The COVID-19 Pandemic's Impact on Bullying Search Intensity with respect to Asian Population*

Will Davidson Jason Ngo Annie Yan

22 February 2023

Abstract

The Covid-19 pandemic incited a wave of anti-Asian hate crimes across the United States including derogatory language in the media, random bullying, and violent, senseless murders. This paper analyzes how high school closures and the shift to online learning by schools throughout the pandemic, impacted incidents of bullying of Asian students compared to non Asian students when compared to pre-pandemic trends and in-person learning. Results suggest that while the overall trend in bullying of high school students has been in decline across all states between 2016-2021, with a larger drop during Covid-19, the states with high Asian populations saw greater incidents of bullying when compared to states with low Asian populations over the six year period. These findings tell both a good news story of declining bullying trends in the US school system and a highly concerning narrative that anti-Asian bullying is not a result of Covid-19, but rather an intensified awareness of pre-existing racism.

1 Introduction

Anti-Asian violence skyrocketed during the Covid-19 pandemic. The Center for the Study of Hate and Extremism published a report showing how anti-Asian hate crimes in the United States grew by 339% from 2020 to 2021 - the height of the global crisis. This increase in racism, fueled by the pandemic, occurred mainly in highly populated urban cities where the population of people of Asian descent are more predominant. For example, the percentages of Asian hate crimes in New York rose from 30% to 133% and in San Francisco from 9% to 60%. American culture pretends Asian Americans face no discrimination or racism. There are countless examples where when the U.S. was faced with an economic downturn, Asian Americans were affected. The 1982 killing of Vincent Chin in Detroit came after the 1980-1982 Detroit recession and The Page Act of 1875, America's first immigration law that banned Chinese women after the Great Panic of 1873. It's safe to assume an economic horror like the pandemic would lead to hate. It was disconcerting reading about the different hate acts that occurred, and it was clear there needed to be culturally appropriate and accessible community safety programs. From the data provided, we decided to clean it, focusing on the states with an Asian population. There has been mainstream media coverage of anti-Asian racism but little effort toward the Asian American Youth.

1.1 Estimand

In our study, our estimated population varies between different datasets. The population depicted in Figure 1, Figure 2, and Figure 3 contains people that searched up bullying online that live in the states with the top 10 highest percentages of Asian population. These states are: California, Florida, Hawaii, Illinois, Massachusetts, New Jersey, New York, Texas, Virginia, and Washington. ("Asian American Population by

*Code and data are available at: https://github.com/AnnieYan0807/Analysis-on-The-COVID-19-Pandemic-Disrupted-Both-School-Bullying-and-Cyberbullying. The replication on the SSRP can be found at : https://doi.org/10.48152/ssrp-54f4-p919

State 2023" (n.d.)) The population depicted in Figure 5, Figure 6, and Figure 7 contains people that searched up bullying online that live in the states with the 10 lowest percentages of Asian population. These states includes Arkansas, Maine, Mississippi, Montana, North Dakota, South Dakota, Alabama, West Virginia, Wyoming, and Kentucky. The population shown in Figure 4 shows people who searched up bullying online nationwide.

2 Data

2.1 Data collection

The raw data used in this study was downloaded from the Replication Package within the article "The COVID-19 Pandemic Disrupted Both School Bullying and Cyberbullying." (Bacher-Hicks et al. (2021)) According to the article, raw data was provided from Google Trends, Youth Risk Behavior Survey, U.S. Census Stata Population, and Burbio. However, the Burbio data was not provided in the Replication Package.

Our analysis of this data was done through the R programming language (R Core Team (2020)) with the tidyverse (Wickham et al. (2019)), dplyr (Wickham et al. (2023)), and knitr (Xie (2014)) packages being used to clean the data. ggplot2 (Wickham (2016)) was used to produce all the figures in this paper. The Lubridate (Grolemund and Wickham (2011)) package was also used to reformat dates.

2.2 Measurements

The data from Youth Risk Behavior Survey was collected from high schools throughout the United States. Data from Google Trends was collected by analyzing search intensity for specific topics and keywords pertaining to school bullying and cyberbullying. Data from the U.S. Census Stata Population was gathered nationwide from all civilians that participated. Information on the measurement of Burbio data is only available via email request, so we did not inquire.

