Understanding Public Opinion Toward the #StopAsianHate Movement and the Relation With Racially Motivated Hate Crimes in the US

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***Abstract*—#StopAsianHate and #StopAAPIHate are two of the most commonly used hashtags that represent the current movement to end hate crimes against the Asian American and Pacific Islander communities. We conduct a social media study of public opinion toward the #StopAsianHate and #StopAAPIHate movement based on 46 058 Twitter users across 30 states in USA ranging from March 18, 2021 to April 11, 2021. To facilitate fine-grained analyses, the demographic information of the Twitter users, including age, gender, race/ethnicity, social capital, political affiliation, geolocation, family, income, and religious status, is either retrieved from the user profiles or inferred using classifiers. We find that the movement attracts more participation from women, younger adults, Asian, and Black communities. It is noteworthy that most of them are also active in other online movements related to racial or social issues, such as #BlackLivesMatter or #SayHerName; 51.56% of the Twitter users show direct support, 18.38% are news about anti-Asian hate crimes, and 5.43% show a negative attitude toward the movement. By conducting logistic regression, we find that the public opinion varies across user characteristics. Furthermore, among the states with most racial bias-motivated hate crimes, the negative attitude toward the #StopAsianHate and #StopAAPIHate movement is the weakest. The majority of the top influencers are Asian–American reporters, journalists, or politicians. To the best of our knowledge, this is the first large-scale social media-based study to understand public opinion toward the #StopAsianHate and #StopAAPIHate movement. We hope that our study can provide insights and promote research on anti-Asian hate crimes and ultimately help address such a serious societal issue for the common benefits of all communities.**

***Index Terms*—#StopAAPIHate, #StopAsianHate, public opinion, social media.**

I. Introduction

A RECENT report found that in 16 of America's largest cities, anti-Asian hate crimes have surged around 145% in 2020.[1] On March 16, a series of mass shootings occurred at three spas or massage parlors in the metropolitan area of Atlanta, GA, USA.[2] Six out of eight victims who were killed were Asian women. Since then, many anti-Asian-violence rallies have been held across the world. The discussion and debate around #StopAsianHate and #StopAAPIHate, which represent the social movement that aims to end hate crimes against Asian American and Pacific Islander communities, is becoming heated on social media platforms such as Twitter.

Previous studies have investigated social movements, such as #BlackLivesMatter [1]–[5], #HeForShe [6], and #MeToo [7]–[10]; however, few research is about the online movements of stopping hate crimes against Asian American and Pacific Islander communities. To fill the gap in understanding the #StopAsianHate and #StopAAPIHate movement, we conduct a social media study of public opinion of 46 058 Twitter users across 30 states in USA ranging from March 18, 2021 to April 11, 2021, and make five major contributions. To summarize, using the publicly available self-disclosed information of Twitter users, our study analyzes the participation patterns in the movement. Based on the content and opinion of the tweets, we classify them into six major topics. By conducting logistic regression, we find that public opinion toward the #StopAsianHate and #StopAAPIHate movement varies across user characteristics. We show that the rate of state-level racial bias-motivated hate crimes is negatively associated with the proportion of tweets that show a negative attitude toward the movement. We identify the top influencers of the retweet network. To the best of our knowledge, this is the first large-scale social media-based study to understand public opinion toward the #StopAsianHate and #StopAAPIHate movement.

The remainder of this article is structured as follows. In Section II, we describe the related work. In Section III, we discuss the data we use in this work. Next, the methodology is illustrated in Section IV. Results are presented in Section V. Finally, discussions and conclusions are given in Section VI.

II. Related Work

According to a national report [11] of the "Stop AAPI Hate" coalition, the number of reported hate incidents increased significantly from 3795 to 6603 in March 2021. Specifically, physical assaults rose from 10.2% of the total hate incidents in

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[1]https://www.csusb.edu/sites/default/files/FACT%20SHEET-%20Anti-Asian%20Hate%202020%20rev%203.21.21.pdf

[2]https://www.cnn.com/2021/03/17/us/robert-aaron-long-suspected-shooter/index.html

2020 to 16.7% in 2021. The proportion of online hate incidents almost doubled from 5.6% to 10.2%. Gover *et al.* [12] argued that the increase in anti-Asian hate crimes during the pandemic may be because COVID-19 has prompted the spread of racism and created national insecurity and xenophobia. Asian Americans are blamed for the COVID-19.[3] Scholars have also investigated the correlation between the concept of Asians as perpetual foreigners and the increase of anti-Asian hate crimes [13], [14]. More importantly, besides the harms of physical assaults, Asian Americans are facing mental inequity issues that are related to anti-Asian hate. Symptoms of depression, anxiety, and stress have been shown in Asian Americans who have experienced racism [15]. Therefore, it is critical to detect and understand the sentiment regarding anti-Asian hate so that future studies may analyze the effect and design practices or policies to reduce the negative impact.

