

# My title\*

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February 15, 2024

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## 1 Introduction

With pandemic outbreaks, most schools in the United States turned to online teaching models, and students moved from physical places with more social interaction to screens (Lebanon staff 2021). While the transition to virtual education has been accompanied by a variety of challenges, including academic setbacks and economic disparities, significant gaps remain in understanding the impact of virtual education on the social dynamics within schools. Most research has focused on education, i.e., whether this change to an online delivery model will affect student achievement. In this article, we will focus on a new aspect of the pandemic that is having a positive impact: school bullying.

Bullying in schools is pervasive and can have significant social costs. In the US, 1 in 5 students ages 12-18 has been bullied during the school year, and approximately 160,000 teens have skipped school because of bullying (staff 2019). The COVID-19 pandemic has fundamentally changed the context of bullying dynamics. With the shift to online learning across the United States in March 2020, there is a sudden decrease in in-person communication and interaction while the use of technology increases dramatically. In fact, prior COVID-19 research has suggested that the higher the frequency of the Internet, the more incidents of cyberbullying and cyber-victimization reported by youth (Robin M. Kowalski 2019). However, in this paper, we conclude that both school bullying and cyberbullying have been decreased during the pandemic by analyzing a long panel of publicly available Google Trends online search data. These results provide insights into how schools can reduce bullying in a post-pandemic world and highlight a possible mechanism by which COVID-19 may have a differential impact on broader mental health.

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\*Code and data are available at: [LINK](#).

## 2 Data

### 2.1 Data Source

This paper will replicate the data that was originally collected for the paper “The COVID-19 Pandemic Disrupted Both School Bullying and Cyberbullying” by [citation]. Using the online platform “Google Trends”, which provide monthly internet search behavior for a given term or topic by states over a period of time, they collected three types of bullying data (“School Bullying”, “Cyberbullying”, and “Bullying”) before, during, and after the pandemic COVID-19 from January 2012 to February 2021. They filtered the data to keep male and female individuals between ages of 5 and 17 (roughly the k-12 schooling population). Each dataset contains 5661 rows and 5 variables, each indicating a detailed summary of the month and position of the search, search keyword, number of searches and the ratio.

The researchers state that data from Google Trends are less likely to be subjected to potential bias, since the data are not self-reported. Moreover, the data from Google Trends represents the full population of Google search users in the United States, thus it does not have the potential issue of under-representation of a certain group.

### 2.2 Methodology

Since it is difficult to observe through 16683 ( $5661 \times 3$ ) rows with 5 variables, this report will only observe and analyze through specific aspects. The original dataset contains information through all the 51 states in the US. This paper focuses only on data and trends for three states, which are “US-LA”, “US-NY” and “US-NJ” (Louisiana, New York, and New Jersey respectively). Some data cleaning is performed, such as renaming column names, filtering and mutating the column, etc. The cleaned data will be analyzed and performed using R (R Core Team (2022)) with `tidyverse` (Wickham et al. (2019)), `dplyr` (Wickham et al. (2023)), `ggplot2` (Wickham (2016)).

### 2.3 Features

The original dataset contained 5 variables, which are named as “dma\_json\_code”, “date”, “keyword”, “hits”, and “ratio”. 1. dma\_json\_code: the states of the United States 2. date: the first day of every month from 2012. 01 to 2021. 02 3. keyword: specific words that the people search on Google Trends that relate to bullying. 4. hits: number of searchers of keywords in each month. 5. ratio:

Talk way more about it.