2.3 Data Analysis

2.3.1 Bullying and Cyberbullying Searches Decreased During COVID-19

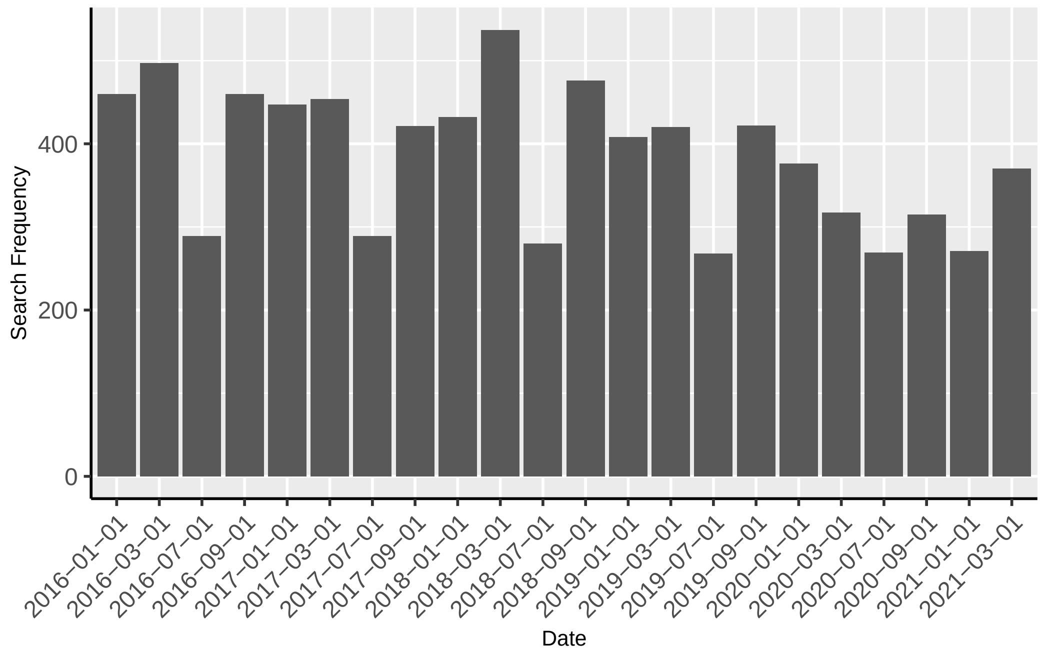

Figure 1: All Bullying Searches in High Asian Population States

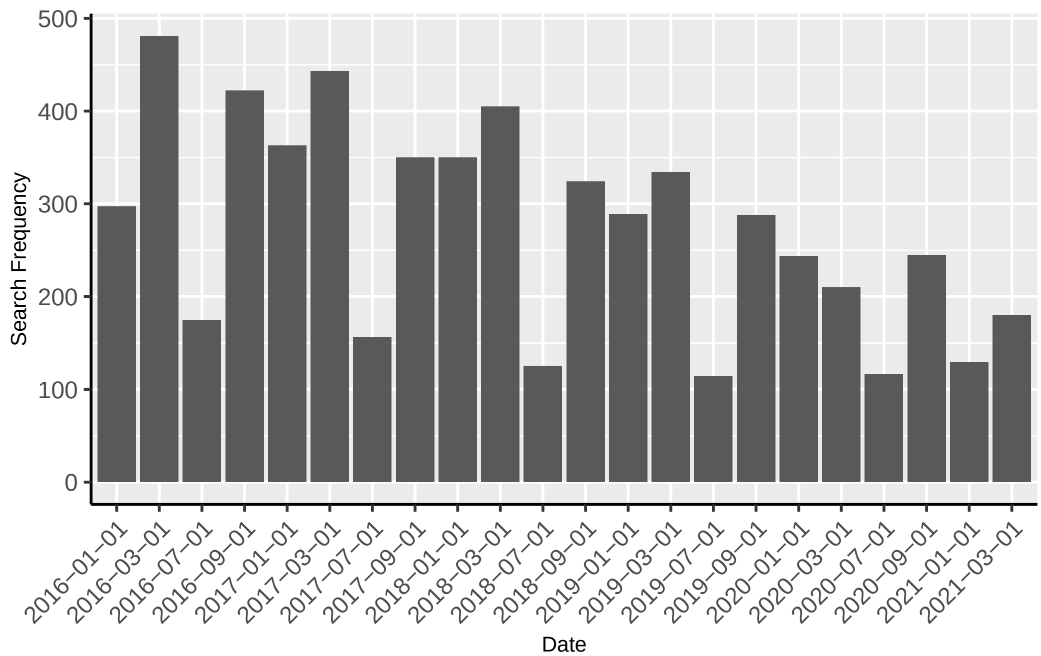

Figure 2: Cyberbullying Searches in High Asian Population States

Figure 1 shows the number of hits for all ‘bullying’ searches in the top 10 states with the highest Asian population. According to (Bacher-Hicks et al. (2021)), there is a positive correlation between search intensity and frequency of victimization (Bacher-Hicks et al. (2021)). The overall trend from 2016 to the start of the pandemic shows a decline in bullying searches, despite a high peak between March 2017 and 2018. At the start of the pandemic, there continued to be a decline in overall search intensity. On average, the search intensity in 2020 was lower in comparison to previous years. The drop in search intensity occurred when most schools were shut down and classes swapped to online delivery. This leads to the conclusion that bullying decreased when students were not attending classes in person.

Figure 2 shows the number of hits for all “Cyberbullying” searches. From the naked eye, cyberbullying searches have slightly decreased every year from 2016. The lowest points of the graph occured from 2020 onwards, after pandemic regulations took place. The summer months, when schools are closed, have the lowest search intensity within a year interval. The peak of the data happens in March of 2016 climbing up to 500 compared to March 2020 when it’s 250. This is a stark difference between bullying searches during and before the pandemic.