The extensive use of digital social media is widely credited with contributing to the successful mobilizations of social movements [16]. Many studies have analyzed the public opinion toward these movements. Bonilla and Tillery [17] found that the identity frames generate differential effects on respondents' opinions about the #BlackLivesMatter movement. Olteanu *et al.* [18] characterized the demographics behind the #BlackLivesMatter movement. Using the discourse analysis, Reyes-Menendez *et al.* [19] explored the key indicators of social identity in the #MeToo movement. However, given the relatively shorter history of the #StopAsianHate and #StopAAPIHate movement, there are few relevant studies. Fan *et al.* [20] identified a set of more than 300 frequently used related hashtags. Tran [21] explored the differences and similarities between the discourses of anti-Asian racism during the pandemic in online Canadian news media.

With the large amount of user-generated content, Twitter data have been used to understand public opinions on various areas, such as climate change [22], politics [23], [24], and energy issues [25]. As COVID-19 proliferated across the world, researchers have started to use Twitter to investigate the public opinion on vaccinations [26], [27], mental health [28], [29], and suppression policies against the spread of the disease [30], [31]. In this study, we focus on analyzing the public opinion on the #StopAsianHate and #StopAAPIHate movement, which allows us to further understand the sentiment regarding anti-Asian hate in USA.

III. Data Collection

A. Twitter Data

We use the Tweepy API[4] to collect the related tweets that are publicly available. The search keywords and hashtags are related to the #StopAsianHate and #StopAAPIHate movement or `Asian` community, including "#StopAsianHate," "#StopAsianHateCrimes," "#StopAAPIHate," "#stopaapihate," "#stopasianhate," "asian," "aapi," "#asian," "#aapi," "#AAPI," "#AsianLivesMatter," "#AsiansAreHuman," "#AntiAsianHate," "#AntiAsianRacism," "#JewsForAsian," and "#SafetyinSolidarity."[5] We only include the Twitter users that are located in USA by resolving the location information in the user profile. A set of 678 959 tweets that were posted by 248 973 unique users is collected. Using or adapting multiple computational methods that are also applied in previous social media studies [27], [28], [32], [33], we infer user characteristics including gender, age, race/ethnicity, income, religious status, family status, population density, as well as political affiliation. Only the states that have at least 300 unique Twitter users are retained. The 1162 unique tweets from March 18, 2021 to April 11, 2021 that are retweeted for at least 20 times by 46 058 unique Twitter users are included in the study.

B. Hate Crime Data

We use the Hate Crime Statistics, 2019, from the Federal Bureau of Investigation [34], which comprises the hate crime incidents, per bias motivation, and quarter, by State, Federal, and Agency of 2019. By the time this study is conducted, the data of 2020 and 2021 are not available yet.

IV. Methodology

To facilitate fine-grained analyses, the demographic information of the Twitter users, including age, gender, race/ethnicity, social capital, political affiliation, geolocation, family, income, and religious status, is either retrieved from the user profiles or inferred using appropriate classifiers. All the information we use is publicly available and disclosed by the Twitter users themselves. For the analysis, we only report the aggregate data.

A. Feature Inference

1) Gender and Age: Following the methods of Lyu *et al.* [32], we use Face++ API[6] to infer the gender and age information of the users using their profile images. To maintain as much original picture information as possible and increase the inferring speed, we resize each profile image in an antialiasing manner. Each image is resized if the larger value of the original length or width is greater than a threshold t. In this case, the threshold is 300 pixels. Let OL, OW, NL, and NW denote the original length, original width, new length, and new width, respectively. The new length and new width are calculated as follows:

$$\mathrm{NL} = \begin{cases} \mathrm{OL} \times \dfrac{t}{\max(\mathrm{OL}, \mathrm{OW})}, & \text{if } \max(\mathrm{OL}, \mathrm{OW}) \geq t \\ \mathrm{OL}, & \text{otherwise} \end{cases} \tag{1}$$

$$\mathrm{NW} = \begin{cases} \mathrm{OW} \times \dfrac{t}{\max(\mathrm{OL}, \mathrm{OW})} & \text{if } \max(\mathrm{OL}, \mathrm{OW}) \geq t \\ \mathrm{OW}, & \text{otherwise.} \end{cases} \tag{2}$$

