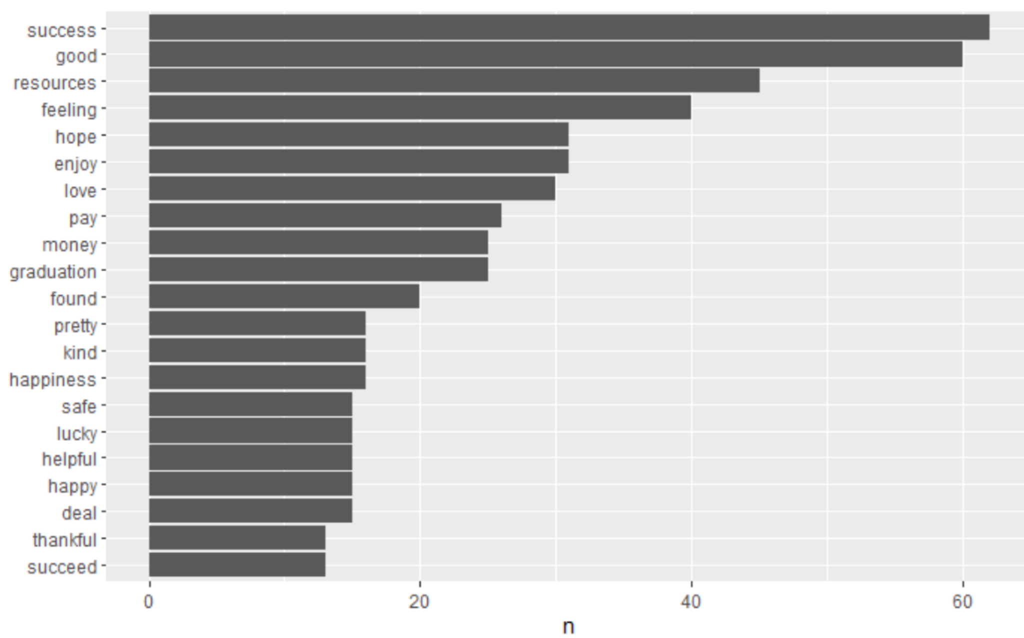


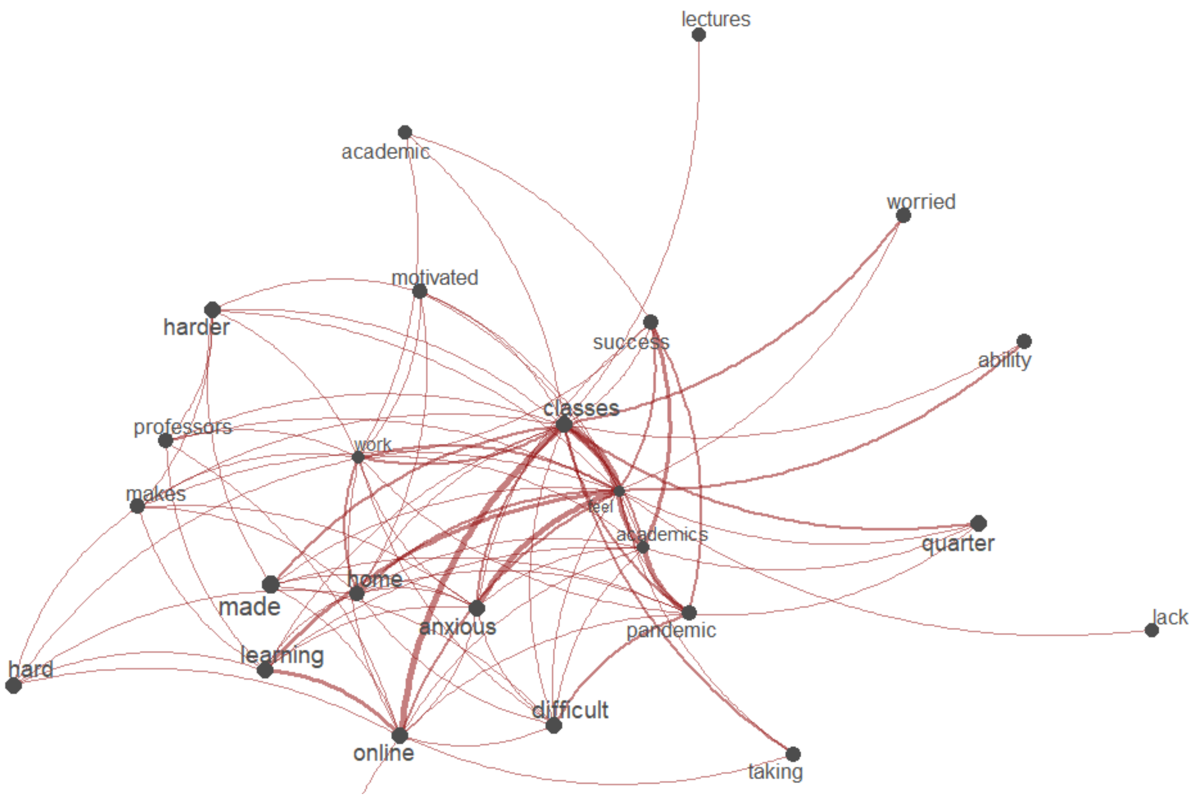
Figure 13: Post-Pandemic Word Counts for “Joy” Sentiment



