Proceedings of the 2nd International Conference on Interdisciplinary Humanities and Communication Studies
DOI: 10.54254/2753-7064/31/20232009

Temporal Dynamics of Online Sentiments: Investigating the Impact of Real-World Events on #StopAsianHate Twitter Movement

Li'an Ren[1,a,*,†], Tianlin Liu[2,b,†], Junming Zheng[3,c,†], Luyao Zhao[4,d,†], Haobo Zhang[5,e,†]

[1]School of Humanities and Social Sciences, Xi'an Jiaotong University, Xi'an, 710049, China
[2]Del Norte High School, San Diego, 92127, United States
[3]Changwai Bilingual School, Changzhou, 213000, China
[4]Affiliated High School of South China Normal University International Department, Guangzhou, 510000, China
[5]High School Affiliated to Renmin University of China, Beijing, 100080, China
a. 1206295216@qq.com, b. liutianlin135135@gmail.com, c. eddiezjm8@gmail.com, d. zhaoly.ashley2022@gdhf.com, e. haobozh8@gmail.com
**corresponding author*
[†]These authors contributed equally.

Abstract: Stop Asian hate has been a heated topic on social media platforms because of the increase in Asian hate after the breakout of COVID-19 and hate crimes caused by Asian hate. The hashtag #StopAsianHate on Twitter points out that making proper consensus decisions can be an effective way to spread the impact of hate crimes and attract more attention to Asian hate to call for actions to stop Asian hate. To gain more theoretical knowledge for consensus decisions and guidance of public opinion, this study used MDCOR and tools developed by our researchers to analyze posts under tweets (opened answers) posted under the hashtag #StopAsianHate (from March 1, 2022, to August 31, 2023). The tools being used can directly analyze the open answers on Twitter, providing the study with the identification of topics and sentiment analysis. Through the analysis of 5-month data, which is far longer than other research, the dynamic of the public's opinion and sentiment is clearly shown. By understanding the shifts in public opinion and sentiment, more valid strategies for advocacy of anti-racism are hoped to be found.

Keywords: Stop Asian Hate, Data Mining, Social Media, Sentiment Analysis

1. Introduction

Due to the pandemic that raised prejudices against the Asian community, the Asian community has been burdened with an increasing amount of negative sentiment or hate speech. Data that intuitively reflects the extent of discrimination Asian Americans suffered during the COVID-19 pandemic cannot be available without the surveys done by previous researchers. According to Federal Bureau of Investigation data, the number of crimes triggered by Asian Hate increased by 77% in 202012 [1]. In addition, according to a nationally-representative survey conducted by SAH and the Edelman Data & Intelligence Team in 2020, nearly one in five Asian Americans (21.2%) and Pacific Islanders

(20.0%) have experienced a hate incident in the past year [2]. A significant racist incident named the Atlanta Spa Shooting originates from anti-Asian sentiments. On the evening of March 16, 2021, Robert Aaron Long pulled the trigger in three separate spas in Atlanta, Georgia, killing eight people–six of whom were Asian women. It is worth mentioning that social media platforms play a critical role in providing users with an online sphere to respond to incidents. Twitter, which is considered to be one of the most popular contemporary social media, classifies different topics with the function of hashtags.

This study's understanding of the topic has been greatly strengthened by the previous studies concerning the discrimination against Asians during the COVID-19 pandemic. Some scholars have summarized several significant themes regarding the hashtag #StopAsianHate through content analysis of TikTok videos during the pandemic, and the themes include Asian abuse/attack, awareness of Asian hate & hate crimes, somber tone/expression of sadness, etc. [3]. Another study has divided four categories of oppression towards Asians, which include ideological, institutional, interpersonal, and internalized oppression [4]. All these previous studies provide methodological or theoretical guidance for us to form topic and sentiment analysis methods that are particularly suitable for this research.

Differ from previous studies, this study is going to analyze the data using the MDCOR, which is able to analyze large amounts of open-ended questions, which are tweets in this paper, without the need to delete duplicate responses, which means this research can deal with larger amounts of data and show the traffic on each topic. Furthermore, the research team uses the tweets data on the topic - StopAsianHate - for a long period of time, and the team can analyze any subtopic under StopAsianHate during the time of analysis. Also, the research further enriches understanding of this topic by doing a sentiment analysis before/after the event (overtime).

Relying on a portion of Twitter data where users are using the hashtag #StopAsian Hate, this study offers a content analysis of the evolution of #StopAsianHate movement after the Atlanta Spa Shooting and insights into the patterns that can be discerned in the temporal fluctuation of the #StopAsianHate movement on Twitter, particularly about other key socio-political incidents like the Black Lives Matter campaign and the implementation of the Biden COVID-19 Hate Crime Act. By doing this research, the relationship between time and the dynamics of public opinion is hoped to be found, giving an effective consensus decision on how to enlarge the impact of those anti-racism events and advocate more discussions about anti-racism. Such discussions are urgently needed to make the public better aware of the evilness of racial discrimination and raise the minority's social status by attracting more attention from scholars, politicians, and charities.