Face++ can achieve a high accuracy in the gender and age inference of Twitter data [35]. Another advantage of using profile images as a source to infer user demographics is that lack of such imagery might be a sign of a Twitter bot account [36]. The invalid image URLs and images with multiple or zero faces are excluded. The gender and age

[3] https://www.nbcnews.com/news/asian-america/over-30-americans-have-witnessed-covid-19-bias-against-asians-n1193901

[4] https://www.tweepy.org/

[5] The nonhastag keywords are case-insensitive in the Tweepy query.

[6] https://www.faceplusplus.com/

information of the remaining users (i.e., there is only one intelligible face in the profile image) is inferred. Since our study focuses on the opinion of U.S. adults, the users who are younger than 18 are removed.

2) Race/Ethnicity: Unlike previous studies [30], [33] that used only one method or one media to infer race/ethnicity, we use multiple classifiers, extract information from both the text and image content, and assign different priorities to optimize the race/ethnicity inference.

a) Image-based inference: We use profile images from Twitter users and apply the DeepFace API to analyze facial attributes [37]. DeepFace is a hybrid facial analysis framework, which concludes facial recognition stages of detect, align, represent, and verify.

b) Text-based inference: We include user description and user name in this part of inference and apply the Ethnicolr API[7] and CLD3 API[8] for text analysis.

1) *Description:* For each user description, we look for self-identified keywords, such as "Chinese," "Korean," and "Japanese" for `Asian`; "African," "Algerian," and "Nigerian" for `Black`; and "Latino" and "Hispanic" for `Hispanic`.
2) *User Name:* We apply the Ethnicolr API on the user's last name. To extract the last name, we remove emoji icons, hyphens, unrelated contents, and special characters. Next, we split the remaining strings and keep the last part as the last name. Finally, we apply "census_ln" from Ethnicolr to infer the race/ethnicity, which contains `White`, `Black or African American`, `Asian/Pacific Islander`, `American Indian/Alaskan Native`, and `Hispanic`.
3) *Language Detection on Name:* We apply the CLD3 API to user name, which can predict the language of the user name.

There are four methods used in race/ethnicity inference (one for image-based inference and three for text-based inference). In order to produce a final prediction of race/ethnicity, we decide to assign priorities for these four methods. Profile descriptions have the highest priority because we think the self-identified information is the most accurate among all these methods. An image-based method is the second. The Ethnicolr API and CLD3 language detection are placed the third and fourth. In the end, we keep the users of `White`, `Black`, `Hispanic`, and `Asian` in the study population and remove the race/ethnicity groups with few respondents. We manually labeled 200 randomly sampled Twitter users in our dataset and the accuracy of the race/ethnicity inference is 0.735.

3) User-Level Features: Seven user-level features are crawled by the Tweepy API as well, which includes the number of `Followers`, `Friends`, `Listed memberships`, `Favorites`, `Statuses`, the number of months since the user account was created, and the `Verified` status. Moreover, we normalize the number of `Followers`, `Friends`, `Listed memberships`, `Favorites`, and `Statuses` by the number of months since the user account was created.

4) Geolocations: For Twitter, we choose to resolve the geolocations using users' profiles. Similar to the study of Lyu *et al.* [32], the locations with noise, such as "my home" and "Mars," are excluded. To extract the population density at the zip-code level, we use the python package uszipcode. If the population density is greater than 3000 persons per square mile, this location is labeled as urban. If the population density is between 1000 and 3000 persons per square mile, this location is labeled as suburban. For other cases, the location is labeled as rural. Although the uszipcode package provides fuzzy city name and state name searches that do not require the exact spelling of the city or state and is case, space-insensitive, having high tolerance to typos (e.g., if the input is "cicago, il," the output is "Chicago, IL"),[9] we still observe several null values when applying uszipcode directly to the locations we have resolved. After manually checking the original disclosed locations, we find that except for the locations that are indeed unknown, another location that causes the null output is "Manhattan, NY." With the population density being over 70 000 persons per square mile,[10] we impute the population density label of this location with urban.

