COVID-19 Impact on NYC Asian Restaurants & Crime

Sophia Deng (sd5718), Jiashu Liu (jl4345), Jasmine Siswandjo (js13294)

Introduction

Racial tensions have existed and ballooned into conflict countless times in both recent and past history. Given that New York City is a mecca of various cultures and tensions, it is important to study and consider the impact of race-based tensions and how they propagate further into the community. New York City has numerous small businesses that are either explicitly advertised as beinlg owned by a particular ethnic subculture or that directly belong to a particular ethnic subculture (whether through the food they sell, the products they market, or the language they provide their services in). Our project aims to investigate how the COVID-19 pandemic and the emergence of the Stop AAPI Hate movement and coalition has affected Asian restaurants, leveraging both crime and review data.

It is incredibly important to examine this problem. Most existing research published on the impact of COVID-19 and subsequent racism towards Asian Americans is centered around mental health, and while this is undoubtedly important, it is not the only impact of the pandemic. We chose to examine this issue under the lens of restaurant reviews, as this is a frequently interacted with and extremely public medium. As a public medium, reviews inherently influence subsequent interactions in a way that has much larger effects than individual action. Reading a negative, racially charged review may either stoke the emotions of those who thoroughly disagree or those who thoroughly agree, which leads the way for strong waves of amplification. These patterns can be studied through foot traffic, and by proxy, number and general sentiment of restaurant reviews. Contributions and consumption of food reviews are also collected on individuals of all demographics, from race to social class to gender, which makes it an ideal medium through which to study general public discourse.

By anchoring our analysis on the COVID-19 and the Stop AAPI Hate movement, we aim to understand the interplay between macro-level socio-political dynamics and the micro-level business operations in Asian restaurants. From the start, COVID-19 has been inextricably linked to China, largely due to its initial emergence in Wuhan, China. This sparked a racial association, in no small part driven by Trump's xenophobic and anti-Asian sentiments, calling the virus the "Chinese virus" and continuing a pervasive culture of systemic racism and prejudice in the United States. As the US entered various forms of lockdowns or stay-at-home orders beginning from March 2020, anti-Asian bias, discrimination and hate surged, culminating in a tragic series of shootings in Atlanta on 16 March 2021. These shootings targeted Asian-run businesses, taking the lives of six Asian women. Amidst this backdrop of heightened racism and prejudice, the national Stop AAPI Hate coalition, and the Stop Asian Hate campaign in NYC were launched. These were founded to bring awareness to the racially motivated attacks targeting Asian Americans and Pacific Islanders, to document hate incidents, provide resources and support to victims, and to advocate for policies addressing anti-Asian racism and discrimination.

In order to garner context into existing racial tensions, we took a look at the following paper: Discrimination Experiences during COVID-19 among a National, Multi-Lingual, Community-Based Sample of Asian Americans and Pacific Islanders: COMPASS Findings. This paper by Park et al. (2022) showed that prior to COVID-19, 13–50% of Asian Americans (ASAs) reported discriminatory experiences associated with race across different settings (e.g., healthcare, employment, housing), but since the COVID-19 outbreak, ASAs have been victims of social stigma, racist incidents, and hate crimes related to COVID-19. A poll found 32% of the adult U.S. respondents have witnessed Asians being blamed for the coronavirus epidemic, and among Asian respondents, 60% have witnessed the same problem. The “Stop AAPI Hate” website received nearly 1500 reports of COVID-19-related discrimination against ASAs within the first four weeks despite shelter-in-place (SIP) orders having been implemented across many parts of the country. Between March 19, 2020 and June 30, 2021, incident reports were received from all 50 states and the District of Columbia, with 54.6% of the reports from California and New York. Race was cited as the primary reason for discrimination (90%). To consider the importance of looking at businesses, it is worth noting that the most frequent locations of discrimination were in public streets (31.6%), **at businesses (30.1%)**, 9.4% in private residences, and 8.8% were online. Ethnic Chinese became targets, exemplified by the fact that 48.1% of the hate incident reports contained at least one xenophobic statement (e.g., anti-China). While this is certainly important, we wanted to also examine the larger implications across different racial groups, as well as find a way to truly quantify the volume of discrimination that various ethnic groups face in light of controversy and unwarranted hate.

Similar studies have been conducted, however, none quite revolve around the realm of study that our project is examining. One previous study that has been conducted was The cost of anti-Asian racism during the COVID-19 pandemic. While Huang et al. (2023) examined anti-Asian racism, they did not delve specifically into other forms of racism or other marginalized groups. Additionally, they only looked at mobile phone and location data and not at reviews or sentiment analysis related to the restaurants. While foot traffic is an important delineator of restaurant success, the more public profile of a restaurant, such as its online reviews, drive further traffic and are an important indicator of how a restaurant will fare in the future. This paper did provide some notable results, specifically that “during the period after the onset of COVID-19, Asian restaurant traffic decreased by a substantial 18.4% (two-sided t-test, P<0.001, 95% confidence interval (CI)=−15.9% to −20.8%) relative to non-Asian restaurant traffic during the same period and after controlling for COVID-19 case rates. Chinese restaurant traffic dropped 10.9% (two-sided t-test, P<0.001, 95% CI=−8.4% to −13.3%), whereas non-Chinese Asian restaurant traffic saw a greater (two-sided Z-test for comparison of regression coefficients, P<0.001, 95% CI=12.6% to 22.0%) decrease of 25.0% (two-sided t-test P<0.001, 95% CI=−22.1% to −27.9%)". This inspired our project to look further at restaurant review data – simply because restaurant traffic was down did not mean that reviews would be implicated, which was something that we were curious about. We were also curious about other ethnic groups and the implications, and how different ethnic groups would fare in their relative scenarios.

Another similar study was the following paper: Do Online Reviews Enable Political Consumerism? An Empirical Analysis of "Black-Owned Business" Reviews on Yelp.com by Mitkina, Ananthakrishnan and Tan (2022). This paper provided guidance in choosing our framework. The data that was used in this paper consisted of GPS-enabled foot traffic data, business details from Yelp, and zip code level social capital data. The results of this paper showed that "Black-owned restaurants that receive reviews mentioning Black ownership experience a 10.8% increase in foot traffic compared to Black-owned restaurants that do not receive these reviews. Further, reviews that mention black ownership provide a 4.6% increase in foot traffic to these restaurants during increased consumer interest in supporting Black causes." This paper was quite interesting as it highlighted both foot traffic as well as the implications for review data. Their exploration of the demographic composition of neighborhoods and its influence on foot traffic also added important context to our understanding of how local context shapes consumer behavior, and the effectiveness of online activism in driving real-world outcomes.