### 3 Results

Table 1: Table-of-Search-Intensity by School Bullying and Cyber Bullying

Table 1: Sample Table for Search Intensity by School Bullying and Cyber Bullying (2012-2021)

US State	Date	Number of Searches	Bully Type
US-LA	2012-01-01	60	sch_cyb_bully
US-LA	2012-02-01	70	sch_cyb_bully
US-LA	2012-03-01	72	sch_cyb_bully
US-LA	2012-04-01	81	sch_cyb_bully
US-LA	2012-05-01	58	sch_cyb_bully
US-LA	2012-06-01	40	sch_cyb_bully

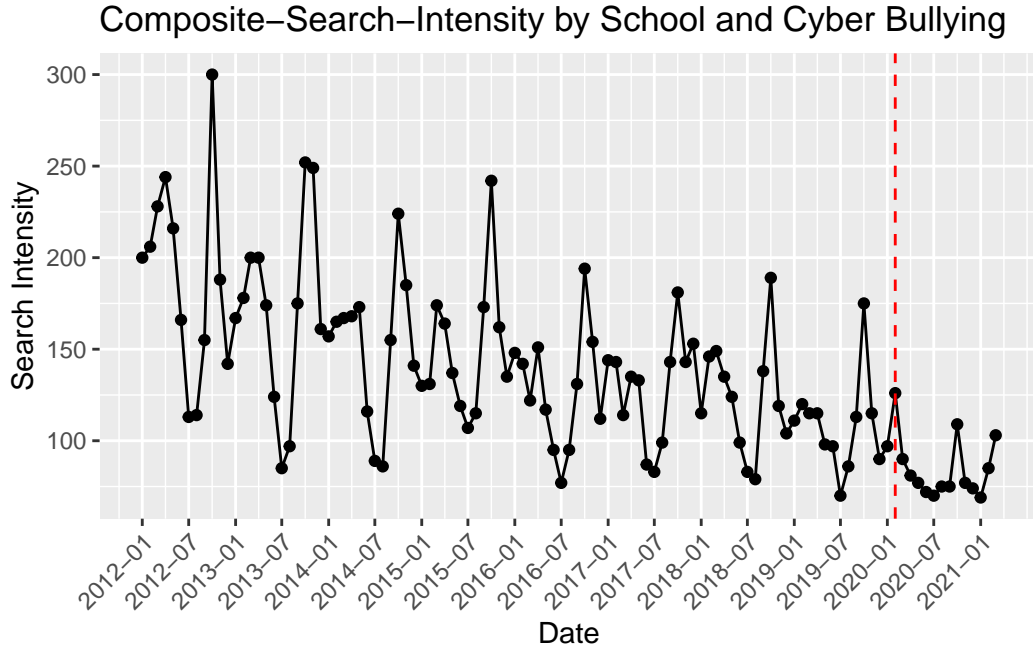


Figure 1: Composite-Search-Intensity by School Bullying and Cyber Bullying

The dataset represented by the table labeled Table 1 furnishes a comprehensive overview of the cumulative number of searches related to bullying over the specified time frame. This table is a valuable resource for conducting a nuanced analysis, as it delineates key variables crucial for understanding the extent of harm experienced by individuals affected by bullying. The primary variables include time, state, the total number of searches, and the categorization of bullying incidents. The categorization of bullying incidents into different categories provides a nuanced