5) Income: The median household income of the census data at the place level [38] is matched to represent the income of the Twitter user. Instead of the American Community Survey 1-Year Data, we choose to use the five-year data because, with the multiyear estimates, it has increased statistical reliability for less populated areas and small population subgroups.[11] More specifically, it provides the estimates for all geographic areas down to block group levels.

6) Religious Status: We assign each user a Boolean value for whether she/he is religious based on the description in the profile using a list of keywords, including "pray," "prayer(s)," "jesus," "bless," "blessing(s)," "muslim(s)," "christian(s)," "mosque(s)," "buddha," "synagogue(s)," and "church(es)" [28].

7) Family Status: By applying regular expression search, we identify users who show evidence that they are either fathers or mothers [28]. We search for tweets containing patterns such as "my/our (1–20) year old," "my/our,..., X," and "I have,..., X" where X stands for kids including "boy(s)," "girl(s)," "kid(s)" and "child(ren)." With expressions like "my X," people tend to reveal the attribute, quality, or event that they possess [39]. Besides, if the profile description of the Twitter user indicates the role of a parent such as "father," "dad," "mother," and "mom," the Twitter user will be labeled as a parent.

8) Political Affiliations: The political attribute is labeled based on whether this Twitter user followed the Twitter accounts of the top political leaders. The incumbent president (Joe Biden) and the former president (Donald Trump) are included in the analysis.[12]

[7]https://ethnicolr.readthedocs.io/

[8]https://github.com/google/cld3

[9]https://uszipcode.readthedocs.io/index.html

[10]https://worldpopulationreview.com/boroughs/manhattan-population

[11]https://www.census.gov/data/developers/datasets/acs-5year.html

[12]Due to the limitation of Twitter API, only about half of Donald Trump's follower IDs were crawled.

TABLE I
TOP TEN KEYWORDS OF EACH TOPIC

Topic	Keywords
Love	love, friend, family, good, time, today, share, watch, hope, post
Hate crime	hate, Asian, crime, anti, stop, racism, violence, year, rise, report
Racial problems	people, white, black, Asian, race, supremacy, racist, problem, medium
News about anti-Asian attacks	American, Asian, attack, Atlanta, shooting, victim, week, news, Georgia, Biden
Violent crime	women, man, kill, day, bad, murder, target, shoot, sex, police
Community support	community, violence, support, stand, racism, AAPI, solidarity, act, fight, action
Individual support	Asian, people, happen, feel, life, speak, tweet, live, word, care
Call for change	Asian, work, experience, face, time, hard, speak, learn, kid, change
History	Asian, read, history, story, long, show, part, important, thread, write
Politics	Asian, country, call, china, American, Chinese, America, Trump, virus, Covid
Culture	Asian, make, culture, thing, talk, lot, point, comment, good, Japanese
Irrelevant	Asian, racist, fuck, guy, shit, give, girl, fucking, back, big

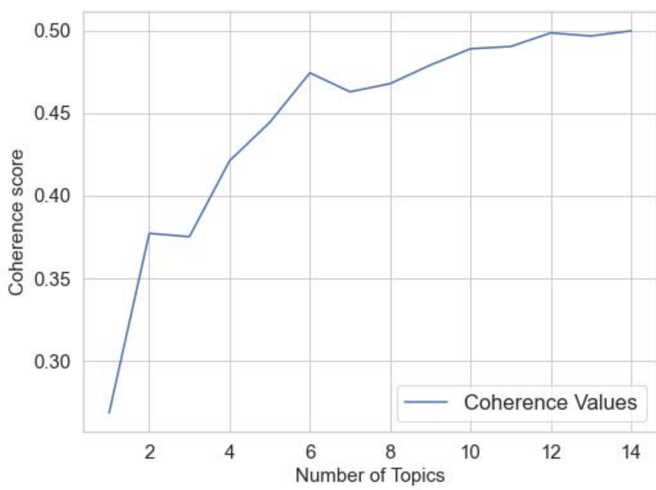


Fig. 1. LDA coherence scores versus number of topics.

B. Topic Encoding

To figure out what topics are discussed in the collected tweets, we first apply the latent Dirichlet allocation (LDA) topic modeling [40] to obtain a general view of topic distribution. Next, we read and label the tweets that have been retweeted for at least 20 times.