2. Literature Review

Before the breakout of the COVID-19 pandemic in 2019, the relevant discussions mainly focused on the general hate crimes or bias crimes towards Asians, assessing the connotations, types, offenders and victims. A study in 1999 has mentioned that though crime based on prejudice against Asians has generated far less research and writing than crime against blacks, a considerable amount of prejudice and violence against Chinese immigrants early in the century and against Japanese Americans during World War II still have been documented [5]. In the United States, Asians has been discriminated in two primary ways: made hyper-visible as the "perpetual foreigner" or invisible as the "model minority" [6]. This finding corresponds to some qualitative studies that have suggested that Asian Americans may face unique types of discrimination, mainly in the former situation. For instance, a study using key informant interviews has found that Hmong adults experienced discrimination based on nativity and English proficiency in addition to the same types of discrimination faced by African Americans [7].

DOI: 10.54254/2753-7064/31/20232009

These studies, however, analyze the emergence and characteristics of Asian discrimination mostly from the traditional aspects of psychology or politics and very few surveys are conducted on social media platforms. The new era of big data tremendously facilitates information exchange and public opinion propagation. With the extensive application of Internet technology, the establishment of various social media platforms has broken traditional geographical boundaries and time and space restrictions, and hundreds of millions of Internet users can exchange and share data, views and ideas at the same time. These characteristics of new mass media act as the trigger conditions for the formation and outbreak of public opinion, and a plain topic may be amplified and spread rapidly. Therefore, the previous studies do not anticipate the virus from nature can become "racialized" and the xenophobic sentiment during the COVID-19 pandemic will present a new dilemma for Asians in cyberspace, which arouses new discussions regarding the discriminatory treatment of Asians and Asian communities.

After the breakout of the COVID-19 pandemic, there have been a number of discussions focusing on quantitative assessment based on the indicators obtained from the social platform. Some scholars have summarized several significant themes regarding the hashtag #StopAsianHate through content analysis of TikTok videos during the pandemic, and the themes include Asian abuse/attack, awareness of Asian hate & hate crimes, somber tone/expression of sadness, etc. [8]. In addition, there has been interest from academics in more sophisticated patterns, classification standards and other qualitative features of hate crimes, aggressions and other negative actions against Asians during the COVID-19 pandemic. It is worth noting that a large proportion of qualitative research is based on data collection and analysis. For instance, a research team has used data mining to create a quantitative descriptive study on the tweets under the topic of stop Asian hate and ultimately built their analysis on five themes [9]. Another study has examined how a specific identity group occupies the #StopAsianHate hashtag on TikTok to counter anti-Asian racism and its narrative characteristics by Critical Technocultural Discourse Analysis (CTDA), which is a multimodal analytic technique [10]. Another study has employed a discourse analysis model developed from the theory of Teun A. van Dijk, which includes three stages, namely the text structure, social cognition, and context. This model is used to analyze data extracted from Twitter [11]. Other qualitative studies are mostly based on grounded theory and interview methods to carefully examine and summarize the discrimination faced by Asians. A study conducted in 2023 has divided four categories of oppression against Asians, which include ideological, institutional, interpersonal, and internalized oppression [12]. This classification provides a comprehensive framework for further understanding the different forms of oppression that Asians may face and sheds light on how the oppressions may have been alleviated or aggravated under the political and social environment during the pandemic and even the post-pandemic era.

Also, by analyzing the attribute indexes, for instance, the age, gender, race, social capital, political affiliation, and religious status of the Twitter users who participate in the relevant topics, more fine-grained analyses indicate how public opinion and topics vary according to user characteristics [13]. Due to the limited data access, this article does not include fine-grained analyses.

What's more, several studies have mentioned that the relevant events of anti-racial discrimination, for instance, the Black Lives Matter movement on Twitter, are also important reflections of confrontation politics, popular and righteous rage, and grassroots resistance [14]. The modern social media platform, Twitter, can be used as an emerging public sphere to investigate public attitudes and debates after some high-profile tragedies [15]. Some scholars have created a large dataset of anti-Asian hate, namely the COVID-HATE, to examine over 30 million tweets and a social network with over 87 million nodes in three months, and have found that hate emotions are contagious and individuals are highly likely to become hateful after being exposed to hateful content. Also, this study reveals how anti-hate messages can influence users' attitudes and discourage users from turning

DOI: 10.54254/2753-7064/31/20232009

hateful in the first place, which indicates the specific mechanism of emotional transmission on social media [16].

All these previous studies provide guidance on how to form topic and sentiment analysis methods that are particularly suitable for this research. However, there is a dearth of theoretical and empirical studies that satisfy all the following aspects simultaneously.

(1). Dynamics analysis and longer time span. In most literature, only the current and static public attitudes are studied within a short time span of one or two weeks before and after certain racial discrimination incidents or anti-racism movements. The innovation of this paper is to study the change in online public perceptions over 5 months after the Stop Asian Hate Movement.

(2). Including other social factors. It is precisely because of the longer time span that many other social factors will be inevitably integrated into the fermentation progress of one particular event, and various related events may affect public opinions on the Internet to some extent. The previous literature only analyze the relationship between current public attitudes and the issue itself without considering other social factors.

(3). Using more representative samples. This article adopts the method of machine learning and NLP to examine texts instead of manually analyzing them, so as to extract the attitude of the public from massive data. Other literature basically uses small samples, focusing on specific groups that are not representative enough.

3. Research Method

3.1. Data Collection and Selection

The data for this study consisted of tweets posted under the hashtag #StopAsianHate, which was a social movement that emerged in response to the rise of anti-Asian hate crimes and discrimination worldwide. The tweets were collected using the Academic Twitter API, filtered by language (English only) and date (from March 1, 2022, to August 31, 2023), and duplicate tweets were deleted. This paper then used a random sample of 5,000 tweets each month, resulting in a final dataset that contains 20,000 tweets relevant to the #StopAsianHate movement, which accounts for 2.00% of the entire accessible dataset.