To avoid improperly counting “joy” words in a negative context, we limited our responses in the post-pandemic data to the last question which asked about positive aspects of the quarantine. We see that in both cases, success and resources are the top words used. Beyond these words, however, we see a divide between pragmatic and material words pre-pandemic, to more emotional wording used post-pandemic. Words like “hope” and “love” appear much higher on the post-pandemic data relative to their positions pre-pandemic.

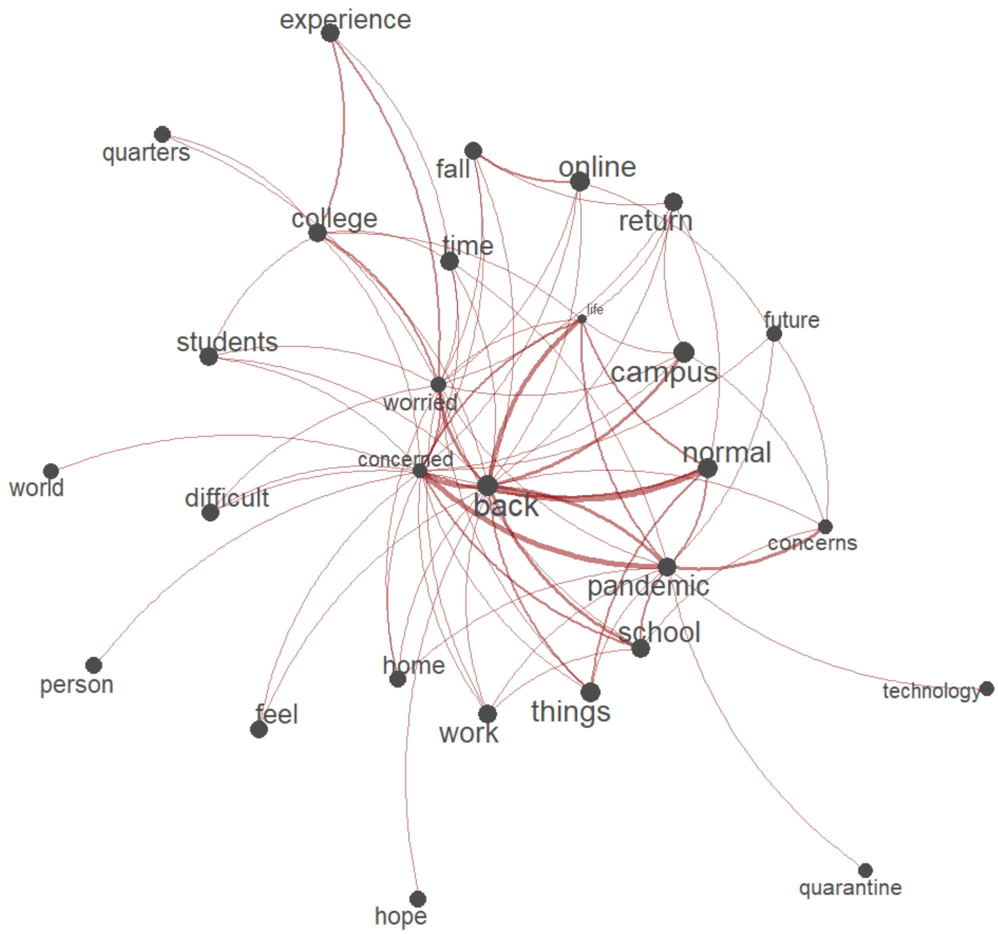
Text-Networks

Figure 14: Word Network for Post-Pandemic Academic Stress (Question 3)



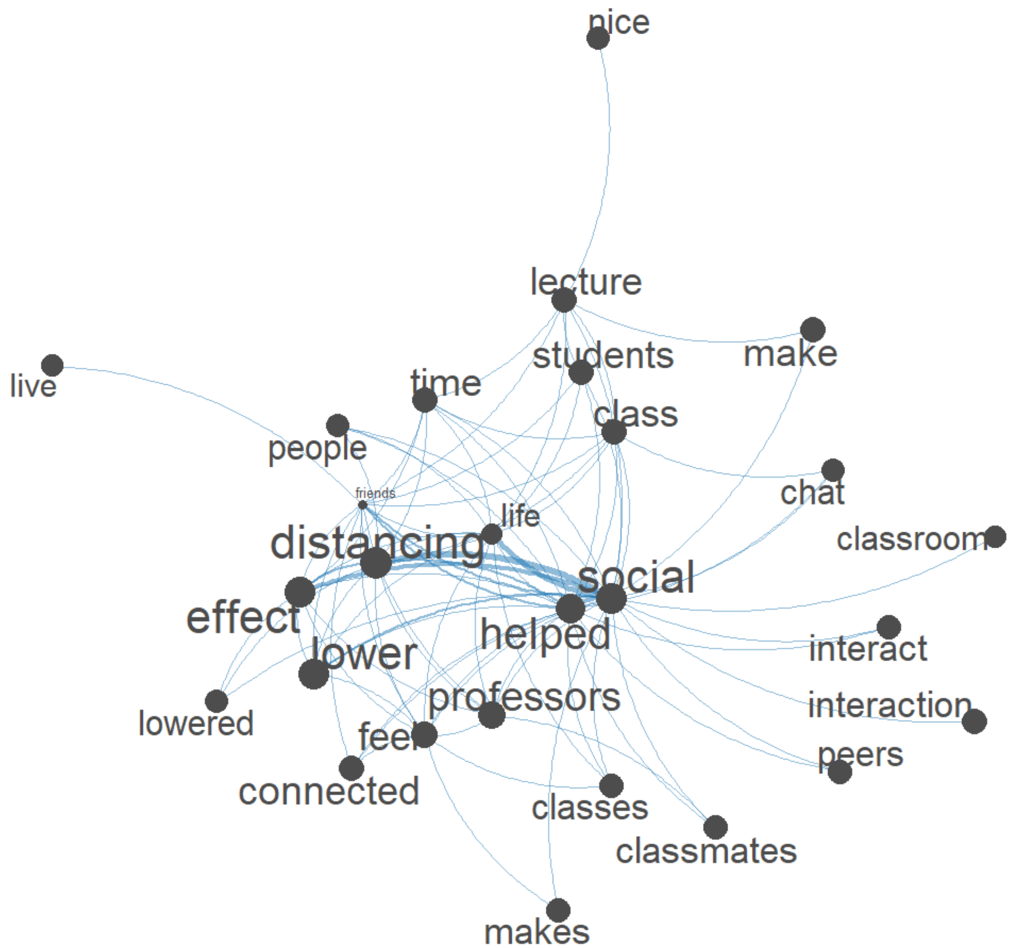
With academic stress, we see students strongly use and relate the difficulty of online classes and learning due to the pandemic. Most of the other prominent words are closely tied to this idea of classes and the changes in experience making them harder, more difficult to be motivated, worried, etc.