1) LDA Topic Modeling: We remove the stop words by applying the stop words package of the Natural Language Toolkit library and further retain nouns, verbs, adjectives, and adverbs using the spaCy package. The coherence score is used to select the optimal number of topics. Based on the trend of coherence scores (Fig 1), we choose 12 topics (Table I), which include Love, Hate crime, Racial problems, News about anti-Asian attacks, Violent crime, Community support, Individual support, Call for change, History, Politics, Culture, and Irrelevant. The results of the LDA guide us to further explore topics through manual labeling.

2) Labeling: Two researchers read the 1335 tweets that have been retweeted for at least 20 times and construct the topic classification, as shown in Table II. There are 6 level-1 topics, 43 level-2 topics, and 1 category with 173 irrelevant tweets. After removing the irrelevant tweets, there are 1162 tweets left. Next, they read the tweets and make judgment of the topic of each tweet independently. The label of the tweet is assigned based on consensus. If the initial labels of two researchers are different, the two researchers will discuss and reach a consensus on the final label.

The opinion of the user is assigned based on the topic of the tweet this user posted. One Twitter user might post tweets of more than one topic, which is rare in our study population. We assign the opinion of this user on the basis of the topic of the tweets that she/he posted the most.

C. Retweet Network

We exclude all nonretweet tweets in this section. To understand the retweeting mechanism, we use the Python library Networkx to generate GEXF files. We use them to analyze and visualize retweet networks in the open-source network software Gelphi [41].

V. RESULTS

A. Participation Patterns

Using the Tweepy API and a list of related keywords and hashtags, we have collected the inferred characteristics of 46 058 unique Twitter users across 30 states in USA ranging from March 18, 2021 to April 11, 2021, who have discussed the #StopAsianHate and #StopAAPIHate movement and obtained the number of state-level racial bias-motivated hate crimes from Federal Bureau of Investigation [34], which are listed in Table III; 55.68% of the study population are women, which is greater than the proportion of women in the general Twitter population. According to the survey conducted by the Pew Research Center, women account for 50% of the Twitter population [42]. This suggests that the #StopAsianHate and #StopAAPIHate movement attracts more participation from women, which might be related to collective identity [43] that women may join the movement based on shared membership of the victims of recent anti-Asian attacks where six out of eight people killed in Atlanta shootings were `Asian` women, and so was the victim of the San Francisco attack.[13] Similarly, `Asian` users comprise 25.29%, which is greater than the proportion in the general Twitter population (less than 8% [42]). There are proportionally more `Black`

[13]https://sanfrancisco.cbslocal.com/2021/03/17/elderly-asian-woman-beats-up-man-attacking-her-in-san-francisco/

TABLE II
LEVEL-1 AND LEVEL-2 TOPICS

Level-1	Level-2	Code
Support	General supportive statement	S.1
	Resources	S.2
	Stories of victims	S.3
	Political figures' support	S.4
	Celebrity's support	S.5
	Historical references	S.6
	Solidarity between `Black` and `Asian`	S.7
	Proud to be `Asian`	S.8
	All lives matter	S.9
News	News about anti-Asian hate crime / talk (no racial identity of the offender)	N.1
	News about `Black` targeting `Asian`	N.2
	News about `White` targeting `Asian`	N.3
	Personal experience	N.4
	News about the support for #StopAsianHate and #StopAAPIHate	N.5
	News or reports that explicitly connect the pandemic to anti-Asian attacks	N.6
Denouncement	Against Donald Trump	D.1
	Against the Republican party	D.2
	Against the officer who justified for the offender of Atlanta shootings	D.3
	Against the bystanders	D.4
	Against the Democratic party	D.5
	Politics and discrimination	D.6
	Against Kamala Harris	D.7
	College admission	D.8
	Asian fetishization	D.9
	White supremacy	D.10
	Western imperialism	D.11
	`Black` is the major offender	D.12
	Victims and offenders are treated differently by police	D.13
	`White` family with `Asian` members	D.14
	Against the attacker	D.15
	General discussion about anti-Asian racism	D.16
	Motivation of the Atlanta shootings is hate	D.17
Double standard	Media bias	DB.1
	`Asian` and `Black` are treated differently	DB.2
	`White` and `Black` are treated differently	DB.3
Negative opinion	Tension between `Black` and `Asian`	NO.1
	Bystanders are not to be blamed	NO.2
	Motivation of the Atlanta shootings is not hate	NO.3
	The offender is a crisis actor	NO.4
	The fight between the `Asian` man and the `Black` man is not about hate	NO.5
	Incite anti-Asian sentiment	NO.6
Policy	Demand for policy change in general	P.1
	Gun control	P.2