3.2. Subtopic Identification and Categorization

The tweets were analyzed using the software MDCOR [17]. First, the research team uploaded the CSV data file separated by month and used the software to generate the initial text mining output. Second, the research team removed frequently occurring words that were related to the topic name and negatively affected the result. Third, the research team used the parameter according to previous research and generated a matrix to show four models of correlation or dissimilarity [18]. Fourth, referring to the generated matrices, the research team tried several different numbers of codes that were almost the closest solution to a correlation of 0 and a dissimilarity of 1. The research team selected the one that successfully separated the topics and didn’t have similar subtopics in different codes based on the most representative data. Lastly, the research team saved the output and named each subtopic with a suitable name.

3.3. Sentiment Analysis and Graph Generation

The research team conducted sentiment analysis using an application (Google Drive link: https://drive.google.com/file/d/1auSkXHGPQVtHnkx6RnR9TyBv-zdAWyG4/view?usp=sharing). The research team selected the "type" column as the "code number" and the "text" column as the "quote". The team obtained the graph and data of sentiment categories for every single subtopic. Then,

DOI: 10.54254/2753-7064/31/20232009

the research team divided each sentiment data by the highest in their subtopic to ensure that every sentiment has a scale from 1 to 0, which can be displayed by a heat graph and association graph. Lastly, the revised data was put into the R code for the heat and association graph [19].

4. Results

As of the period of time the data was extracted, massive amounts of tweets are presented to the study. In order to guarantee that the input data could be analyzed by MDCOR, the group utilized R language to generate clean data, which means there would be no meaningless characters emerging (e.g.: emojis, abbreviations and so on).

4.1. Preparing process outcomes

By inputting the clean data of each month into MDCOR, the study group got the list of word frequency, which shows the most frequent words that appeared on the platform in a specific month. The study regulates the range of the list from the most frequent to the 20th, so that the group can relatively accurately and readily remove stop words or phrases that express no sentiments, from the inventory. For data in May, the study excluded ‘stopasianhate’, ‘Asian’, ‘much’, ‘have’, ‘people’; for June, ‘stopasianhate’, ‘Asian’, ‘have’, ‘people’, ‘much’ were excluded; for July, the group canceled ‘people’, ‘stopasianhate’ due to their abnormally high word frequency; for August, ‘stopasianhate’, ‘Asian’, ‘have’ are excluded.

Then, based on the processed word frequency inventory and the clean data, MDCOR generates a Metrics plot to showcase the relationships between the number of topics and (dis)similarities.

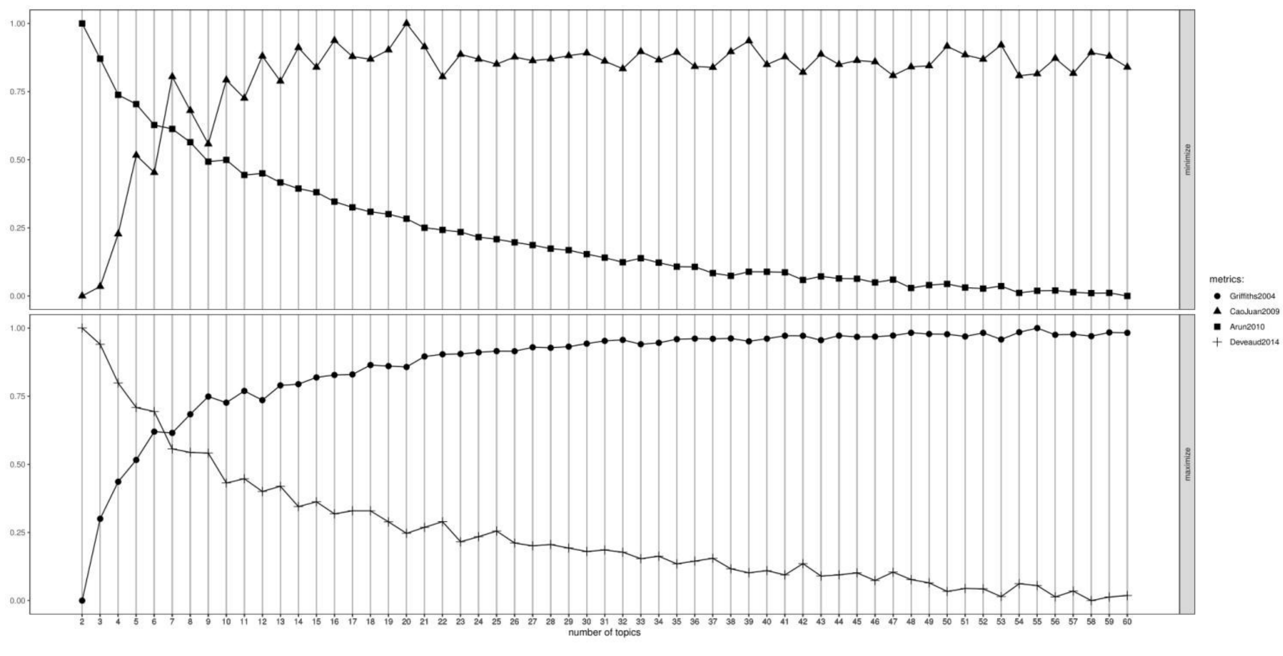

Figure 1: Metrics plot for July topics

For example, as figure 1 shows, in both graphs, the x-axis is designed to be the number of topics. For different numbers of topics, the researchers choose to use for topic sorting, the upper Metrics will show various outcomes of similarities, while the one below will show outcomes of dissimilarities. The standard the study uses to choose the proper number of topics is to focus on the maximum discrepancy between y value of points from the two graphs, which means the goal is to find the optimum number of topics to make the topics more separate from each other. To avoid contingency,

DOI: 10.54254/2753-7064/31/20232009

the group also spent time inspecting the output of the topic division. Finally, the study group chose to continue with 5 topics in May, 7 topics in June, 2 topics in July and 3 topics in August.