Search frequency and therefore, victimization, has been slightly decreasing up to the start of the pandemic. From there, we see more drastic declines as a result of online learning, school closures and isolation during COVID-19.

2.3.2 Correlation Between Asian Population of States and School Bullying Numbers

We conducted a study to determine if there was a correlation between the anti-Asian sentiment and school bullying in the United States. To do this, we analyzed the correlation between the search frequency for the term “school bullying” and the Asian population of each state. Figure 3 and Figure 4 were used to compare the search frequency of the keyword “school bullying” from 2016 onwards.

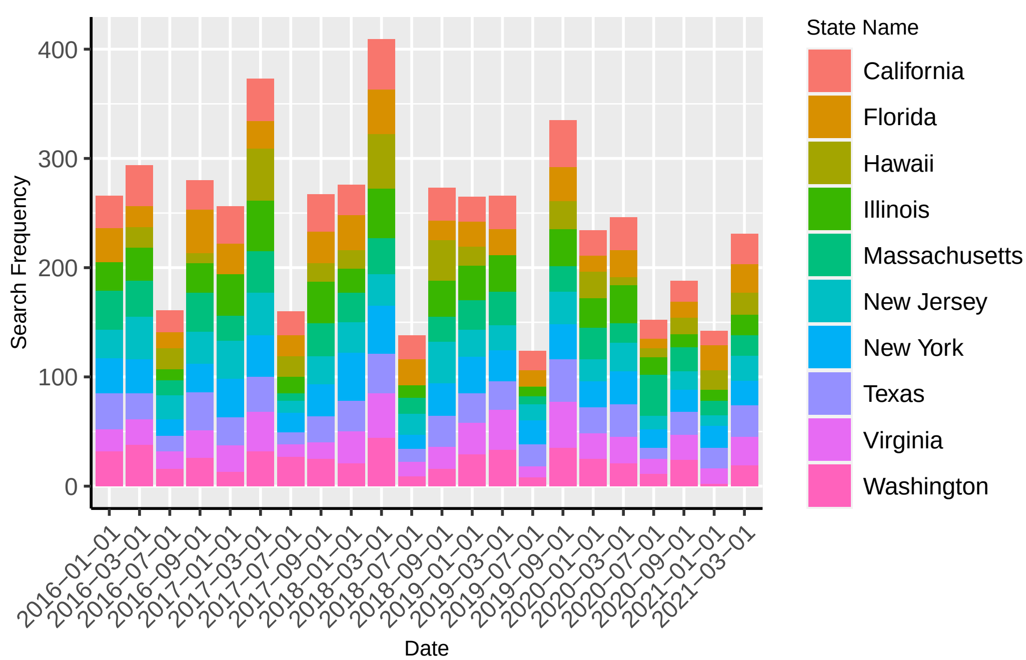

Figure 3: School Bullying Searches in States With The Highest Asian Populations

Figure 3 shows the frequency of the keyword “school bullying” searched online within the top ten states with the highest Asian population. The graph indicates that March 1st, 2018, had the highest number of searches for “school bullying” at over 400. Typically, the search frequency for “school bullying” is highest in March, and there is a significant drop in search frequency every July at approximately 150 searches due to summer vacation. In contrast, data for September and January are relatively closer to the average, ranging from 150 to 300, due to those dates coinciding with the start of new school semesters.