By building on the insights from the previously mentioned studies, our research project aims to investigate similar dynamics within the context of Asian restaurants in NYC, and the impact of the Stop AAPI Hate movement.

Methods

We began our research by analyzing crime data, with a particular focus on hate crime incidents in NYC. Our primary goal during this phase was to identify overarching trends before and after the pandemic, as well as to examine the timeline of the Stop AAPI Hate movement. We also aimed to analyze the spatial distribution of hate crimes across NYC, specifically looking at whether these crimes occurred in locations or districts where Asian restaurants are concentrated.

To achieve these goals, we created data visualizations to better understand the hate crime data and identify potential spatial correlations between the locations of Asian restaurants and the occurrence of anti-Asian hate crimes (Jaber et al., 2022). We calculated Moran's I statistics for spatial analysis, which is useful for identifying patterns in spatial data, such as whether anti-Asian hate crimes tend to cluster in specific areas or are randomly dispersed across NYC. Values close to +1 indicate strong spatial autocorrelation, while values ranging from 0.2 to 0.4 suggest a moderate level of spatial autocorrelation. Values near 0 indicate random spatial patterns (Ryadi, 2023). Our exploration of anti-Asian hate crimes was then followed by a further investigation of review data on Asian restaurants.

For analyzing reviews, the methodology was broken down into two portions: firstly, the pre-processing of review data and sentiment extraction, followed by the subsequent analysis of sentiment. Sentiment analysis, defined as "the process of obtaining meaningful information and semantics from text using natural processing techniques and determining the writer's attitude, which might be positive, negative, or neutral" (Nandwani, 2021), was the basis of our approach. Our goal in this process was to determine the polarity of reviews using a benchmarked process where reviews were held to the same classification scale, to ensure consistency and understand the reviews as a whole.

For pre-processing reviews and gathering sentiment, we experimented with several sentiment analysis algorithms. Ultimately we settled on TextBlob, a popular Python library, for processing review text. TextBlob utilizes a pre-defined dictionary that classifies positive and negative words, and represents a string of text as a bag of words. Words are individually scored and then final sentiment is calculated using a pooling operation which keeps words in reference to each other. Thus, a review that classifies a restaurant as "not good" would not be scored neutrally ('not' taken as a negative word, 'good' taken as a positive word) and instead would be scored as a negative sentiment. We also ran our reviews through VADER and examined sentiment scores, but upon further investigation, realized that the sentiment analyzed was not contextual, so reviews were not being taken in light of the greater context. FLAIR was also used and tested, but we noticed that it was trained on IMDB data and the generalization was not as strong due to the fact that movie data and restaurant review data did not share as many signifying words for sentiment analysis. Thus, Textblob became our main sentiment analysis tool.

Our next step in examining review data was to classify sentiment and to observe overall patterns in restaurant reviews, both in terms of pure number of reviews and in terms of general sentiment of reviews. We first examined our data to make sure that comparison points seemed feasible, by first looking at the pure number of reviews as well as the overall distribution of reviews to ensure that the three comparison groups had similar baseline values. After observing general patterns, we wanted to also investigate the change in average ratings and overall polarity of reviews to see if there was a difference both within groups and across groups. We then chose to do a deep dive into each restaurant to see if we could distinguish the polarity of reviews relative to each rating, to see if the positive reviews became more positive, or if the negative reviews became more negative. We did this because of the lack of granularity on the more extreme ratings: if someone loved a restaurant before Stop AAPI Hate but wanted to profess more support after the movement, they would still rate the restaurant as 5 stars but would use more extreme verbiage to display this (so, instead of saying that they liked a restaurant they might say that they loved a restaurant). This was key to our particular study into reviewers' perceptions and expression, because the choice of words can have a tremendous amount of specificity and impact.

In considering how to break down this problem, we chose to use a Generalized Additive Model (GAM) instead of a linear fit predictor. We did so in an effort to isolate the true change in polarity as a function of date and rating. GAMs are "machine learning models that model *smooth*, non-parametric relationships between individual predictors and dependent variables, and are easy to interpret" (Larsen 2015). Under initial consideration, a multilevel-model with linear effects was considered, however, we have reason to believe the relationship between date and rating is not strictly linear, so a GAM was used instead. The advantage of a GAM is that it allows for replacement for a linear effect on a model with a smooth and differentiable effect, which is done using splines. Our model treated each numerical rating value (ranging from 1 to 5) independently and incorporated a smoothed function of date by rating, effectively accommodating non-linear effects and their interaction. To facilitate this, a tensor product with multiple degrees of freedom was employed as the function for the GAM model for each respective cuisine. We tuned the model based on a number of evaluation metrics, setting the number of knots at 4 for rating, and 10 for date. Using the predicted values of polarity, we can visualize the differences in sentiment that have not already been accounted for by rating, over our timeline of interest.

Data

Hate Crime Data

The [NYPD Hate Crimes] dataset from NYC Open Data portal contains hate crime incidents in New York City from 2019 to 2024, with a total of 2870 records. The dataset documents the record date, descriptions of the bias motivation for each incident, the offense category, and the specific NYPD description of the offense. There are 27 types of bias motivations, such as anti-Jewish, anti-Black, anti-Muslim, and anti-Asian. The offense categories include felony, misdemeanor, and violation, with three categories in total. In this project, we will focus on the Anti-Asian bias category. The dataset also includes the precinct number in which each incident occurred.

To better visualize the distribution of the hate crimes in NYC, we later merged the NYPD hate crimes data with the [Police Precincts GIS data] from NYC Open data.