4.2. Inter-topic Distance Map (via multidimensional scaling)

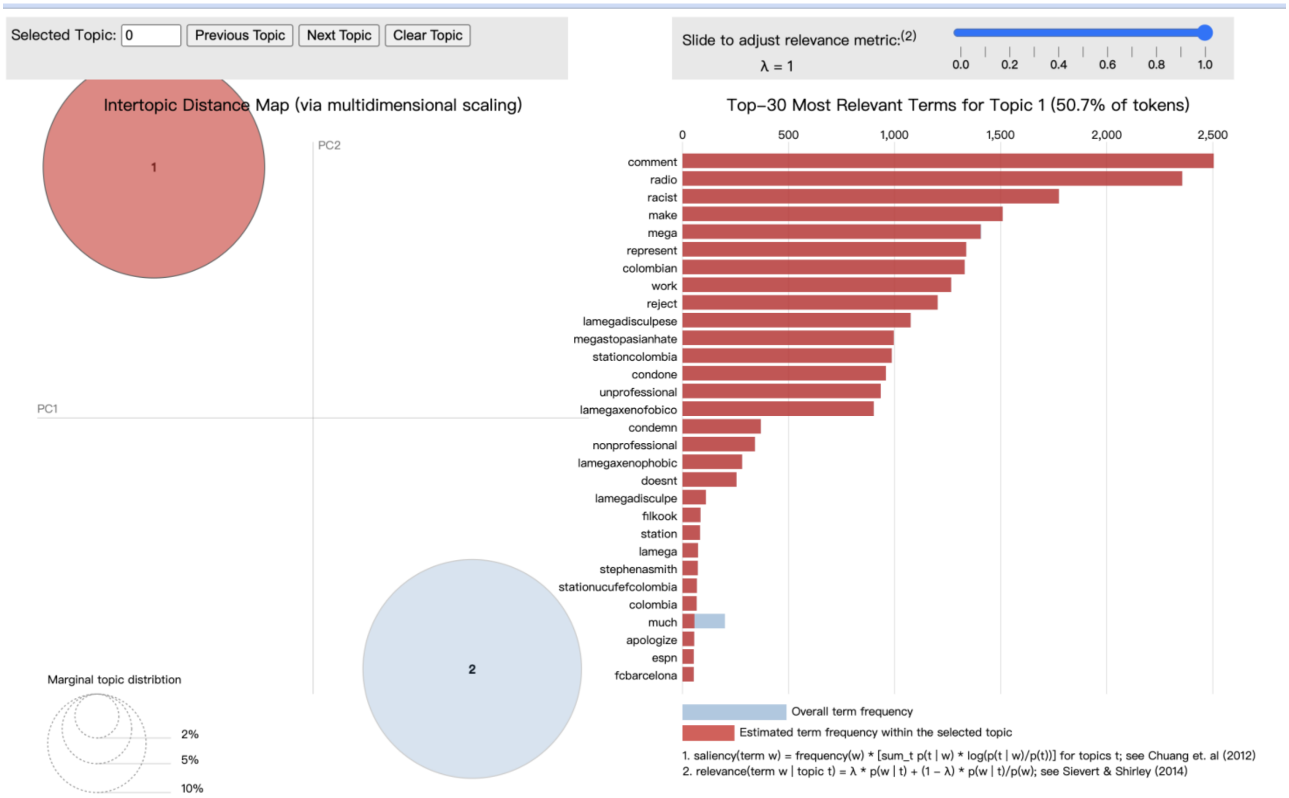

Figure 2: Inter-topic Distance Map of July

Inter-topic Distance Map (IDM), as shown in Figure 2, a kind of interactive graph generated by MDCOR, clearly highlights the extent of separation of each topic. Researchers are able to integrate most of the information analyzed by MDCOR based on the tweets provided. Intuitively, for different topic, different portions of word frequency are displayed in front of readers. This type of graph is an excellent representative of the combination of word frequency study and topic division.

Eventually, the topics are divided as:

May:

(1) V1: Asian American Heritage Month & Solidarity
(2) V2: Legislation to Address Anti-Asian Hate Crimes (Biden's Covid-19 Hate Crimes Act)
(3) V3: Various Current Events & Supportive Expressions
(4) V4: Against Racism & Advocate for Equality
(5) V5: Against Spreading Fake News (Yan Limeng)

June:

(1) V1 - Click bait (TTRPG You Tube channel)
(2) V2 - Against Spreading Fake News (Yan Limeng)
(3) V3 - NY attack
(4) V4 - Opposition to EAGLE Act (Pelosi)
(5) V5 - Donations
(6) V6 - VictoriasSecret & Against Racism

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(7) V7 - Racism in Volleyball: Serbia Incident
July
(1) V1 - Condemn La Mega
(2) V2 - Urge TwitterSupport to Against allkpop
August:
(1) V1 - Condemn La Mega
(2) V2 - Against Spreading Fake News (Yan Limeng)
(3) V3 - Aggressively Condemn La Mega

4.3. Sentiment Analysis

Through R language, the study group took advantage of the sentiment analysis program, which is based on the accurate result of topic division. For the purpose of integrating the outcomes of sentiment analysis, the study adopts three kinds of methodologies to display the result in various dimensions.