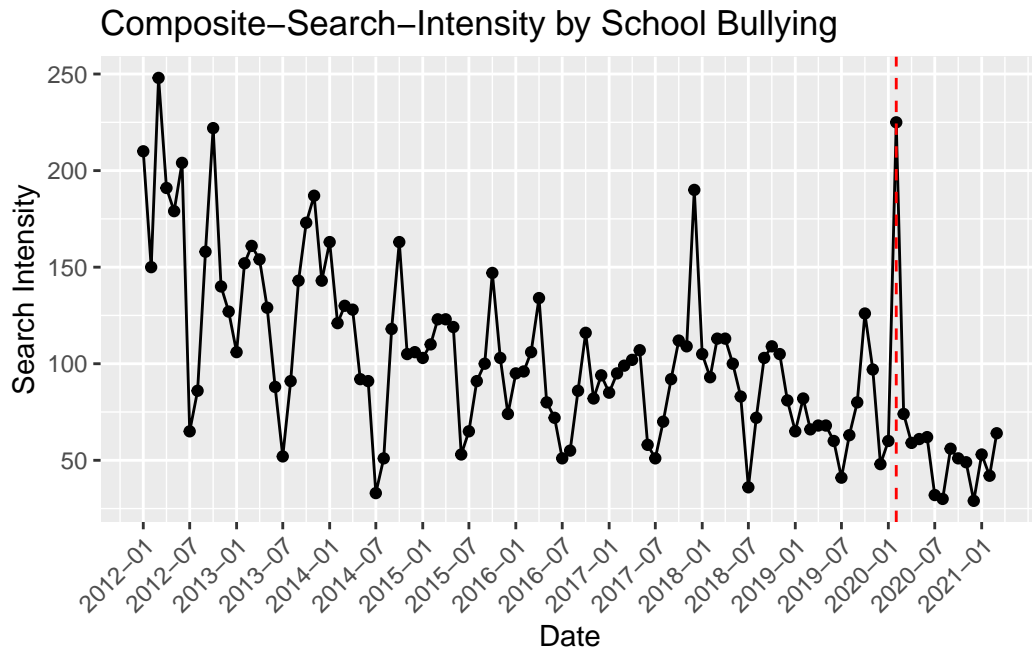


Figure 2: Composite-Search-Intensity school type

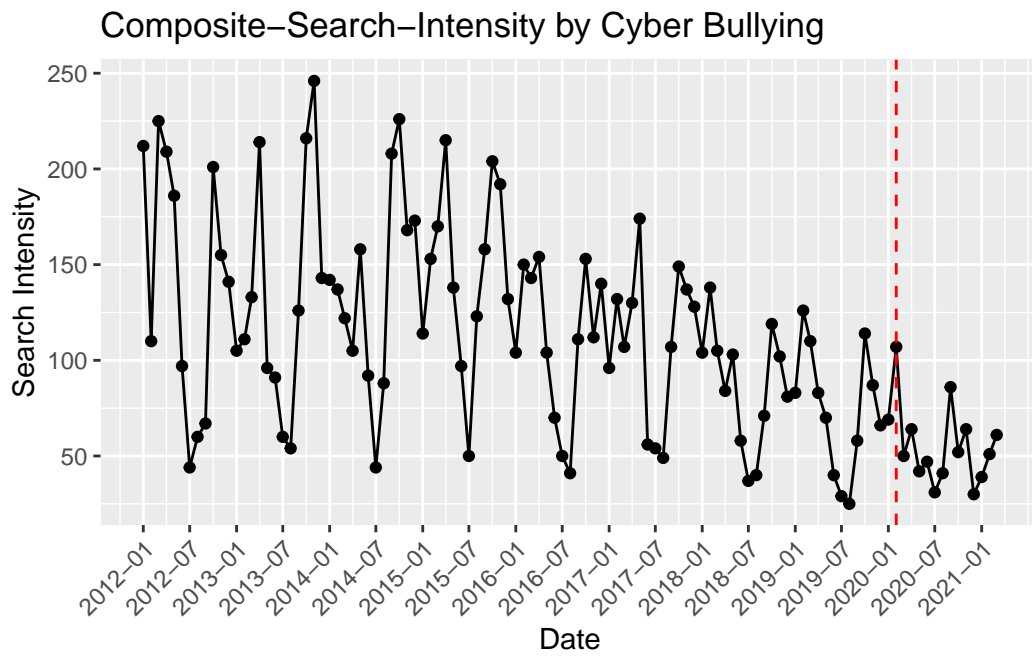


Figure 3: Composite-Search-Intensity cyber type

understanding of the multifaceted nature of bullying. By disaggregating searches based on bullying categories, such as traditional bullying and cyberbullying, analysts can discern which forms of bullying are more prevalent or garner more attention during specific time periods and in particular states.

In essence, the Table 1 table serves as a rich repository of information, offering a multifaceted perspective on the harm suffered by individuals affected by bullying. Researchers can leverage this dataset to uncover temporal trends, regional variations, and category-specific nuances, ultimately contributing to a more comprehensive and targeted approach in addressing the complex issue of bullying.