Review Data

The Google Review dataset [Google Local Data (2021)] was compiled by Tianyan Zhang and Jiacheng Li from UCSD. This dataset contains review information on Google maps and business metadata up until September 2021 in the United States, with over 600 million reviews on over 100 million users. For New York State, the repository contained 33 million reviews for 272,000 businesses. However, it lacked useful cuisine tags, so a supplementary data source was needed to categorize restaurants by cuisine type. Thus, this data was used in conjunction with a list of restaurant names that were gathered from the Yelp API. There were a few interesting takeaways from using Yelp for an up-to-date list of restaurants by cuisine. Notably, the Yelp Academic Dataset is publicly available and has a vast amount of data, however, it contains no data for New York, rendering it unsuitable for our use case. The next step was to collate data from the Yelp API, but we ran into limitations as Yelp restricts API calls to 50 per user, per day. To circumvent this, we used a workaround where API calls were looped with an offset to mask the call, so that at least 1000 restaurant names of a given type (Asian, Mexican, and pizza) were collected. Notably, Yelp also gave us the flexibility to specify restaurant categories, so within Asian restaurants we were able to define a filter of Chinese, Japanese, Korean, Vietnamese and Thai restaurants. We chose to group these restaurants together under a thesis gathered by media observations that a significant amount of the American population would be unable to disambiguate between specific East Asian nations (Huang et al., 2023). Additionally, “individuals reporting discrimination in COMPASS (COVID-19 Effects on the Mental and Physical Health of AAPI Survey Study) included those of Hmong, Chinese, Korean, Filipino, Japanese, Vietnamese, Asian, Indian, and Native Hawaiian and Pacific Islander descent”, which further supports our decision to group these categories together (Park et al., 2022). Mexican restaurants consisted of restaurants categorized as either Tex-Mex, Mexican or New Mexican. Pizza restaurants were those in the pizza category.

When selecting additional types of restaurants to include alongside Asian restaurants for comparative analysis, we opted for Mexican restaurants and pizza restaurants. Mexican cuisine was chosen due to its popularity across a diverse demographic, making it a suitable baseline reference. Reviews of Mexican restaurants served as our control group because they lacked a direct association with the COVID-19 virus. Pizza restaurants were also selected for comparison, as they remained operational to a comparable extent as pre-COVID-19, with a strong emphasis on delivery services.

Results

Hate Crime Analysis

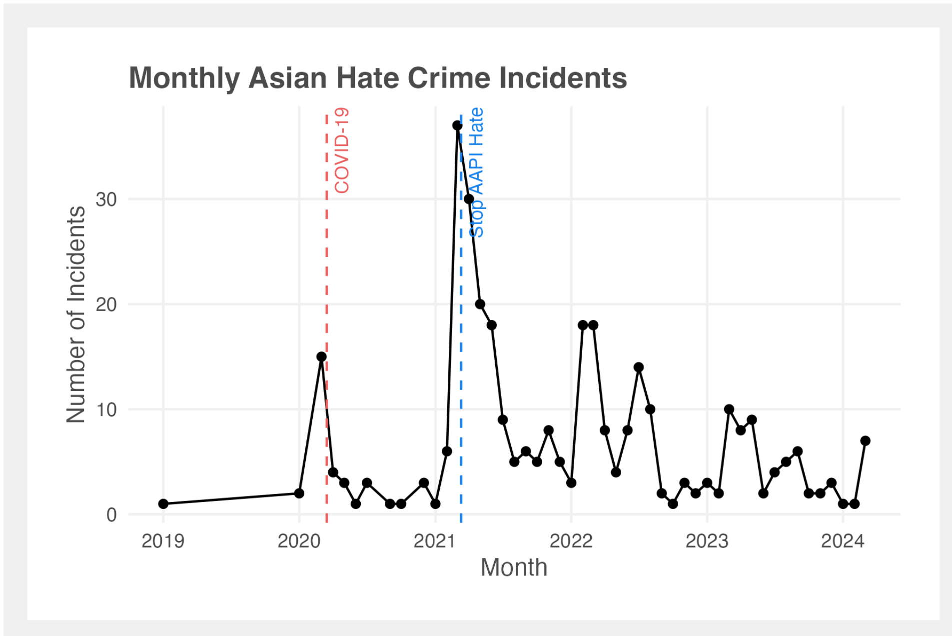

Fig 1. Overview of Anti-Asian Hate Crimes from 2019 to 2024

The plot displays the trends of the number of monthly anti-Asian hate crimes over time, from 2019 to 2024. The plot reveals that there was an increase in the number of anti-Asian hate crimes at the beginning of 2020, specifically in March 2020, when the COVID-19 shutdown happened. The sharp decrease in the number of anti-Asian hate crimes after March 2020 might be due to the impact of the COVID-19 shutdown. Another sharp increase in the number of anti-Asian hate crimes happened in March 2021. The Stop AAPI Hate movement also started in March 2021.