4.3.1. Sentiment Histograms

The study uses sentiment histograms to horizontally compare the dynamic change of each sentiment between the topic changes in every month. All the grams are available through the following links:
https://rpubs.com/haobo8/stopasianhate_May,
https://rpubs.com/haobo8/stopasianhate_June,
https://rpubs.com/haobo8/stopasianhate_July,
https://rpubs.com/haobo8/stopasianhate_August.

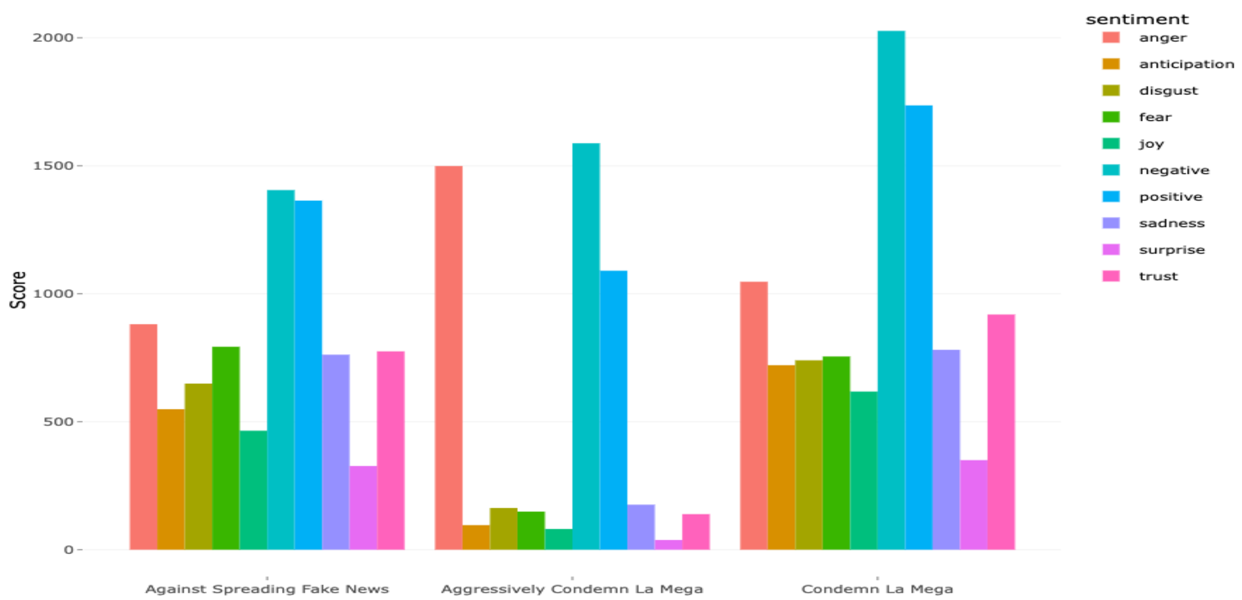

Figure 3: Sentiment Histogram for August subtopics

Due to the massive amount of information available from the histograms, the study has to be limited in a smaller range of information for analyzing artificially. Then, the group gave out the solution that only the top three ranked sentiments would be analyzed.

On the basis of this principle, the group designed a table to collect the top 3 sentiments that occur in each topic, just as Table 1 shows. As shown in Figure 3, for each of the three August subtopics (Against spreading fake news, Aggressively condemn La Mega and Condemn La Mega), the extent

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of different sentiments are quantified as scores. Objectively, 'joy' was the most intense sentiment during August; 'positive' and 'anger' was also obvious and presented an increasing trend.

Table 1: Top 3 sentiments for each topic

	Topics Top 3 emos (scores)	1	2	3
May	V1	Positive(2297)	Trust(1158)	Anticipation(836)
	V2	Negative(1285	Positive(761)	fear(754)
	V3	Negative(1695)	Positive(1436)	Anger(1336)
	V4	Positive(1316)	Trust(856)	Negative(819)
	V5	Positive(987)	Negative(495)	Anticipation(461)
June	V1	Positive(953)	Negative(547)	Trust(538)
	V2	Positive(1206	Negative(705)	Trust(700)
	V3	Negative(859)	Positive(688)	Fear(494)
	V4	Negative(1375	Positive(1011)	Anger(822)
	V5	Positive(516)	Negative(154)	Anticipation/trust(114)
	V6	Negative(773)	Positive(559)	Anger(529)
	V7	Positive(675)	Negative(664)	Trust(492)
July	V1	Negative(4375)	Positive (4089)	Fear(2864)
	V2	Positive(2353)	Negative(1714)	Anger(1576
August	V1	Negative(2027)	Positive(1736)	Anger(1047)
	V2	Negative(1405)	Positive(1364)	Anger(881)
	V3	Negative(1588)	Anger(1499)	Positive(1090)

According to table 1, researchers can vertically find the rule of sentiment fluctuation between adjacent months; at the same time, horizontally, ranks of sentiment scores will present the main, weighted components of the emotions of Twitter users on the specific topic during the month.