The data presented in Figure 1 provides valuable insights into the trends of searches from 2012 to 2021. The observed pattern, with peaks of bullying during the first month of school and troughs in the summer, suggests a recurring seasonal variation in the interest or concern about bullying. This cyclic behavior aligns with the typical school calendar, highlighting a potential correlation between the academic year's start and increased awareness or experiences related to bullying.

The introduction of the red dotted line indicating the onset of the pandemic adds an intriguing layer to the analysis. It appears that the traditional pattern of increased bullying searches during the initial school month was disrupted by the pandemic.(Figure 2 ) With the shift to online learning, there was a noticeable departure from the usual surge in bullying-related searches. This alteration in behavior might be attributed to changes in the educational environment, as students and educators adapted to new modes of interaction.

Surprisingly, despite the overall decrease in bullying searches during the pandemic, cyberbullying searches saw a notable rebound.(Figure 3 ) This suggests that while traditional forms of bullying may have diminished due to reduced in-person interactions, the online realm became a focal point for bullying concerns. The fact that cyberbullying searches did not rebound significantly may indicate that, even in the digital space, the overall awareness or concerns related to bullying remained somewhat subdued during this period.

The findings underscore the complex interplay between societal factors, educational settings, and the digital landscape in shaping the dynamics of bullying searches. Future research could delve deeper into the specific nuances of cyberbullying during the pandemic, exploring how the online learning environment may have influenced the prevalence and perception of such incidents. Additionally, understanding the lasting impact of these changes on bullying awareness and intervention efforts is crucial for developing effective strategies to address this issue in evolving educational landscapes.

The two-dimensional analysis of bullying searches, as depicted in Figure 4, offers valuable insights into the regional variations and the overall prevalence of bullying concerns. By juxtaposing the number of bullying searches in specific states with the nationwide search volume, a nuanced understanding of the relative intensity of bullying-related issues emerges. The substantial discrepancy between the search volumes for bullying in New York State and New

Jersey, with New York registering nearly twice the number of searches, underscores the regional disparities in the perception or awareness of bullying. This contrast could be influenced by a myriad of factors, such as differences in population density, educational policies, cultural dynamics, or varying levels of community engagement in anti-bullying initiatives. The elevated search volume in New York may suggest a higher incidence of bullying incidents or a greater public awareness and sensitivity to the issue. This heightened attention could be attributed to proactive anti-bullying campaigns, robust educational programs, or a more open dialogue surrounding the topic within the state. Conversely, the comparatively lower search volume in New Jersey may indicate a different set of contextual factors influencing the perception and reporting of bullying. The two-dimensional analysis not only provides insights into state-level variations but also allows for a comparison with the nationwide search volume. Understanding how specific states compare to the national average in terms of bullying searches can highlight regions where the issue is particularly salient or, conversely, where it may be relatively underreported or less prevalent. The two-dimensional analysis of bullying searches based on the number of state and nationwide searches reveals a nuanced landscape of regional variations in the perception and awareness of bullying. The disparities observed in Figure 4 provide a starting point for further investigations and interventions to address the complex and multifaceted nature of bullying at both the state and national levels.