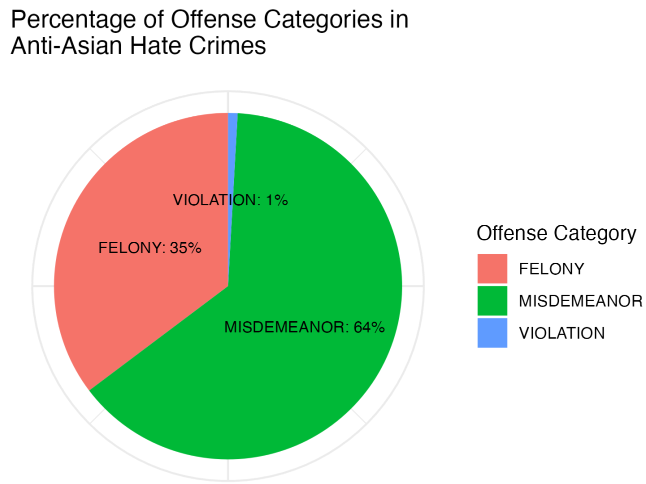

Fig 2. Percentage of Offense Categories in Anti-Asian Hate Crimes

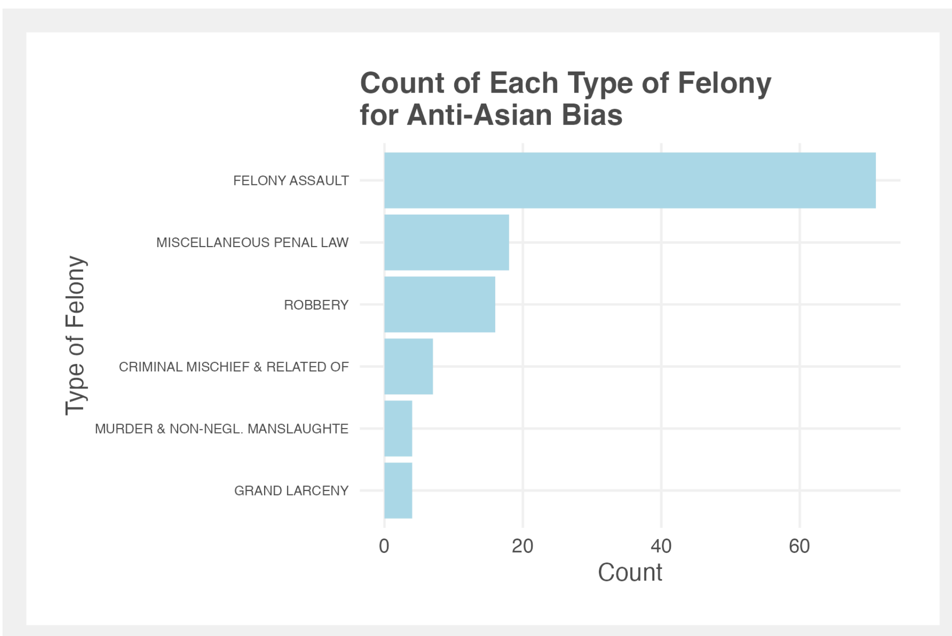

Fig 3. Counts of Each Type of Felony in Anti-Asian Bias

The pie chart in Figure 2 shows the percentage of each offense category in anti-Asian hate crimes. The chart reveals that 64% of the anti-Asian hate crimes are misdemeanors, 35% are felonies, and 1% are violations. The bar chart in Figure 3 shows the total number of cases for each type of felony. The plot indicates that the majority of hate crime incidents are felony assaults.

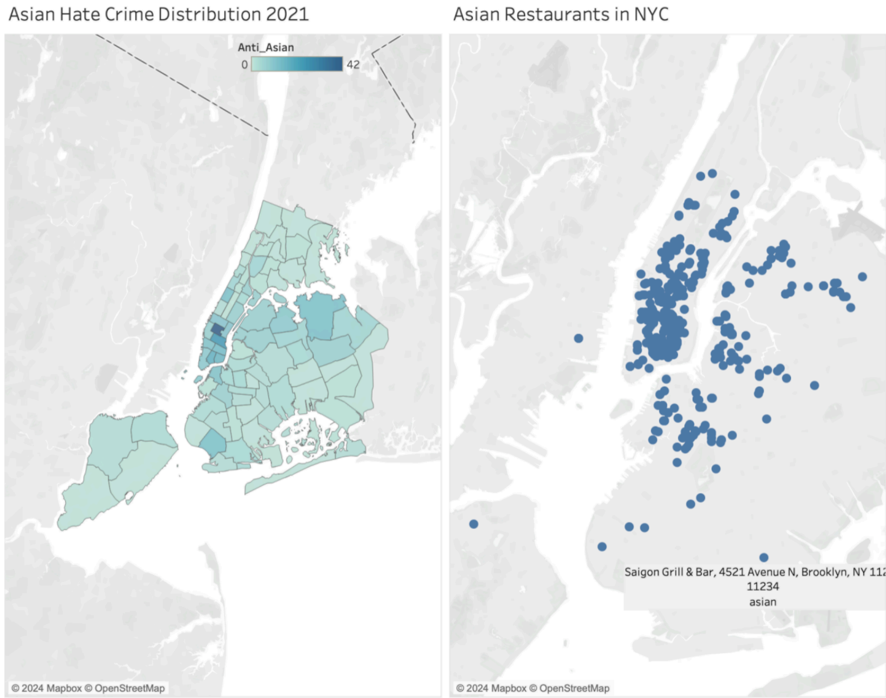

Fig 4. Anti-Asian Hate Crimes Distribution in 2021 and Asian Restaurants in NYC

The previous analysis shows that there is a sharp increase in the number of anti-Asian hate crimes in 2021. The left panel is a choropleth map highlighting the distribution of anti-Asian hate crimes in New York City during 2021. The map shows the city's precincts shaded according to the frequency of anti-Asian hate crimes, with darker shades indicating higher crime counts. The precinct district with highest frequency of anti-Asian hate crimes is the 14th precinct, which is the Midtown South Precinct. This area contains commercial offices, hotels, Times Square, Grand Central Terminal, Penn Station, Madison Square Garden, the Koreatown section, and the Manhattan Mall Plaza. Surrounding precincts, such as the 13th, 17th, and 18th, also show higher crime rates. Precincts 5, 6, and 7 experienced moderate crime density. Other precincts, such as the 109th and 115th in Queens and the 62nd in Brooklyn, also have a higher frequency of anti-Asian hate crimes compared to other precincts in the city.

The right panel is a dot map displaying the locations of Asian restaurants across New York City. Each blue dot represents an Asian restaurant. The map reveals a clear concentration of Asian restaurants in Manhattan. Together, these two maps show that the geographic patterns of anti-Asian hate crimes align with the distribution of Asian businesses in the city. This observation suggests that there might be an interplay between anti-Asian hate crimes and the reviews of Asian restaurants. We want to further explore whether anti-Asian sentiments are reflected in the reviews of these restaurants.

	Year	StatisticsValue	p_value
Moran I statistic	2019	-0.01766917	8.385090e-01
Moran I statistic1	2020	0.14345518	2.079352e-02
Moran I statistic2	2021	0.38205818	3.121182e-08
Moran I statistic3	2022	0.49308334	5.471946e-12
Moran I statistic4	2023	0.15160233	1.425938e-02
Moran I statistic5	2024	0.02406684	2.374297e-01

Fig 5. Moran's I Statistics Values for Anti-Asian Hate Crime Data from 2019 to 2024

The result table of Moran's I statistics provides insights into the spatial clustering of anti-Asian hate crimes in New York City from 2019 to 2024. The Moran's I statistics for 2019 and 2024 indicate no significant spatial autocorrelation, with p-values further confirming the lack of significant clustering. In contrast, the Moran's I statistics for 2020 and 2023 suggest slight positive spatial autocorrelation, with p-values statistically significant at the 5% level. The Moran's I statistics for 2021 and 2022 demonstrate moderate to strong spatial autocorrelation, with highly significant p-values further emphasizing the strength of the clustering.

This finding suggests that certain periods, particularly during or after events such as Covid-19 pandemic and Stop AAPI Hate movement, experienced more significant spatial clustering of anti-Asian hate crimes. This underscores the spatial analysis in understanding the geographical distribution of such incidents while considering the potential influence of external events on hate crime patterns.