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4.3.2. Sentiment Network Analysis

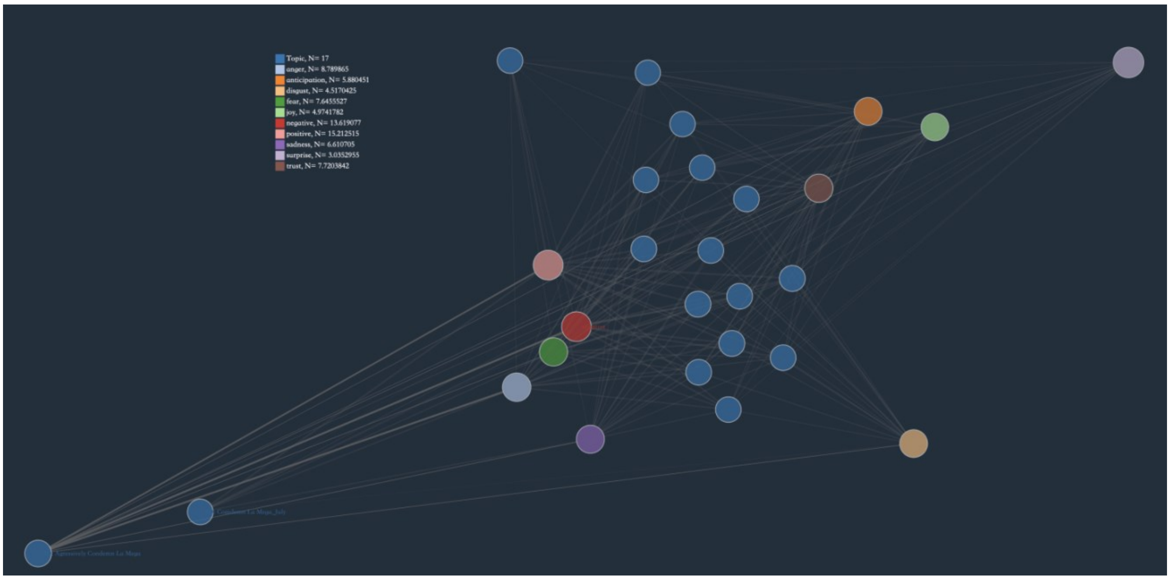

Figure 4: SNA diagram of Topic #StopAsianHate

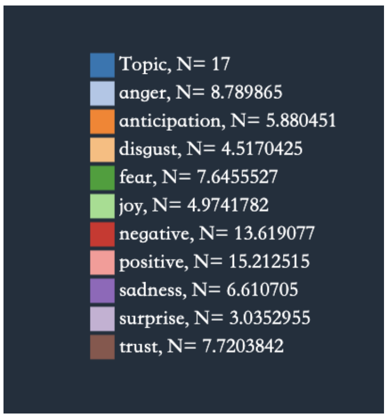

Figure 5: Figure legend (supplementary)

The Sentiment Network Analysis (SNA) graph is also interactive to viewers. The group finds it extremely detailed and is able to showcase any relationship between the topics and sentiments. Researchers can make deductions by observing the sparsity, the distribution, the value of the sentiments and the degree of thickness of threads. The whole SNA graph is accessible through https://rpubs.com/haobo8/stopasianhate_association_graph.

In Figures 4 and 5, it can be seen that the 'surprise' is the farthest from the centre of the graph, which means that 'surprise' is the least represented among all the sentiments. Compared to 'surprise', 'negative' is much closer to the centre, which means that Twitter users tended to hold negative emotions towards all the topics throughout the whole research period of time.

4.3.3. Sentiment Matrix

Apart from the SNA graphs, the group generated a Sentiment Matrix to support the claims and assist data analyzing procedures. The following link will lead to the whole graph on Rpubs: https://rpubs.com/haobo8/stopasianhate_sentiment_matrix.