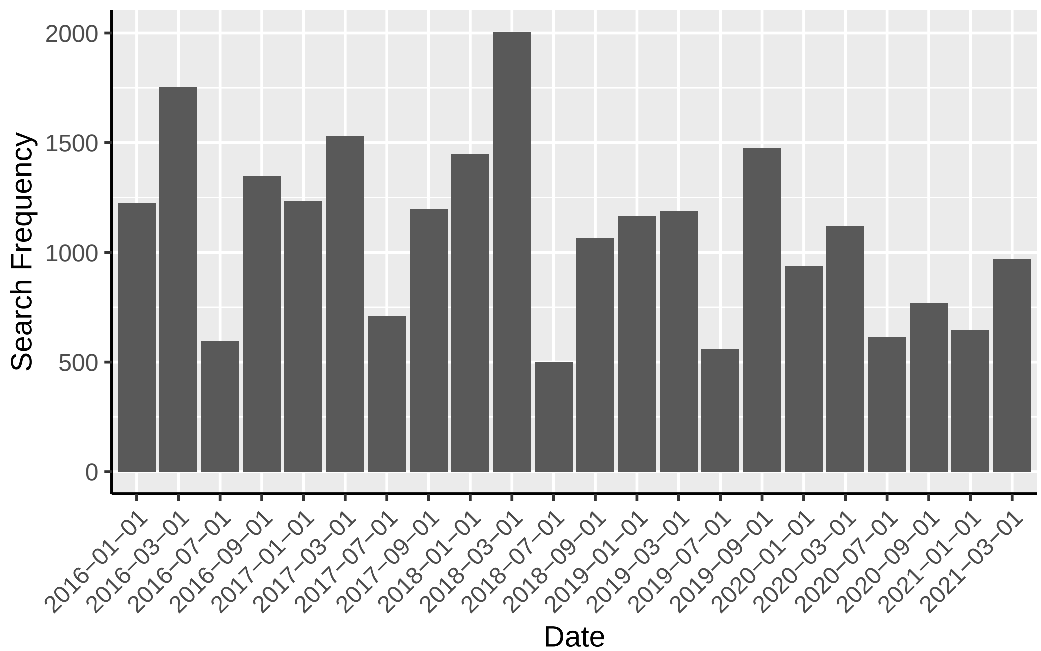

Figure 4: Nationwide Search Frequencies for 'School Bullying'.

Figure 4 presents data on the search frequency of the keyword "school bullying" nationally since 2016. Like Figure 4, March 1st, 2018, had the highest search frequency at 2000 nationally. On the other hand, July's search frequency was always at the lowest level, with data from 2016 to 2021 never exceeding 750. September and January have a similar level of search frequency ranging from 750 to 1500, which is closer to the overall average. In terms of trends, the search frequency with respect to date was relatively consistent in both the top ten states with the highest Asian population and nationwide. Based on our analysis, we did not find a correlation between school bullying searches and the Asian population of the state.

Upon comparing Figure 3 and Figure 4, we observed a consistent trend. Notably, the months of January and September, which mark the beginning of school, exhibit comparable search frequency levels for the keyword "school bullying." Meanwhile, March, which falls in the middle of the semester, experiences a significant surge in search frequency, as seen in both national data and the top ten states with the highest Asian population. On the other hand, July, which is in the middle of summer break, displays a considerable drop in search frequency in both graphs. Overall, the trend in search frequency with respect to date remains relatively consistent across the top ten states with the highest Asian population and the entire nation. Therefore, the comparison of these two graphs did not establish any significant correlation.