Review Analysis

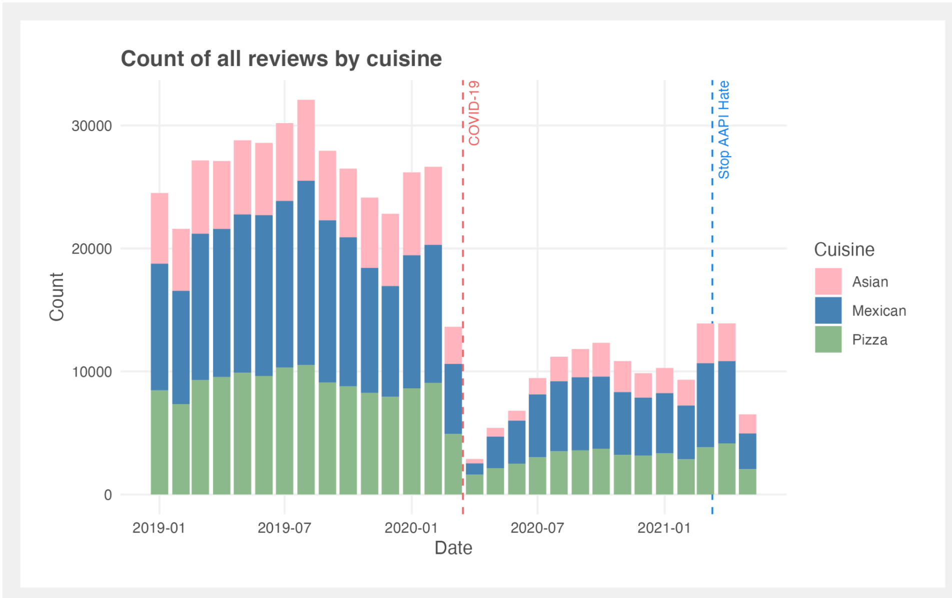

Fig 6. Stacked bar chart of count of all reviews for Asian, Mexican and pizza restaurants

The COVID-19 shutdown for New York City started on March 17 2020, with restaurants becoming limited to take-out and delivery only. This was visible in review counts, which we use as a proxy for restaurant visitation as well. Reviews dropped precipitously from February to March, hitting its lowest point in April 2020. Even though Asian restaurants were already receiving fewer reviews than Mexican and pizza places, likely because there are fewer Asian restaurants than the others, the drop in April 2020 was the largest for Asian cuisine. Reopening in NYC began on 8 June, in phases. From June 22, NYC moved to Phase 2 of its reopening plan, which marked the beginning of outdoor dining at restaurants, which is visible on the bar chart, as the number of reviews increased. However, the number of Asian restaurant reviews never reached its pre-pandemic levels, and neither did the other cuisines. The number of Asian restaurant reviews also does not seem to rise as quickly as Mexican or pizza restaurant reviews numbers do.

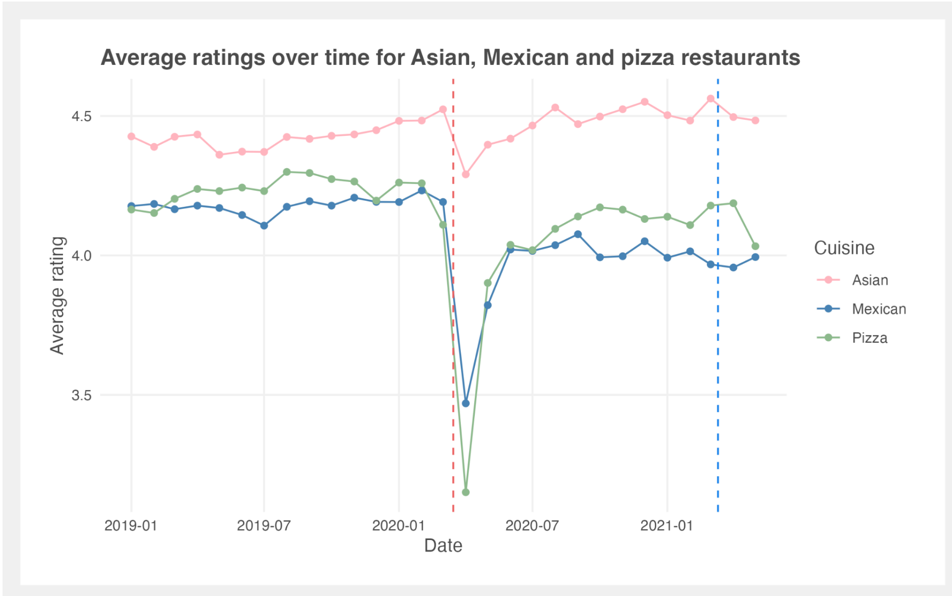

Fig 7. Average ratings over time for Asian, Mexican and pizza restaurants

While observing average ratings over time, we saw that generally, Asian restaurants had the highest average rating to begin with, while both pizza and Mexican restaurants had relatively lower ratings which dipped quite substantially at the start of COVID-19. Looking at the number of reviews themselves in April of 2020, pizza restaurants had about 1,600 reviews while in contrast, Mexican restaurants had 920 reviews and Asian restaurants had only 351 reviews. Part of the subsequent data analysis operates off of this implication, where especially during lockdown, many Asian restaurants were not operating and thus comparably, review quality may not be as accurate. Generally though, it seemed like average ratings dipped for all restaurants, and there was not a large noticeable trend of average ratings even after the Stop AAPI Hate movement started in March of 2021.

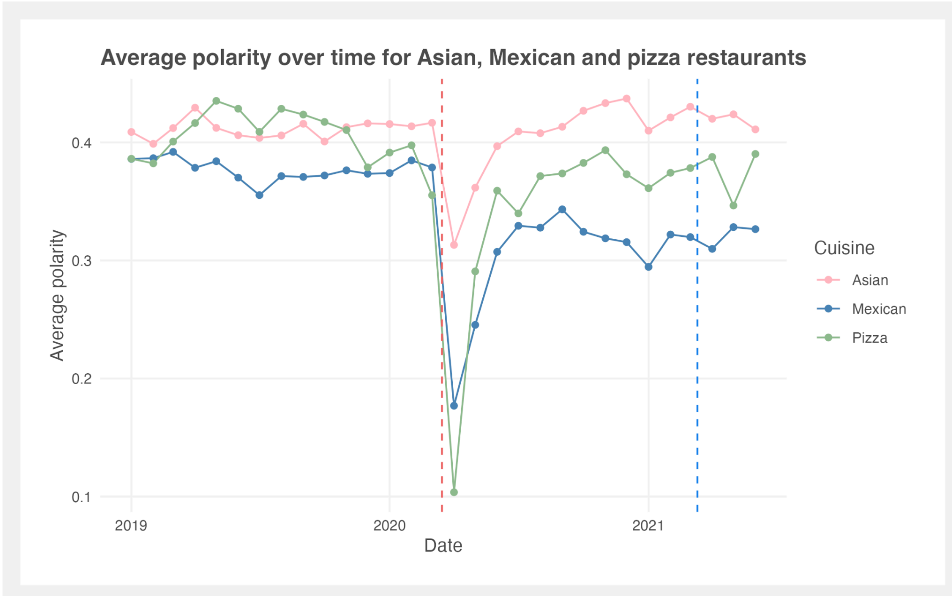

Fig 8. Average polarity over time for Asian, Mexican and pizza restaurants

We then examined the average polarity of restaurant reviews over time. Average polarity shared a similar trend to average ratings, which we found to be in part due to the number of reviews and the fact that pizza restaurants were the most likely to be open during April 2020, since they were already heavily delivery and take-out focused. Upon examination of reviews, we found that the reviews were centered around poor delivery experience, extremely long waits, and related to order mistakes. In general, upon examination of reviews of all cuisines, none contained any specific racist sentiment. Subsequently, we mapped specific sentiment changes over time.