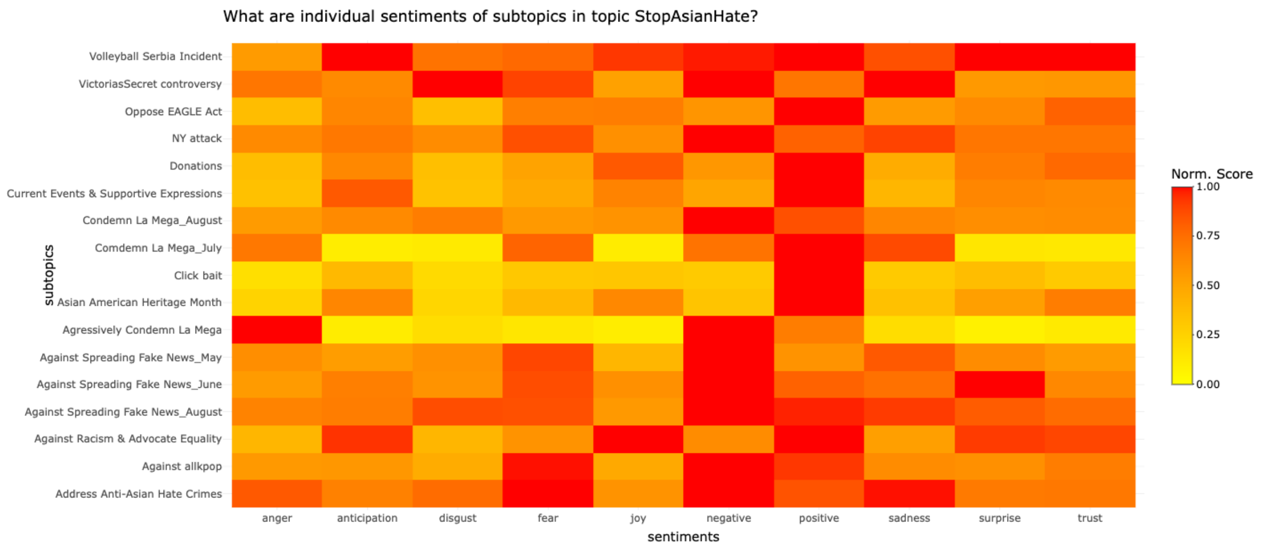

Figure 6: Individual sentiments of subtopics in StopAsianHate

Figure 6 shows that in different periods of time, people will make different extent of reactions towards a similar subtopic. For example, Condemn La Mega in July and August shows different components of sentiments. In July, people held fewer negative opinions but more positive sentiments. So, the emotional trend of public consensus will be altered as time passes.

4.4. Findings

By synthesizing the deductions made according to the several types of graphs previously mentioned, the study group acquired general patterns of sentiment changes.

4.4.1. Purposes

Basically, the group summarized the purposes of all the events as (1) The shifting of topics on a monthly basis underscores the transient nature of public focus, often fueled by emergent events or incidents capturing rapid attention; (2) While topics have changed over the months, certain consistent themes persist, particularly advocacy against racism and the spread of fake news, condemnation of current incidents of racism, and support for unity and equality; (3) Continued condemnation of racist incidents and fervent calls for unity and equality remained overarching themes; (4) Instances of racially motivated incidents are a huge influence on the topics of that month, indicating that people are using #StopAsianHate to condemn and advocate against racism; (5) Some are using the hashtag as a way to attract attention for personal gain.

4.4.2. Comparisons

The topics are mostly different between months, and the variations are related to specific events of that month, but some topics reappear in other months. For this phenomenon, several statements are proposed: (1) New topics surfaced each month, aligned with significant events in that time frame (e.g., support for the Covid-19 Hate Crime Act in May, the New York Attack in June), which underscores a discernible correlation between the thematic content of Twitter posts and the prevailing events of a given month. (2) A recurring topic (in May, June and August) was the condemnation of spreading disinformation, suggesting its continued relevance across periods. (3) Another recurring topic was the condemnation of La Mega (in both July and August) and there is an escalation of aggressiveness in its rhetoric in August.

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4.4.3. Further Analysis

The study conducts a more comprehensive analysis of sentiment fluctuation. It is separated into 3 parts so that clues and phenomena can be stated clearly.

4.4.3.1. Monthly Analysis

May

(1)Positive sentiment dominates the topics: Asian American Heritage Month & Solidarity, Against Racism & Advocate for Equality, and Various Current Events & Supportive Expressions, including advocating for unity.

(2)Negative sentiment dominates the topics: Legislation to Address Anti-Asian Hate Crimes and Against Spreading Fake News, including condemning the spreading fake news incidents of hate crime, accompanied by a feeling of fear.

(3) Expecting a high proportion of positive sentiment for the Covid-19 Hate Crime Act, it is surprising that people responded to this act with a mixed and more average sentiment of negative, positive, fear, and a comparatively high proportion of anger.

June

(1) The NY attack contains a higher percentage of all emotions with a high percentage of negative sentiment and anger (most discussions and emotions).

(2) Clickbait acts as a way to promote a YouTube channel. The percentage of emotions is really low.

(3) Anger is more associated with racist incidents like the NY attack and the Victoria's Secret Controversy.

July

(1) Against allkpop's sentiment distribution resembles June's Against Spreading Fake News' distribution with top 3 sentiments of negative, positive, and fear.

(2) It is unexpected that the topic of condemning La Mega has a relatively high percentage of positive sentiment.

August

(1)Aggressively condemning La Mega reflects negative sentiment and anger dominates the topic, which creates an obvious comparison between condemning La Mega and aggressively condemning La Mega.

4.4.3.2. Between Month Analysis

Depending on the table constructed previously, the group made inferences about the sentiment change: (1) In May and June, there were relatively more positive sentiments, with a medium extent of trust and anticipation (2) In July, more intense negative sentiments with some fear and anger presented. (3) In August, it is dominated by intense negative sentiments and anger.

A change towards negative and furious sentiments from May to August is discovered. The reason why it presents is that according to the topics of Twitter content, May and June still contain positive advocacy of equality and unity, but July and August are completely urging and condemning racist incidents.

4.4.3.3. Special Topic Analysis

For the two overlapping topics, 'Against Spreading Fake News' and 'Against La Mega', change in sentiments indicate the increase intensity of negative public sentiment towards this topic as time passed. Maybe in August, the La Mega incident, with the publicity of BTS and the attention it brings

(Kpop fandom), incited a more aggressive and furious sentiment for other incidents in that entire month.