Figure 15: Word Network for Post-Pandemic Career Stress (Question 2)



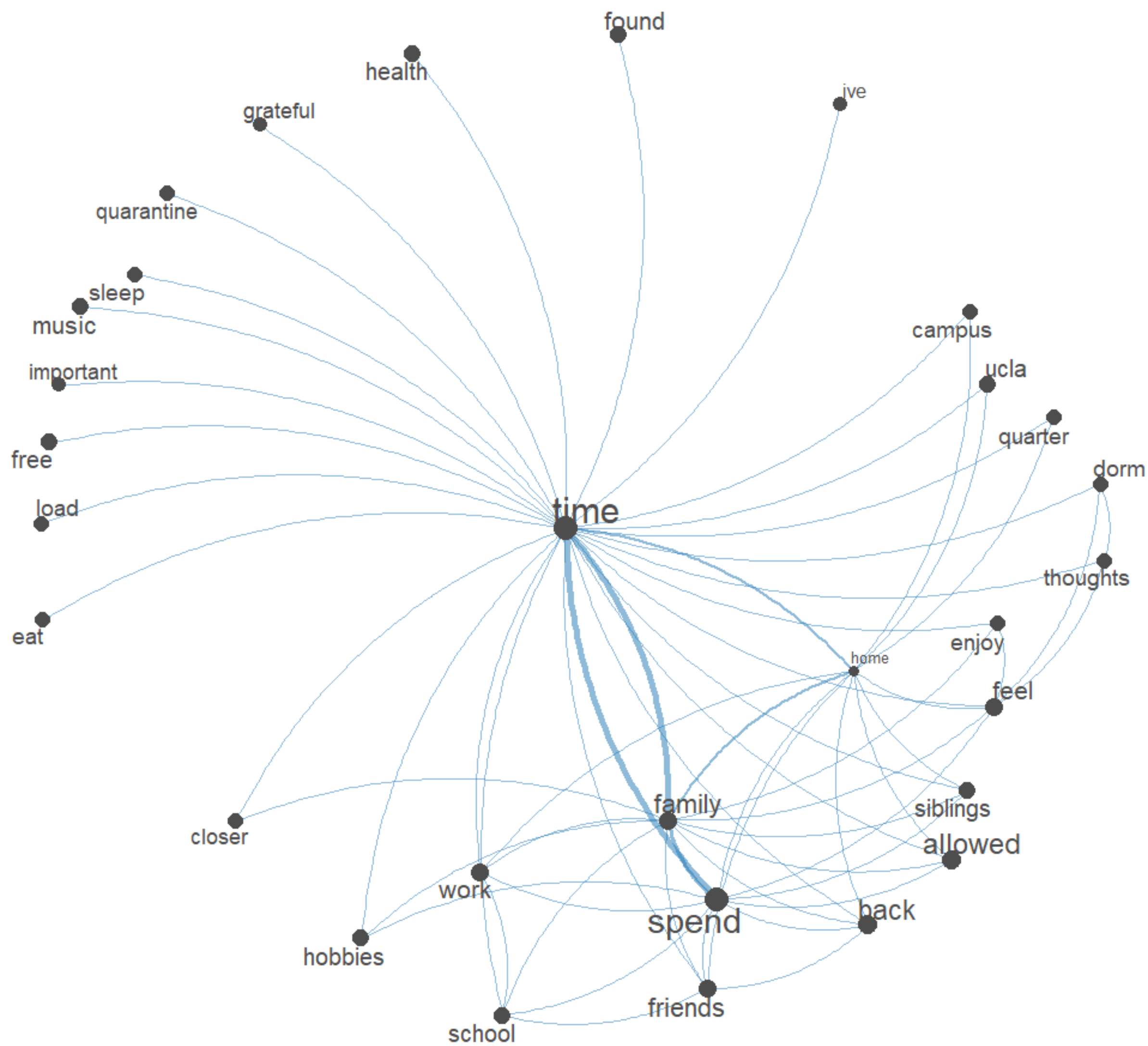
Students relate most of their post-pandemic concerns around the transition back into “normal” life and the uncertainty about the future, whether it be class or work related.