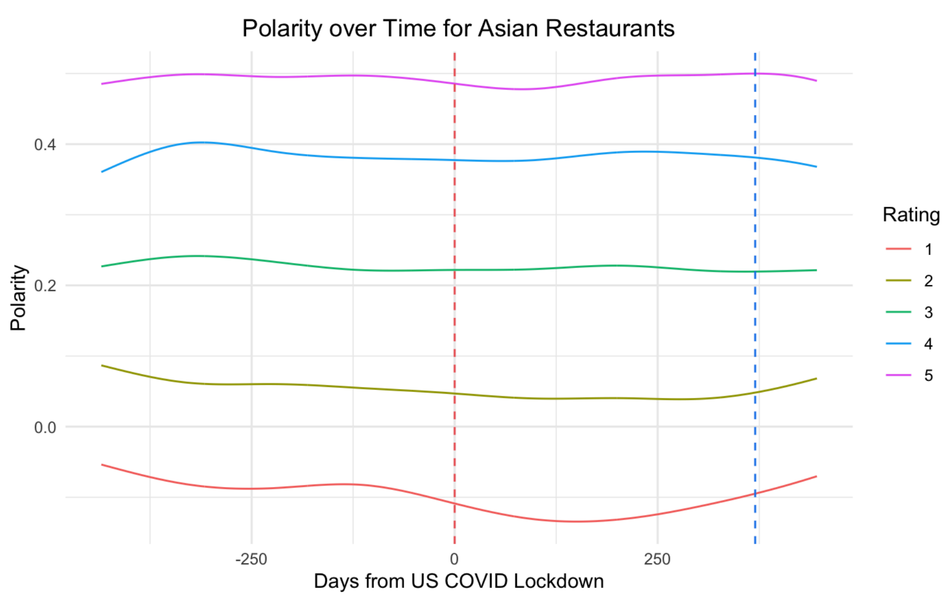

Fig 9. Predicted polarity over time for Asian restaurants

The analysis of predicted polarity in review text over our selected timeline for Asian restaurants revealed a notable trend in sentiment. Specifically, there was a decrease in polarity for 1-star reviews just before the start of the COVID-19 pandemic. This decrease continued for several months, reaching its lowest point after the implementation of lockdown measures. However, there was a subsequent increase in polarity observed shortly before the emergence of the Stop AAPI Hate movement. This trend suggests a fluctuation in sentiment towards Asian restaurants, which might have been caused by the rise of anti-Asian sentiment due to COVID-19, and then of support during the Stop AAPI movement. It also seems as if sentiment increased even before the actual movement was started, which aligns with the growing awareness and discourse surrounding the issues faced by Asian communities.

```
Analysis of Deviance Table

Model 1: polarity ~ rating * date_lub
Model 2: polarity ~ 1 + te(rating, date_lub, k = c(4, 20))
  Resid. Df Resid. Dev     Df Deviance  Pr(>Chi)
1     61356     4713.0
2     61328     4695.8 27.504   17.209 < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Figure 10. Anova Goodness of Fit table comparing linear model and GAM with a tensor product

To confirm the suitability of the GAM for our data, we conducted an ANOVA analysis. We see a significantly improved goodness of fit compared to a linear model.

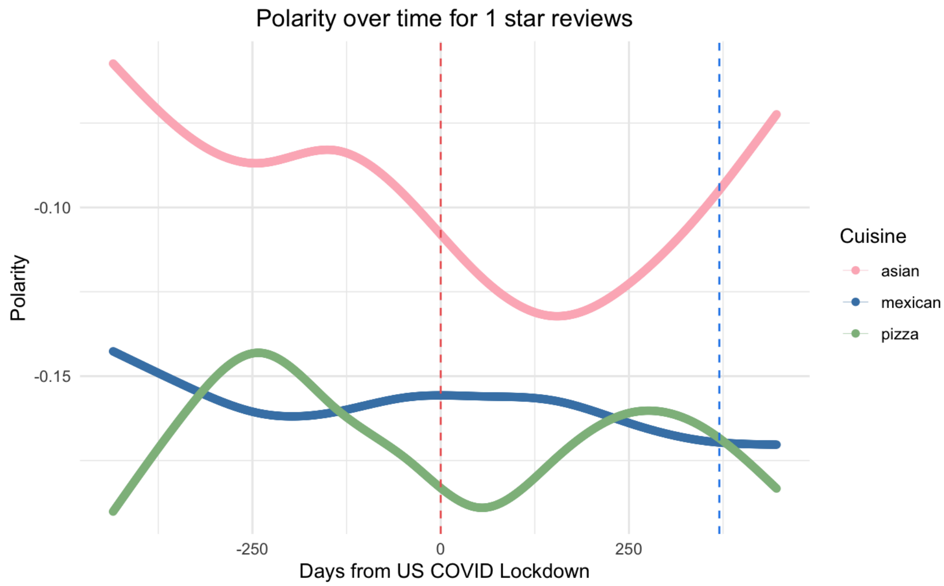

Fig 11. Polarity over time for 1 star reviews for Asian, Mexican and pizza restaurants

The direct comparison of polarity over time for 1 star reviews for Asian, Mexican and pizza restaurants show a pronounced dip in the polarity of Asian reviews, even more so than Mexican and pizza places. Remarkably, this negativity starts approximately 100 days before the start of the US COVID-19 Lockdown, which maps to around when lockdowns began in several Asian countries. The overall negativity of Mexican 1 star reviews remained somewhat similar before and after lockdown, and pizza sentiment wavered greatly between, with a dip during the start of the pandemic and a dip back down. There was a noticeable uptick in polarity towards Asian restaurants, even for 1 star reviews, after the rebound.

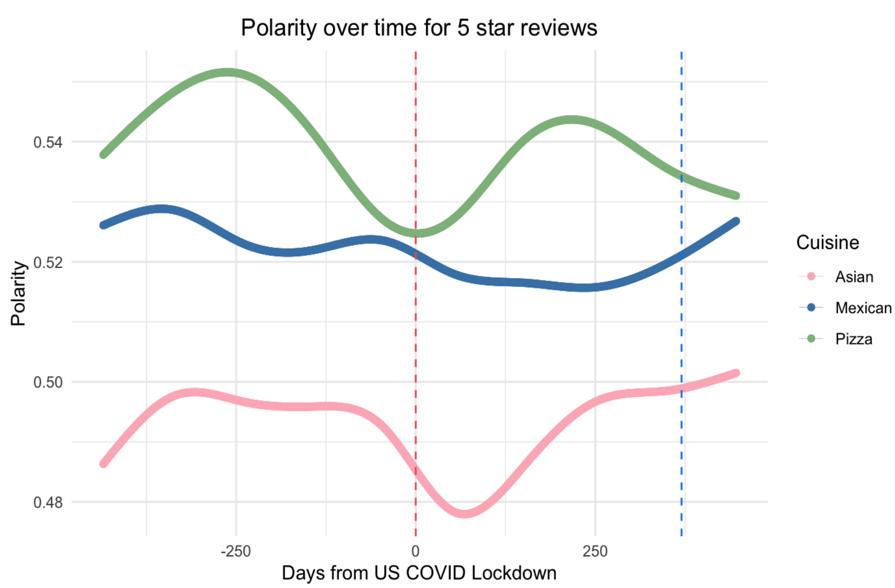

Figure 12. Polarity over time for 5 star reviews for Asian, Mexican and pizza restaurants

Examining polarity over time for 5 star reviews also produces quite interesting results. Generally, the polarity of 5 star reviews for Asian restaurants remain the lowest out of all restaurants even though Asian restaurants had the highest average review rating. Even for 5 star reviews, there was a significant dip in polarity for Asian restaurants at the beginning of US COVID-19 lockdown. Meanwhile, Mexican polarity remained somewhat stable throughout the lockdown, and pizza remained continually volatile with dips slightly before COVID-19 and a subsequent rise and drop in the middle of lockdown.

Discussion

Our analysis sheds light on the complex dynamics surrounding Asian restaurants in NYC during the COVID-19 pandemic and the emergence of the Stop AAPI Hate movement. We found several interesting trends in both review sentiment and hate crime incidents.

Notably, there was a significant increase in the number of anti-Asian hate crimes in March 2020 and again in March 2021, corresponding to the COVID-19 shutdown and the Stop AAPI Hate movement, respectively. This spike highlights the vulnerability of the Asian community during these periods. In addition, the distribution of hate crime incidents in NYC roughly mirrors the locations of Asian restaurants, particularly in 2021. This spatial correlation indicates that areas with higher concentrations of Asian restaurants also experienced more anti-Asian hate crimes, suggesting that these locations might be targeted.

Our spatial analysis, conducted using Moran's I statistic, further supports these observations. The Moran's I values for 2021 and 2022 show moderate to strong spatial autocorrelation, indicating that anti-Asian hate crimes during these years were not randomly distributed but clustered in specific areas. This suggests that certain precincts or neighborhoods might be more susceptible to these incidents, possibly due to higher Asian populations or a concentration of Asian businesses.

However, we are hesitant to use hate crime data for any time-series predictive analyses, as the significant increases and decreases in anti-Asian hate crimes are very likely to have been largely influenced by external factors like the COVID-19 pandemic. The unpredictable nature of such incidents makes reliable forecasting challenging, and we recommend exercising caution in interpreting such trends without considering broader contextual influences.