5. Discussion

This research provides insights into the relationship between social events and online public perceptions during the #StopAsianHate movement following the outbreak of the COVID-19 pandemic. Recognizing the impact of other social factors on online perceptions, data collected for this study captured how different events affect online topics under the StopAsianHate movement and how certain online topics change or sustain over time. Utilizing machine learning and natural language processing (NLP) to analyze massive data sets provides a more representative sample of public sentiment. The use of sentiment histograms, sentiment network analysis, and sentiment matrix allows for a multifaceted examination of how sentiments change over time and their relationship with specific topics.

From the topics of the five-month data that the research group summarized, online perception and discussions have a close connection to current events such as the following:

(1) Spreading fake news - Yan Limeng, a Chinese virologist, claimed coronavirus was created in a Chinese lab, but her research was widely discredited. Critics suggest she's influenced by Steve Bannon and Guo Wengui to spread false claims about COVID-19's origin. (2) Biden signed the Covid-19 Hate Crime Act to address hate crimes during the pandemic, particularly the rise in violence against Asian Americans. (3) New York attack - A man attacked a woman of Asian descent on a New York City sidewalk in Chinatown, hitting her in the face, which sparked concern about hate crimes against Asians. (4) The EAGLE Act prompted China's National People's Congress to condemn it as a Cold War mentality, asserting it interferes with China's development path and policies. (5) Soccer star Megan Rapinoe faced backlash over an old tweet many considered racist after signing with Victoria's Secret. (6) A Serbian volleyball player was suspended for making a racist gesture by stretching her eyelids, mocking Asian heritage, during a match against Thailand. (7) A Colombian radio program, "La Mega," insulted K-pop group BTS and South Korea, falsely referring to BTS as Chinese and attributing their success to money and sponsorship. (8) Concerns were raised over allkpop's posts promoting racism and xenophobia toward Southeast Asian people, leading to calls for TwitterSupport to take action against the website.

The findings and results offer the following insights: (1) The shifting of topics on a monthly basis underscores the transient nature of public focus, often fueled by emergent events or incidents capturing rapid attention; (2) While topics have changed over the months, certain consistent themes persist, particularly advocacy against racism and the spread of fake news, condemnation of current incidents of racism, and support for unity and equality; (3) Continued condemnation of racist incidents and fervent calls for unity and equality remained overarching themes; (4) Instances of racially motivated incidents are a huge influence on the topics of that month, indicating that people are using #StopAsianHate to condemn and advocate against racism; (5) Some are using the hashtag as a way to attract attention for personal gain; (6) Certain topics that relate to certain popular culture fan groups (e.g. Kpop fan group) sustain across months and even incite a more aggressive sentiment over time.

6. Conclusion

In recent years, Asian hate has increased due to the pandemic. As a result, hate speech was raised, and hate crimes like the Atlanta shooting occurred, while people were also using social media platforms to spread stop-Asian hate. Social media platform, such as Twitter, was considered an essential role in reflecting people's response to Asian-hate crimes and racism. In this study, hoping to

DOI: 10.54254/2753-7064/31/20232009

make a distribution to anti-racism, MDCOR and tools developed by researchers were used to analyze tweets (opened answers) posted under the hashtag #StopAsianHate (from March 1, 2022, to August 31, 2023). The 5-month data can help the research to get a more comprehensive result as well as a consensus dynamic. Through subtopic identification of each month and sentiment analysis derived from the data, the main findings are as follows:

(1). The focus of public opinion is basically ephemeral and often fueled by emergent events and incidents, mostly changing monthly, while certain themes maintained appearing in the hashtag, particularly advocacy against racism and the spread of fake news, condemnation of current incidents of racism, and support for unity and equality.

(2). Certain topics that relate to certain popular culture fan groups (e.g., K-pop fan groups) sustain across months and even incite a more aggressive sentiment over time. Other posts, such as calls for unity and equality, usually do not have that much negative sentiment.

(3). Some people were using the heat of hashtag #StopAsianHate to attract attention for personal gain.

6.1. Limitation

The research data came from a portion of the posts on Twitter Academic that contain the hashtag #StopAsianHate and cannot be generalized to all social media platforms. The analysis only covered the data form of text data. Due to the limitations of the computation source, it was not feasible to process all data but a portion of it - 5000 text data in 30,000+ text data every month.

Due to the lack of data on March (38) and April (3), the study didn't cover the entirety within the five-month timeframe. The topics separated by MDCOR were generally probability-based and their accuracy cannot be guaranteed. In addition, MDCOR only categorized the data into similar groups without specifying the content. The specific topics for each month were summarized by the research group, and relatively irrelevant information was eliminated based on the research team's discussion and consensus.

6.2. Implication

These findings have several implications for comprehending the online dynamics of social movements and public perceptions:

(1). This research underscores the significance of considering the temporal dynamics of online discussions, as public attention and sentiment can alter significantly over time. Researchers should account for these changes when analyzing social media data related to social movements.

(2). Current events and incidents play a notable role in shaping online discussions. Researchers and policymakers need to be aware of how real-world events can trigger and influence online conversations.

(3). The shift from positive sentiments to negative sentiments within months suggests that online activists adapt their messaging and emotional tone based on the prevailing circumstances. Understanding these shifts can advise strategies for advocacy and awareness campaigns.

While this research focuses on Twitter, future studies could gain a more comprehensive understanding of public perceptions across various social media platforms by conducting a cross-platform analysis.

Acknowledgement

Lian Ren, Tianlin Liu, Junming Zheng, Luyao Zhao and Haobo Zhang contributed equally to this work and should be considered co-first authors.

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