2.3.3 Comparing the Top 10 Asian Population States with the Bottom 10

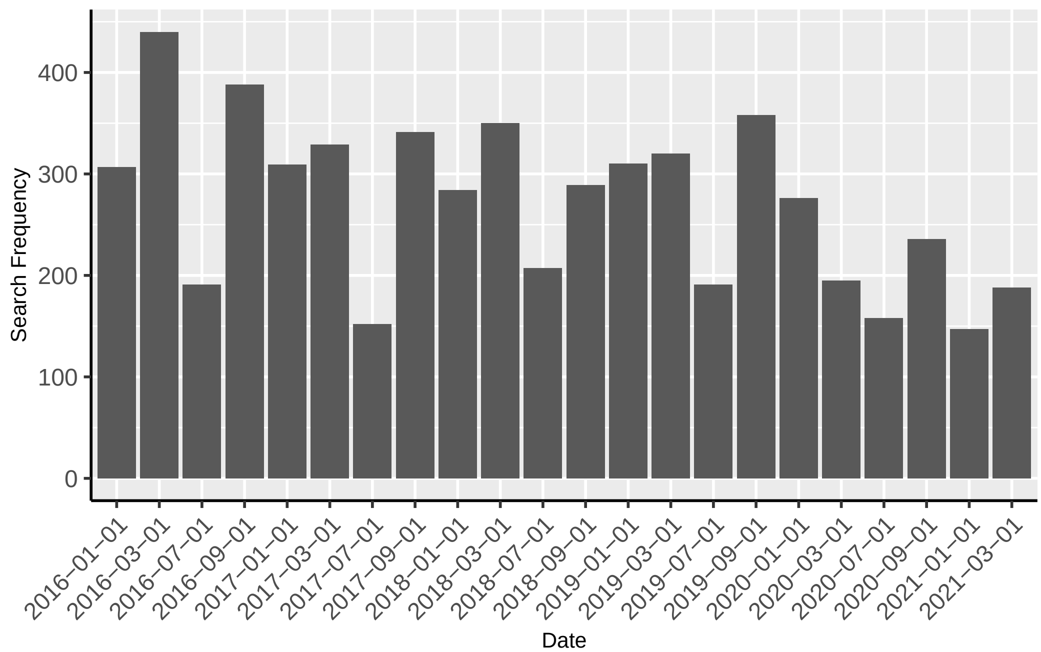

Figure 5: Bullying searches in the lowest Asian population states.

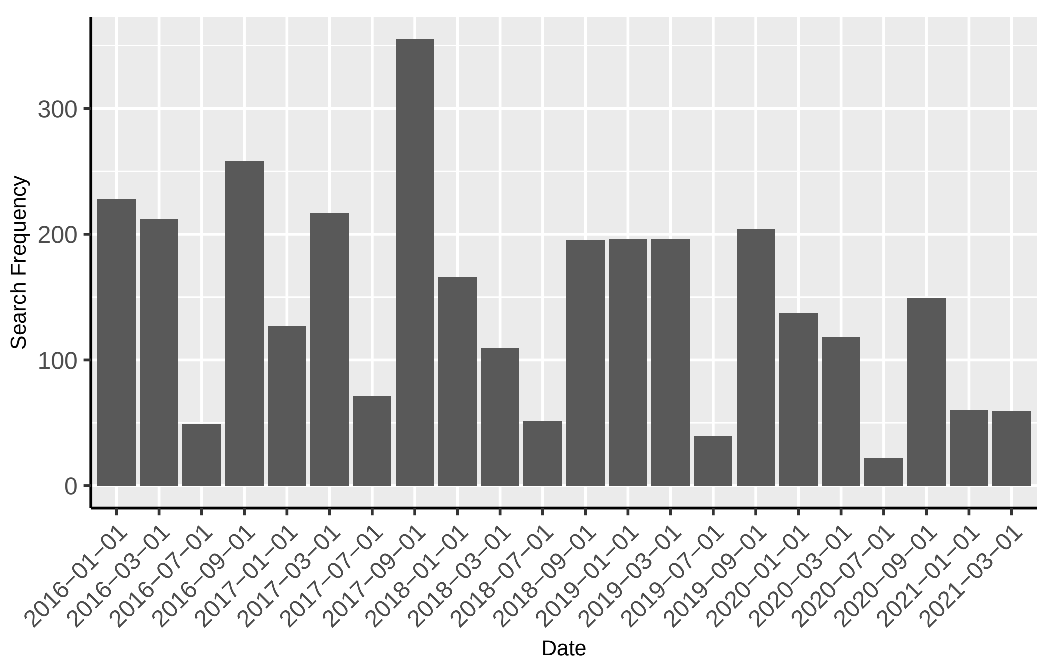

Figure 6: Cyberbullying searches in the lowest Asian population states.