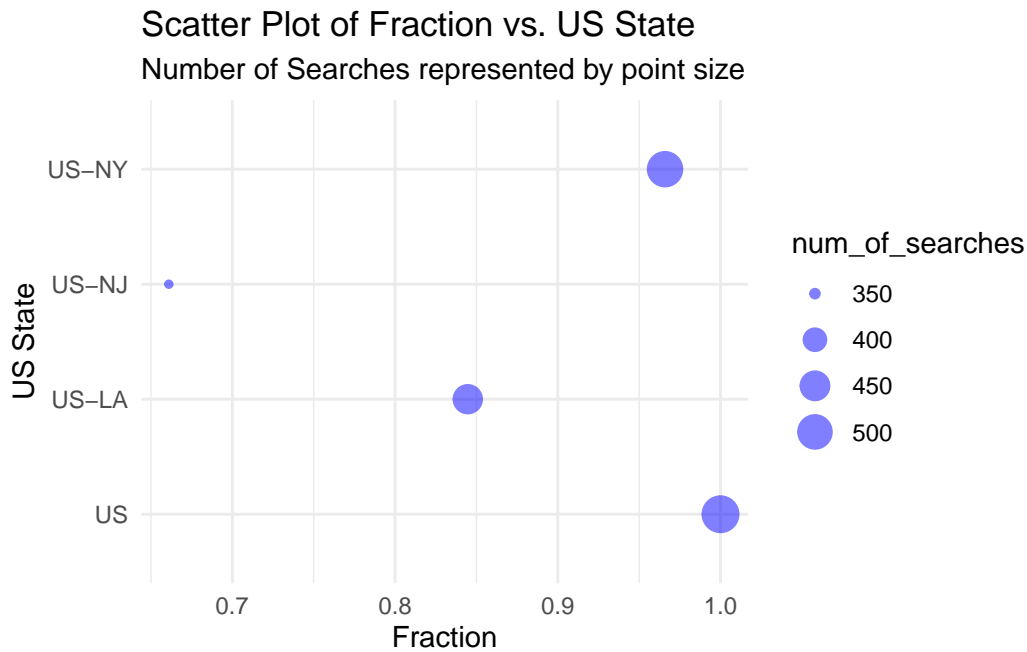


Figure 4: Composite-Search-Intensity by type

## 4 Discussion

### 4.1 COVID-19 Effects on Bullying

The overall bullying (Figure 1) displays a decreasing trend over time, with a significant decline when COVID-19 pandemic emerged. The impact of COVID-19 on bullying cases results in a reduction to the lowest levels observed. The search intensities of bullying during and after remote learning sometimes almost reached zero.

It is clear that the incidence of school bullying has generally been decreasing over time. The original paper [cite] states that COVID-19 pandemic and remote learning has caused a decrease in school bullying cases. Our data has a slight different conclusion compared to the original paper (Figure 1). It is observed that with the sudden COVID-19 outbreak in the United States around January 2020, instances of school bullying experienced a notable surge, almost reaching global maxima in February 2020. The unexpected rise in bullying during the pandemic could be attributed to various factors, for example, individuals seeking to alleviate stress through harmful behavior to other people. Furthermore, a disturbing trend of Chinese-hate emerged during this period, due to the misguided assumptions that China was responsible for spreading the virus (Jianhua Xu 2021). Asian students, especially Chinese ethnicity, might experience discriminatory actions, verbal abuse, or physical assaults due to this misinformation. So it most likely contributed to an increase in school bullying cases. As schools closed down in February 2020, a consequential decline in bullying cases was observed, at times nearly reaching zero. This is understandable since student interactions have declined due to remote learning. They did not have as much opportunity or motivation to bully others as they had before.

Surprisingly, the shift to remote learning during the COVID-19 pandemic did not lead to an expected increase in cyberbullying cases. Given that students spent the majority of their time on digital devices (Fayiqah Ahamed Bahkir 2020), it was natural to assume that cyberbullying would increase. Instead, there was a noticeable decrease. This challenges the assumption about the relationship between online activity and cyberbullying. The reduction in personal interactions during remote learning may have played a role in diminishing students' motivations or reasons to engage in cyberbullying. Also, since students stayed at home, there would always be adult supervision, for students under 12 years old (Mónica Ruiz-Casares 2021), which may have regulated their behaviour. This indicates that face-to-face interactions and the environmental factors have a strong impact on the prevalence of online harassment.

### 4.2 Cyclic Pattern of Bullying During Semesters and Vacations

In all three types of bullying (school bullying, cyber-bullying, and bullying), a cyclic pattern can be observed. It is clear that the data peaks during the months of January and September, which are the commencement of school terms, followed by a gradual reduction in bullying cases as the semester progresses. The local trough occurs during the summer vacation when

students are away from school. It can be inferred that there might be a positive correlation between academic stress and bullying and between in-person interactions and bullying (Hui Chen 2022).