Figure 16: Word Network for Social Connection via Zoom (Question 4)



Students primarily talk about the social connection made possible in spite of social distancing and how Zoom has helped decrease the difficulty. We particularly see a connection between Zoom and lowering distance with both professors and classmates.

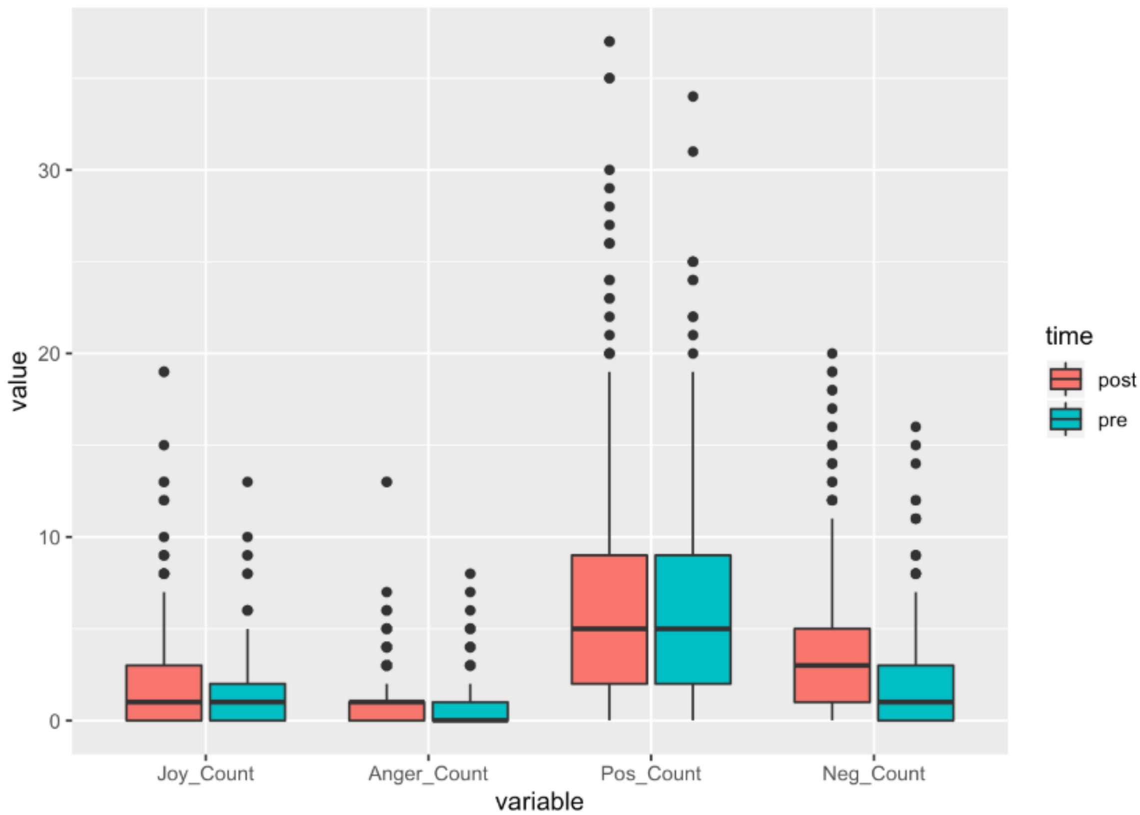
Figure 17: Word Network for Positive Aspects of Pandemic (Question 6)



When asked about the positive aspects about pandemic, a majority of student responses centered around the idea of time. Having more time for family, friends, sleep, and hobbies seemed to be the central theme of responses regardless of student, as evidenced by time's central position in the network.