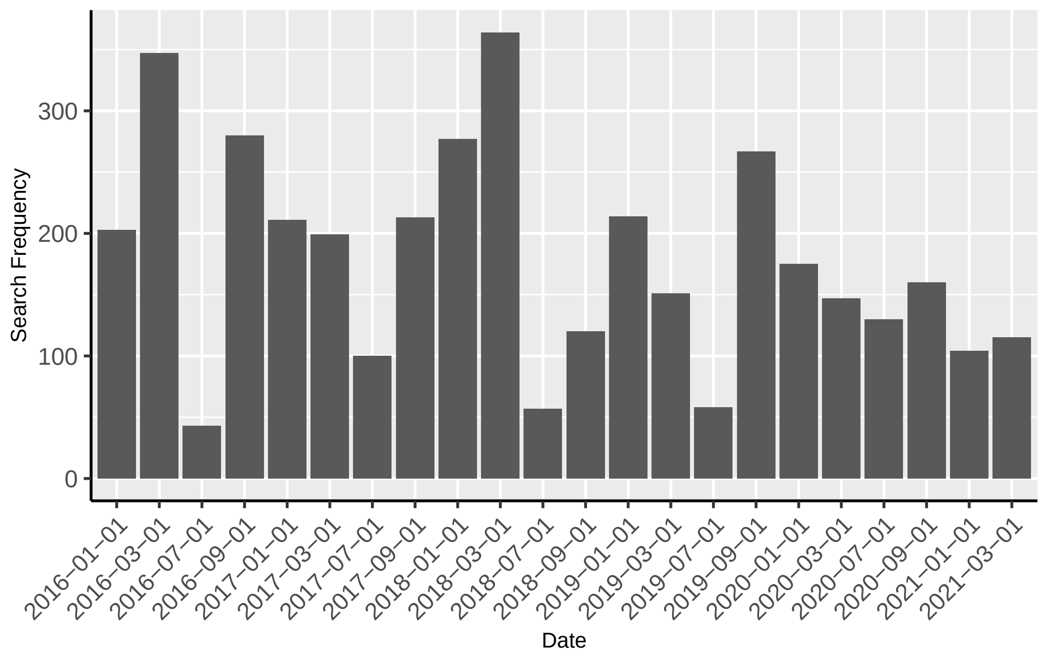

Figure 7: School bullying searches in the lowest Asian population states.

Figure 5, Figure 6, and Figure 7 shows, respectively, the "bullying" searches, "cyberbullying" searches and "school bullying" searches in states with the 10 lowest percentages of Asian population. In all three metrics, there is a decrease in bullying searches in comparison to bullying searches in the top 10 states. The data shows that having a high population of Asian people did have an effect on school bullying searches during the pandemic. The higher the Asian population, the more bullying searches there were.

3 Results

According to our findings, search frequency for bullying in the top ten states with the highest Asian population slightly decreased after the start of the pandemic. This trend was also applied on the search intensity for cyberbullying. Our observations indicate that the pandemic did not increase bullying towards Asian American students. The analysis that examined the correlation between the Asian population of states and school bullying numbers showed similar results. The study compared search intensity trends for the keyword "school bullying" in the top 10 states with the highest Asian population to nationwide data, but found no correlation between school bullying searches and the Asian population of the state. Further evaluation compared data from the top 10 states with the highest Asian population to the bottom 10 states with the lowest Asian population. This research showed that having a high population of Asian people did have an effect on school bullying searches during the pandemic, with higher Asian populations resulting in more bullying searches. Our study took three different angles to observe the relationship between the Asian population and search frequency in bullying, but only one of them showed a correlation. Therefore, future studies are needed to determine if a statistically significant correlation exists between the Asian population and bullying in schools. It's important to continue investigating and addressing the issue of bullying in all populations and to develop effective interventions and prevention strategies to reduce its occurrence.

4 Discussion

4.1 Bullying and Cyberbullying Searches Decreased During COVID-19

The COVID-19 pandemic saw a decrease in bullying and cyberbullying searches. Students were no longer learning in-person, so it is natural that bullying searches would decrease. However, cyberbullying searches also decreased despite students spending more time online with eachother. There are multiple factors attributing to the decrease of cyberbullying searches during COVID-19.