As the semester begins, students need to transition from a relaxed vacation state to a rigorous school learning state. As they navigate the challenges of academic demands, they may experience stress and peer pressure from many sources (Adele Pitt 2018). This will urge students to release their emotions and stress by bullying other students. It is important for teachers and schools to see this trend and understand its implications. Effective strategies for mental health support should be carried out to deal with this, in order to reduce bullying.

Furthermore, there is obviously a clear positive correlation between in-person interactions and incidents of bullying. During the semesters, students engage in regular face-to-face interactions, potentially creating opportunities for bullying to occur. During summer vacation and the Christmas holiday, students typically limit their interactions to family members, with occasional exceptions when hanging out with friends. This reduction in direct, in-person interactions tends to reduce social pressures. Some individuals may feel the need to show dominance within the school by performing bullying behaviors in the presence of others (Albert Reijntjes 2016). However, during vacations, the reduced personal interaction may reduce their need for such assertive actions, resulting in a decrease in bullying activities.

### **4.3 Regional Dynamics in Bullying Patterns**

The bullying searches show some regional variations, with New York state having the highest number of bullying searches. This could be due to New York's large population and the heightened personal physical interactions. The busy and dynamic environment of New York may contribute to increased stress for everyone, from various sources such as work, school, societal judgments, and economic pressures. All these pressures may induce bullying behaviours to happen. Also, the city's frequent occurrences of violent incidents might also potentially influence some students to engage in bullying behaviors.

On the other hand, states like New Jersey (NJ) and Louisiana (LA) report fewer bullying cases. These states may have less intense environments, potentially resulting in decreased stress, hence less bullying to happen.

It is apparent that different regions have different effects on bullying. Considering the physical environment students find themselves in, it can significantly impact their decisions to engage in bullying or not. External factors have strong influences on students' judgments and behaviors. Therefore, it is important to have different measures to prevent bullying in different states to better address this issue.



## **4.4 Limitations**

### **4.4.1 Limited Comprehensive Representation**

One key limitation of the study is the relatively low number of data entries for each bullying type within each state, which are only 111 entries. This sample size may not be able to provide a comprehensive representation of the entire state. The analysis about bullying might be skewed.

### **4.4.2 Biases in Data Collection**

The paper has several biases in its data collection process. Firstly, it seems to lack consideration for various minority groups, such as those based on ethnicity, gender, or belonging to the LGBTQT community. This could potentially cover up the bullying experiences faced by these groups, which limits the study's inclusivity.

Additionally, socio-economic status is a critical factor influencing the bullying situation. Communities facing economic challenges lack sufficient teaching resources, and children might learn negative behaviors due to their challenging circumstances. However, the current dataset does not seem to account for these socio-economic factors, which should be added as a data feature.

Moreover, the data collection method is conducted on Google Trends, which introduces another bias. People without access to a computer or Internet may not have their experiences included in the dataset. Unfortunately, these students, who face economic difficulties, are more likely to be targets of bullying. The data does not have their perspective which compromises the comprehensiveness of the study. Also, public data from Google Trends shows the trends in the search intensity. However, there is no information about the person who performed the search. It is hard to decide whether they are the victim, the bully, or a random person.

### **4.4.3 Time Inaccuracy**

The study analyzes the bullying situation before, during, and after COVID-19, specifically focuses on the impact of remote learning. Therefore, there are some limitations related to the temporal aspect of data collection. The closure of schools during the COVID-19 pandemic occurred on different dates across states. This difference in the timing of school closures introduces potential inaccuracy in the analysis.

## 4.5 Future Steps

Future research should focus on gathering more inclusive and representative data by increasing the volume of data entries and mitigating bias in data collection. Beyond simply collecting data about bullying, researchers should investigate the mental well-being of students affected by bullying. By investigating their mental well-being, researchers can arrive at conclusions if the mental health support system is effective for students in the school. It is important to ensure that individuals who experience bullying have access to the necessary resources and support. This makes sure that the research not only analyzes the situation, but also contributes to actionable improvements for those affected.

## **Appendix**

### **A Additional data details**

### **B Model details**

#### **B.1 Posterior predictive check**

#### **B.2 Diagnostics**

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