Word Frequency Analysis

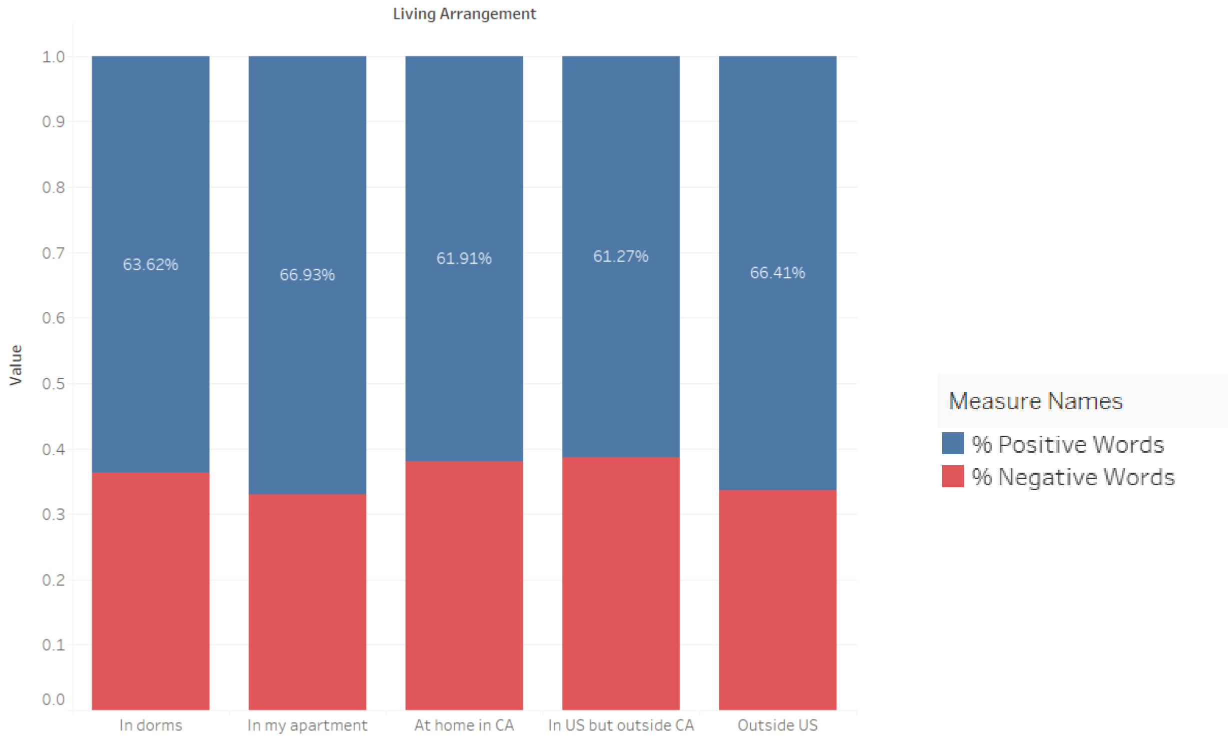
Figure 18: Word Count per Line by Sentiment and Pre/Post Pandemic



In order to scale our response for pre and post pandemic, we took the word count per line of text for each of the sentiments. The value plotted represents the density of sentiment words, not the raw count.