(19.43%), fewer `White` (53.73%), and fewer `Hispanic` Twitter users (1.55%) involved in our study population than in the general Twitter population (`Black`: 11%, `White`: 60%, and `Hispanic`: 17%) [42]. The Twitter users of our study population are relatively younger. In particular, 46.96% are adults who are between 18 and 29 years old and 37.08% are between 30 and 49, while in the general Twitter population, only 29% are adults who are between 18 and 29 years old and 44% between 30 and 49 [42]. This pattern is consistent with previous study that older adults are not only lagging behind in terms of physical access to the Internet but also in engaging in political activities in the online environment [44].

It is noteworthy that most Twitter users of our study population are also active in other online movements related to racial or social issues, such as #BlackLivesMatter or #SayHerName. A sample of 967 unique Twitter users of our study population (see the Supplementary Material) shows that 77.66% of them have posted or retweeted at least one tweet about other online

TABLE III
DESCRIPTIVE STATISTICS OF THE TWITTER USERS IN THIS STUDY AND THE RATE OF STATE-LEVEL RACIAL BIAS-MOTIVATED HATE CRIMES

(a) Categorical

	n (%)
Gender	
Female	25,646 (55.68)
Male	20,412 (44.32)
Race/Ethnicity	
White	24,746 (53.73)
Black	8,950 (19.43)
Hispanic	713 (1.55)
Asian	11,649 (25.29)
Political affiliation	
Following Trump	2,718 (5.90)
Following Biden	6,598 (14.32)
Population density	
Urban	33,526 (72.79)
Suburban	5,816 (12.63)
Rural	6,716 (14.58)
Others	
Religious status	3,046 (6.61)
Family status	3,171 (6.88)
Verified	1,158 (2.51)

(b) Continuous

	Mean (SD)
Age	34.76 (13.64)
Income	31,177 (8,894)
# of Friends	1,151 (4,718)
# of Followers	3,533 (149,239)
# of Listed memberships	32.45 (317.44)
# of Statuses	23,156 (45,301)
# of Favorites	34,211 (55,767)
# of racial bias motivated hate crimes per 10,000	0.13 (0.10)

movements related to racial or social issues since 2020. The distributions of the characteristics of these users and those of our entire study population are similar.

As shown in Fig 2(a), the discussion about #StopAsianHate and #StopAAPIHate was most heated on March 19. After that, the number of unique Twitter users decreased gradually. On March 31, there was a surge again, where the most retweeted tweet is the news about an attack against a 65-year-old Asian American woman.[14] Fig 2(b) shows the state-level relative frequency of Twitter users who participate in the #StopAsianHate and #StopAAPIHate movement, which roughly corresponds to the Asian population percentage by state, where the West Coast states, Illinois, Texas, Hawaii, and New York are the states with the highest Asian population percentage. There are also more users in Georgia, which is within expectation due to the Atlanta mass shootings.

B. Topic Encoding

To better understand public opinion toward the #StopAsianHate and #StopAAPIHate movement, we read the tweets that have been retweeted for at least 20 times and classify them into two levels of topics. There are 6 level-1 topics including support, news, denouncement, double standard, negative opinion, and policy. In addition, there are 43 level-2 topics. Table IV shows the breakdown of level-1 topics. The breakdown of level-2 topics is shown in the Supplementary Material.