The significant drop in reviews for Asian restaurants during the initial months of the pandemic highlights the disproportionate impact of COVID-19 restrictions on these businesses. While all restaurants experienced a decline in reviews, Asian restaurants, in particular, saw a sharper decrease, indicating greater challenges in adapting to the new operating conditions. This could be attributed to various factors, including reduced foot traffic, cultural biases, and xenophobic sentiments exacerbated by the pandemic. Moreover, the analysis of review sentiment showed a notable increase in negativity among 1-star reviews during the early stages of the pandemic. This suggests a heightened level of dissatisfaction among customers that was more extreme than for the other cuisines. Interestingly, despite the negative sentiment, there was also an uptick in positivity among the 5-star reviews, which suggests a divergence in customer experiences or perceptions during this period.

Potential ethical implications or concerns

Although we have the reviewers' names for the review data, we lack specific information about the reviewers' cultural background, demographic and neighborhoods. This omission represents the potential for sampling bias within the review data, which we may not be able to detect. If the reviews we analyzed are primarily from a specific neighborhood or demographic, the results might not reflect broader public sentiment. It is important to recognize that such biases could affect the validity and generalizability of our findings and that further steps should be taken to ensure a more representative analysis.

In addition, the sentiment analysis algorithm we used may have inherent biases. Asian culture is diverse, and some reviews might contain cultural references or idioms. If these idioms are written in languages other than English, it becomes even harder for the algorithm to understand their cultural meaning. This can lead to skewed or inaccurate interpretations, especially with sensitive topics like race or ethnicity. A number of reviews were automatically translated by Google Translate, which could also affect sentiment, as words chosen by the translation feature may already be skewed.

Addressing stigma as a potential ethical concern is crucial, especially considering its implications on young adults. As our analysis examines the trends in review sentiment reviews post-COVID-19, there is a risk that individuals, particularly young adults, may internalize negative perceptions reflected in these reviews, or fear future events that could traumatize them again. Exposure to such narratives could potentially perpetuate stigma, leading to lasting psychological effects. Young adults are particularly susceptible to the potentially deleterious effects, and may form lasting impressions based on the sentiments expressed in these reviews, or fear future stigmatization or discrimination (Boden-Albala et al., 2023). It is essential to approach the results with sensitivity and awareness of the potential effect on mental well-being, and to consider the potential consequences for individuals and communities. We tried to provide context for the changes in review sentiment, and also note the uptick in positive sentiment prior to and during the Stop AAPI Hate coalition. Additionally, we aimed to be cognizant of the language used to describe our results and ensure it does not further stigmatize or discriminate against any group. Ultimately, prioritizing the ethical implications of the research ensures that the study contributes to knowledge advancement while minimizing harm to vulnerable populations. This also leads into our first limitation, which was characterizing review data from 2021 onwards in order to paint a picture of current sentiment levels.

Limitations

The lack of easily accessible review data from September 2021 onwards limited us in examining the trends in sentiment in review data after that date. The dynamics post-2021 would have been able to inform us of evolving sentiments towards Asian restaurants and the prevalence of anti-Asian hate. Fortunately, as the number of Anti-Asian hate crime incidents seems to show a return to pre-pandemic levels, and from anecdotal evidence, it seems as if the heightened negative anti-Asian sentiment was a temporary flux due to COVID-19, and may no longer reflect the current situation. Ongoing research to monitor and assess societal attitudes and behaviors towards marginalized populations is still necessary, especially in the aftermath of current significant events.

There are also limitations inherently embedded in the hate crime data. Hate crimes are often underreported due to various reasons such as victims' fear of retaliation, distrust of authorities, or lack of awareness of reporting mechanisms. Inconsistent reporting practices among police or other law enforcement agencies can also lead to disparities in reported hate crimes. Hate crimes are also delineated into specific categories, but these categories might not capture the full spectrum of hate-motivated incidents, with discriminatory intent likely to fall into multiple protected categories. Moreover, New York requires that bias is the whole or substantial factor motivating an attack, which is difficult to prove, and is also subject to the perceptions of law enforcement or societal attitudes towards certain groups. While hate crime data provides valuable insights, we should also consider that they might be under-representing the true number of incidents, and supplement with other sources of data to provide a more comprehensive insight into bias-motivated offenses. For example, the Stop AAPI Hate coalition reported 11,500 anti-AAPI hate incidents in the two years after the pandemic started in the US, from March 2020 (Stop AAPI Hate, 2022). In contrast, the number of federally recognised hate crime incidents totalled 1025 in 2020 and 2021, according to hate crime statistics published by the FBI.