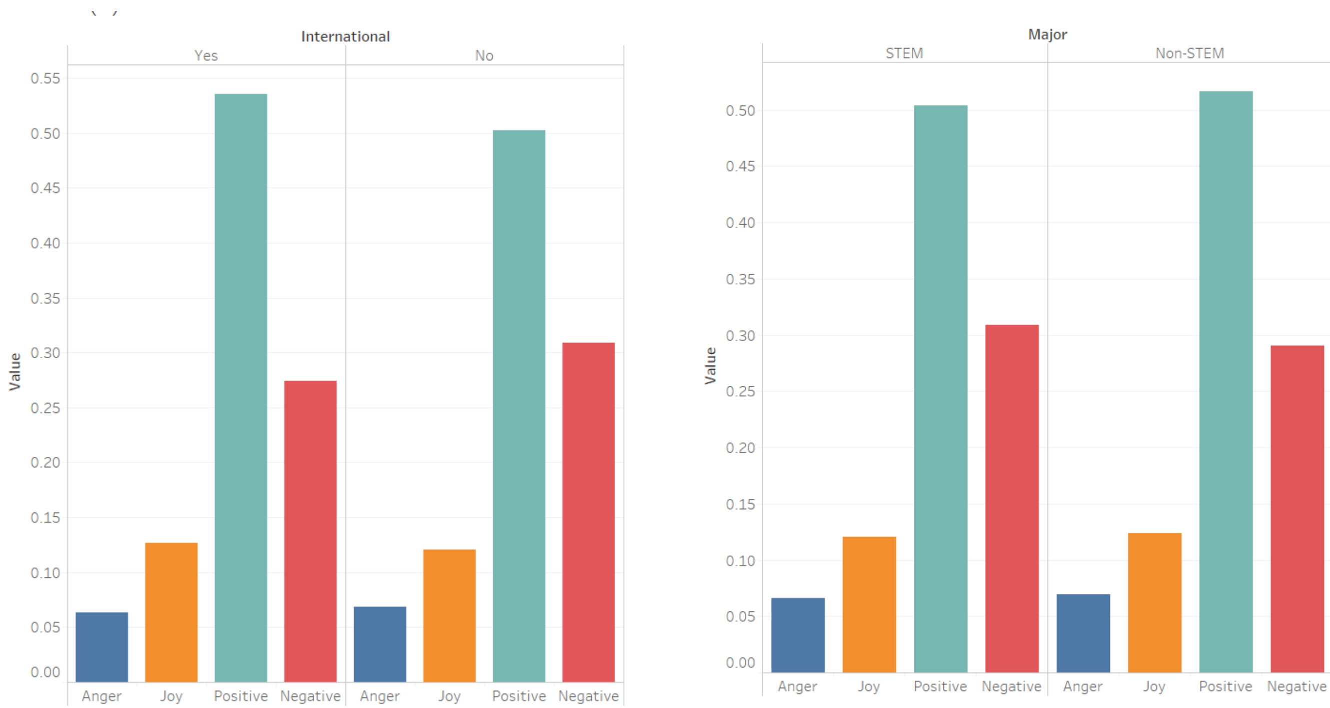
From the frequency plot, we have a near equivalence in the density of positive and joy related words. This suggests students are not much of an effect in positive emotion pre and post pandemic. However, we do see a noticeable difference in the density of negative words, with a clear increase post-pandemic. This implies that while people are just as positive as before, people are more vocal about their negative thoughts once quarantine was enacted.

Figure 19: Positive and Negative Word Counts vs. Living Arrangement Post-Pandemic



In Figure 19, we compare the percentage of positive and negative words extracted from the post pandemic survey in order to compare their usage as well as to see if there is any difference in people with varied living arrangements. This visual shows us that the percentage of positive words are higher compared to negative words, indicating a greater use of positive language. However, there is the possibility that some of the “positive” words extracted from our code were written in a negative context. After going through some of the questions that had the most positive word counts, we were able to confirm that was the case in quite a few responses.

Figure 20: Sentiment Word Percentages by Demographics (International Status vs Major)



The visuals in Figure 20 show that there is little to no difference in the frequency of types of word usage relating to International students along with those who are in a STEM based major. Initially, we had thought there may be some differences in the general sentiment of those with different demographics, however our findings show us that students are equally affected whether they are across the country or in Los Angeles, as well as if they are in STEM or not.

Modeling & Statistical Significance

Table 1: Logistic Model Predicting for Pre-Pandemic Sentiment using Word Counts

Coefficients	Estimate	Std. Error	t value	P-value
Joy_Count	0.012533	0.017913	0.700	0.484720
Anger_Count	-0.046891	0.028792	-1.629	0.104555
Pos_Count	0.049740	0.006259	7.946	5.13e-14 ***
Neg_Count	-0.051571	0.013450	-3.834	0.000157 ***

Table 2: Logistic Model Predicting for Post-Pandemic Sentiment using Word Counts

Coefficients	Estimate	Std. Error	t value	P-value
Joy_Count	0.0148148	0.0166335	0.891	0.374
Anger_Count	0.0005858	0.0216156	0.027	0.978
Pos_Count	-0.0006103	0.0073086	-0.084	0.933
Neg_Count	0.0008086	0.0093261	0.087	0.931

We wished to test whether our sentiment word counts were useful in determining the actual sentiment of our respondents. We manually tagged every response with a sentiment score (0 for negative, 1 for positive) in order to compare it to our word count based sentiment analysis.