One factor is a steady increase of anti-bullying campaigns causing the gradual decrease in cyberbullying. Another factor is that outside of virtual classrooms, students are not spending time amongst their peers. Less exposure to one another leads to less confrontation and cyberbullying. One last factor is due to the digitization of student's lives during the pandemic, some students may have become desensitized to cyberbullying. What one student may perceive as cyberbullying, another would perceive as banter. The nuances of in-person communication is lost over digital communication, and these nuances lead to differences in perception.

4.2 Correlation Between Asian Population of States and School Bullying Numbers

As discussed earlier, there has been a significant increase in anti-Asian rhetoric in the United States over the past year. A source of this rhetoric can be attributed to the spread of misinformation and xenophobic slander related to the COVID-19 pandemic. From (Ruiz, Edwards, and Lopez (2022)), 81% of Asian adults have shared an incident of violence towards them. Over 3800 hate-related verbal and physical assaults against Asian Americans have been reported during the pandemic ("Asian Americans Reported 3,800 Hate-Related Incidents During the Pandemic, Report Finds" (2021)).

This culture of anti-Asian violence has also impacted schools, with many Asian students reporting incidents of racism and discrimination in the classroom. Reports show 68% of attacks were verbal harassment. Some students may have faced racially discriminated comments, while others may have experienced exclusion or isolation from their peers. There is a need to increase education and awareness against misinformation and xenophobia among students, as well as increasing efforts to combat racism and discrimination in all forms.

While our investigation did not reveal any correlation between the Asian population of a state and the frequency of searches related to school bullying, there may have been sampling bias in play. From ("2021 Asian American Bullying Survey Report" (2021)), Asian Americans are less likely to report bullying to adults in comparison to non-Asian Americans. It may be the case that more Asian Americans are getting bullied, but for reasons such as culture, Asian Americans will not report bullying. If someone is not going to report bullying to an adult, will they search it up online or simply internalize it?

4.3 Comparing the Top 10 Asian Population States with the Bottom 10

The top 10 Asian population states experienced more school and cyber bullying than the bottom 10 Asian population states. From ("2021 Asian American Bullying Survey Report" (2021)), there has been a 70% increase in Asian American cyberbullying in 2020. Anti-Asian xenophobia fueled by Covid-19 has led to an increase of hate towards Asian-Americans. With this in mind, Asian population does correlate with respect to the disparity between bullying searches from the top 10 Asian population states with bullying searches from the bottom 10 Asian population states.

However, there is more sampling bias with these data sets. The total population numbers for the bottom 10 Asian population states are dwarfed by the total population numbers of the top 10 Asian population states. So naturally, there would be less bullying searches in a state such as Montana, which has around 2.7% of California's total population. This is where our approach of using raw search data reaches it's limit, as we cannot draw an accurate comparison of search ratios due to the massive difference in total population numbers.

4.4 Weaknesses

While our study provides some insights into the search frequency of school bullying and its correlation with the Asian population, it has several limitations. Firstly, we only looked at the search frequency of the keyword "school bullying" and did not consider other related search terms or social media platforms, which may not fully capture the prevalence of school bullying in schools. Secondly, we did not control for other variables, such as socioeconomic status, which may also impact the prevalence of school bullying. Lastly, as we only analyzed data up until 2021, our study may not reflect any potential changes in search behavior or trends in recent months or years. These limitations should be taken into consideration when interpreting our findings and drawing conclusions.

Furthermore, we did not perform any correlation testing to establish a relationship between the Asian population and the search frequency of "school bullying" accurately. We simply compared the search frequency of the top ten states with the highest Asian population and nationwide data. To determine if there is a statistically significant relationship between the two variables, a formal correlation test is required. However, it is also important to note that correlation does not mean causation. Even if the search frequency of "school bullying" and the Asian population in a state are significantly correlated, it does not imply that the increasing incidence of school bullying is caused by a high Asian population or that anti-Asian culture impacts school campuses. Other factors, such as confounding variables or common causes, may influence the observed relationship. As a result, further studies are needed to examine the impact of anti-Asian culture on school bullying.

In conclusion, our study has some limitations that should be taken into account when interpreting our results. Although we provide some insights into the correlation between the Asian population and the search frequency of "school bullying," future research is required to investigate the potential causes of school bullying, particularly those related to anti-Asian culture.