Our sentiment analysis could have been improved by using an NLP model that has been trained on review data, or one that has been trained to find subtle signs of racism. However, from reading the reviews around the COVID-19 period, there are no explicitly racist or xenophobic reviews, and likely have already been removed. This adds additional complexity as the NLP model would have to be trained to parse out signs of xenophobia that have evaded Google Business's own filters.

Conclusion

Our study offers a unique perspective while contributing to the literature surrounding the impact of COVID-19 and the Stop AAPI Hate movement on Asian communities and restaurants, as it relates to restaurant review data. Reviews are a widely accessible and influential medium, and can shape subsequent interactions and opinions on a larger scale. Our results show that there was a notable impact of COVID-19 and Stop AAPI Hate on the overall sentiment and safety of Asians living in New York City. While initial analyses of average ratings and polarity suggested Asian restaurants did not experience negative impacts akin to Mexican or pizza establishments, a deeper analysis of polarity across 1 star and 5 star reviews uncovered a marked increase in negativity within both 1 star and 5 star reviews, particularly in comparison. Similarly, hate crime spiked sharply during the key months in our timeline. Interestingly, the uptick in positivity starting from before the Stop AAPI Hate coalition seems to precede the movement, and likely continued to raise awareness of anti-Asian discrimination and bias afterwards, along with their stated mission of advocacy, support and equity. In conclusion, our study provided a unique and innovative framework for investigating anti-Asian sentiment, and now that we have a deeper understanding of the sentiment following the pandemic, addressing underlying factors such as reactionary fear to disease, blaming, and racial othering are the crucial next steps to contributing to positive social change within the United States.

Group Member Contributions

Hate crime data, analysis and visualization - Jiashu
Review data, analysis and visualization - Sophia and Jasmine
Report writing and presentation slides - Jasmine, Sophia and Jiashu

References

Boden-Albala, B., Ding, X., Ryan, N., Goodman, S., Wing, J., Runnerstrom, M. G., ... & Drum, E. (2023). Anti-Asian racism related stigma, racial discrimination, and protective factors against stigma: a repeated cross-sectional survey among university students during the COVID-19 pandemic. *Frontiers in Public Health*, *11*, 958932.

Charles Fain Lehman, & Lehman, C. F. (2023, April 4). Understanding and reducing hate crimes in New York City. Manhattan Institute. https://manhattan.institute/article/understanding-and-reducing-hate-crimes-in-new-york-city

Han, S., Riddell, J. R., & Piquero, A. R. (2023). Anti-Asian American Hate Crimes Spike During the Early Stages of the COVID-19 Pandemic. *Journal of interpersonal violence*, *38*(3-4), 3513–3533. https://doi.org/10.1177/08862605221107056

Huang, J. T., Krupenkin, M., Rothschild, D., & Lee Cunningham, J. (2023). The cost of anti-Asian racism during the COVID-19 pandemic. *Nature human behaviour*, *7*(5), 682-695.

Jaber, A. S., Hussein, A. K., Kadhim, N. A., & Bojassim, A. A. (2022). A Moran's I autocorrelation and spatial cluster analysis for identifying Coronavirus disease COVID-19 in Iraq using GIS approach. Caspian Journal of Environmental Sciences, 20(1), 55-60. doi: 10.22124/cjes.2022.5392

Larsen, K. (2015). GAM: the predictive modeling silver bullet. *Multithreaded. Stitch Fix*, *30*, 1-27.

Mitkina, M., Ananthakrishnan, U. M., & Tan, Y. (2022). Do Online Reviews Enable Political Consumerism? An Empirical Analysis of "Black-Owned Business" Reviews on Yelp.com. *Available at SSRN 4042411*.

Nandwani, P., & Verma, R. (2021). A review on sentiment analysis and emotion detection from text. *Social network analysis and mining*, *11*(1), 81.

NYC Mayor's Office of the Chief Technology Officer. (2021, July 16). Preventing hate dashboard. Medium. https://medium.com/nyc-mayors-office-of-the-cto/preventing-hate-dashboard-43883b24924f

Ryadi, Gabriel. (2023). Investigating Crime Patterns in New York City using Spatial Point Pattern Analysis Techniques. 10.13140/RG.2.2.29358.79689.

Stop AAPI Hate. (2022). *Two years thousands of voices: what community-generated data tells us about anti-AAPI hate*. Stop AAPI Hate (US). https://stopaapihate.org/wp-content/uploads/2022/07/Stop-AAPI-Hate-Year-2-Report.pdf

Ta Park, V. M., Dougan, M. M., Meyer, O. L., Nam, B., Tzuang, M., Park, L. G., ... & Tsoh, J. Y. (2022). Discrimination experiences during COVID-19 among a national, multi-lingual, community-based sample of Asian Americans and Pacific Islanders: COMPASS findings. *International journal of environmental research and public health*, *19*(2), 924.