For the pre-pandemic data, we saw some limited success in predicting sentiment using the count of positive and negative sentiment words. However, for post-pandemic data, we have no significance for any of our frequency counts for sentiment. This has implications that there exists a gap between the sentiment implied by individual words that we analyzed quantitatively and the overall sentiment, which was determined based on qualitative factors.

Table 3: ANOVA Predicting for Post-Pandemic # of Positive Words with Demographic Data

Factor	Df	Sum Sq	Mean Sq	F value	P-value
Motivation	3	0.2216	0.073877	1.6615	0.1746
Living_Arrange	4	0.2338	0.058460	1.3148	0.2636
Residuals	438	9.4749	0.044463		

We “sliced” our data to see which demographics, if any, have different frequency of positive words. Note that we used relative frequency scaled by the total number of words used in each response for this ANOVA. Most factors were found to be insignificant in the initial logistic regression model.

We then isolated the two most important factors, motivation and living arrangement to see if these factors were individually significant. Both were not, suggesting that, psychologically, all demographics were fairly evenly affected by the pandemic. We see that this quantitative result is similar to that in our plots in Figure 19, showing us that living arrangements have no significance in the number of positive words.

Conclusion & Discussion

Overall, we saw a clear rise in negative sentiment in the post-pandemic survey. Students used more words associated with negativity, and the use of words within this category changed. As opposed to pre-pandemic preponderance of “stress” and “pressure” that would be expected of students at a rigorous academic institution, words such as “anxiety” and “worry” come up more frequently in post-pandemic responses, showing a troubling shift in sentiment. Furthermore, when seemingly positive words come up, they are shown to likely be part of a larger, negative statement, as shown in the word networks.

In addition, we saw little to no differences in student sentiment across different demographics such as those with altered living arrangements, STEM majors, and International Students. Initially, we thought there would be some differences due to some possibly being farther away from campus, in different time zones, or taking extremely difficult classes online. However, our thoughts were proven to be incorrect. This is a positive finding in our study because our evidence shows there isn’t one demographic which is being overly affected by this pandemic and it is affecting all students in a similar way on a larger scale.

Last, we were able to correctly identify that the current way of interaction between students and their peers or professors are generally affected in a worse manner than before. The Zoom platform has been a useful resource, but our evidence shows that the face to face interaction with others is more effective in terms of interacting. Students also feeling “isolated” and “detached” are even more evidence that Zoom may be less effective for communicating or for virtual social gatherings.

This project struggled with a deficiency in data, and thus we were restricted to primarily explorative analysis, and can’t make definitive statements for larger populations such as all university students in the United States, or adults in the workforce. Still, we were able to make interesting findings about UCLA and its sub-groups.

Future research could involve larger polls that extend beyond one university. Also, more general opinion polls that do not have school-specific questions could be given to a much larger population, and would present sufficient data for more complex language modeling. We could also include age groups to see the effect based on an individual's age.

Near the end of the Harvard Public Health symposium, Harvey Fineberg brought up the topic of the more “mundane” effects the COVID-19 pandemic has had on the social fabric. On how society adapts to this new situation and how people find silver linings in difficult times. For the many individuals who are fortunate enough to have not directly been affected by COVID-19, their lifestyles have still been fundamentally changed, in ways we aim to measure through our study. Individual sentiment, confidence, and hope have a deep, if difficult to quantify impact on our society, and our study aims to build a better understanding of this aspect of our society’s response to the pandemic. Important factors like consumer confidence or the public’s acceptance of a vaccine are very much linked to the emotions individuals are going through on a day to day basis. We believe our study will help shed a little light on this aspect of our collective response.

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