4.5 Bias

Google's reported data doesn't consider the sample of users or data points. There is an evident sampling bias that takes occurs in this study. The general population can be under or overrepresented. It's unsure which students' searches are being used, making their age and ethnicity unclear. The broad population must be represented and used in our data. User behavior is measured by how many hits particular buzzword use. This measurement can be flawed as students may search other buzzwords or not use the internet to gather research on bullying and how to receive help. Google may only report positive trends and ignore negative ones leaving the data skewed.

When on the internet, the average individual is working with information about their personal life, health, and other sensitive topics that they may not want to be shared. When choosing what data to report on, Google must be aware of this and careful that they're not infringing on the human right to privacy. There needs to be more information out there to educate the public on how their information is being used. The average user must be informed that their data is collected and used for reports. Hackers are constantly trying to steal and use innocent users' information for their gain. Security measures must to be implemented to protect search data from unauthorized access. Our dataset needs to be looked at with this in mind. An ethical lens must always be used when looking at people's search data to prevent discriminatory practices.

5 Next steps

Further studies are crucial for a deeper understanding. Some potential steps include establishing more in-depth data analysis, adding more control variables, and conducting formal correlation tests.

To establish a more in-depth data analysis on school bullying and its relationship with the Asian population, we suggest introducing more factors that relate to school bullying, such as other related search terms and various social media, to provide a more complete picture of the issue. Adding more control variables is another direction to further testing school bullying and its relationship with the Asian population. Age range, race, gender, or even socioeconomic status all can influence school bullying. Taking these factors into consideration can help us to identify potential areas for intervention.

Furthermore, it is important to conduct formal correlation tests to determine the statistical significance of the relationship between school bullying and the Asian population. Gathering more data, such as Asian population in different states, can be helpful in this regard. Additionally, gathering data and performing analysis on specific schools with varying Asian student populations would also be beneficial. The correlation coefficient can be calculated to determine the strength and direction of the relationship between the two variables.

Additional research is necessary to identify the underlying factors driving the relationship between school bullying and the Asian population.

References

"2021 Asian American Bullying Survey Report." 2021. Act To Change. https://acttochange.org/wp-content/uploads/2021/05/Asian-American-Bullying-Report_FINAL.pdf.

"Asian American Population by State 2023." n.d. *Asian American Population by State 2023*. https://worldpopulationreview.com/state-rankings/asian-population.

"Asian Americans Reported 3,800 Hate-Related Incidents During the Pandemic, Report Finds." 2021. *The Guardian*. Guardian News; Media. https://www.theguardian.com/us-news/2021/mar/16/asian-americans-hate-incidents-pandemic-study.

Bacher-Hicks, Andrew, Joshua Goodman, Jennifer Greif Green, and Melissa K. Holt. 2021. "Data and Code for: The COVID-19 Pandemic Disrupted Both School Bullying and Cyberbullying." *Home Page*. American Economic Association. https://doi.org/10.3886/E156901V1.

Grolemund, Garrett, and Hadley Wickham. 2011. "Dates and Times Made Easy with lubridate." *Journal of Statistical Software* 40 (3): 1–25. https://www.jstatsoft.org/v40/i03/.

R Core Team. 2020. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. https://www.R-project.org/.

Ruiz, Neil G., Khadijah Edwards, and Mark Hugo Lopez. 2022. "One-Third of Asian Americans Fear Threats, Physical Attacks and Most Say Violence Against Them Is Rising." *Pew Research Center*. Pew Research Center. https://www.pewresearch.org/fact-tank/2021/04/21/one-third-of-asian-americans-fear-threats-physical-attacks-and-most-say-violence-against-them-is-rising/.

Wickham, Hadley. 2016. *Ggplot2: Elegant Graphics for Data Analysis*. Springer-Verlag New York. https://ggplot2.tidyverse.org.

Wickham, Hadley, Mara Averick, Jennifer Bryan, Winston Chang, Lucy D'Agostino McGowan, Romain François, Garrett Grolemund, et al. 2019. "Welcome to the tidyverse." *Journal of Open Source Software* 4 (43): 1686. https://doi.org/10.21105/joss.01686.

Wickham, Hadley, Romain François, Lionel Henry, Kirill Müller, and Davis Vaughan. 2023. *Dplyr: A Grammar of Data Manipulation*. https://CRAN.R-project.org/package=dplyr.

Xie, Yihui. 2014. "Knitr: A Comprehensive Tool for Reproducible Research in R." In *Implementing Reproducible Computational Research*, edited by Victoria Stodden, Friedrich Leisch, and Roger D. Peng. Chapman; Hall/CRC.