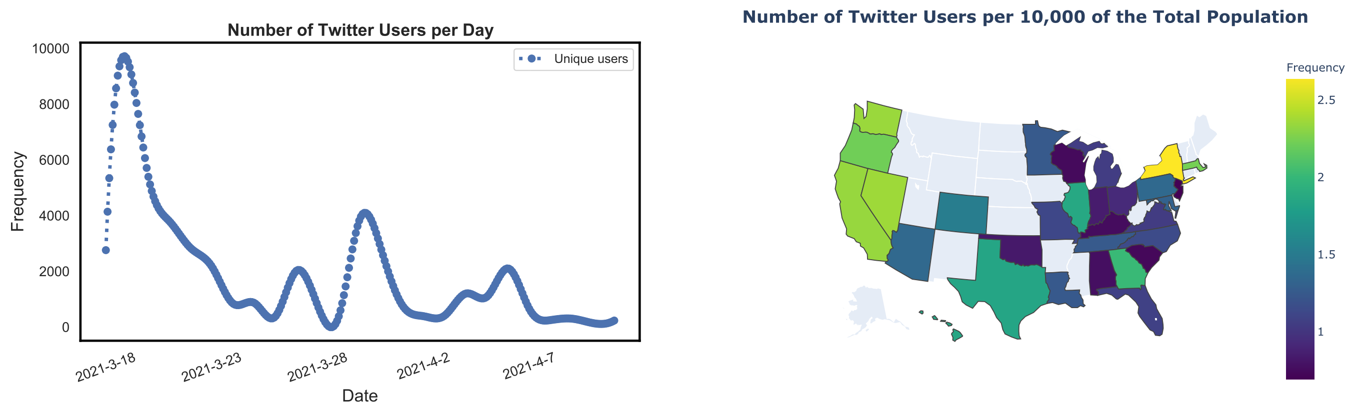
1) Support: The majority of the users posted tweets that are direct support which comprise 51.56%. People post direct supportive statement to support the #StopAsianHate and #StopAAPIHate movement, specific groups, and people. For instance, one of the most retweeted tweets with direct supportive statement is: "#StopAsianHate Pass it on." In addition, tweets that are attached with links to external resources such as funding campaigns for victims, and documentaries about Asian American history are prevalent in our study. The support from political leaders and celebrities is included in this category as well. Furthermore, there are tweets that talk about or encourage solidarity between Black and Asian communities. Besides that, Asian Americans post "Proud to be Asian" to build solidarity within the Asian community, which can be supported by previous study that boundary-setting rituals and institutions that separate them from those in power can strengthen internal solidarity [1].

2) News: This topic accounts for 18.38%. The tweets of this category are the news about anti-Asian crime/talk. For some of them, the racial identity of the offender is not disclosed, while for some of them, the tweets explicitly state the racial identity of the offender.

3) Denouncement: The third most tweets are denouncement (14.69%). It is noteworthy that these tweets are not against #StopAsianHate or #StopAAPIHate. People express positive opinion toward the #StopAsianHate and #StopAAPIHate movement by denouncing specific people/groups or systematic problems. For instance, one of the most retweeted tweets criticizes Donald Trump for calling COVID-19 as "China virus." Some tweets denounce the Republican party for their vote against the Violence Against Women Act. One of the democratic political figures is criticized for spreading misinformation. Apart from the denouncement of people/groups, there is denouncement of racism (white supremacy), culture (Asian fetishization), and education (college admission).

4) Double Standard: Nearly, 8.37% of the users discuss the double standard issues about media bias and different treatment. For instance, some tweets argue that Asian and Black are treated differently: "Asian American "survivors" of assault are being allocated 50 million dollars???? < url >." Some tweets claim that White and Black offenders are treated differently: "Why aren't the two girls who murdered

[14]https://www.nytimes.com/2021/03/30/nyregion/asian-attack-nyc.html



(a) (b)

Fig. 2. (a) Number of Twitter users per day. (b) Number of Twitter users per 10 000 of the total population.

TABLE IV

LEVEL-1 TOPIC DISTRIBUTION BY USER CHARACTERISTICS

	Support (1)	News (2)	Denouncement (3)	Double standard (4)	Negative opinion (5)	Policy (6)
Total	51.56%	18.38%	14.69%	8.37%	5.43%	1.56%
Male	46.18%	21.51%	15.04%	9.83%	6.08%	1.37%
Female	55.84%	15.89%	14.42%	7.21%	4.92%	1.72%
Age (18-29)	54.24%	15.31%	12.96%	9.36%	6.90%	1.23%
Age (30-49)	51.00%	19.74%	15.18%	7.84%	4.58%	1.66%
Age (50-64)	46.44%	23.25%	18.05%	6.72%	3.30%	2.25%
Age (65+)	40.90%	27.01%	20.45%	6.66%	2.54%	2.44%
Asian	58.96%	17.43%	12.56%	6.26%	3.92%	0.87%
White	50.74%	20.34%	16.56%	7.06%	3.21%	2.08%
Black	43.97%	14.17%	12.29%	14.86%	13.71%	1.01%
Hispanic	54.56%	18.65%	14.87%	6.87%	3.23%	1.82%
Following Trump	37.05%	28.37%	16.89%	9.16%	7.14%	1.40%
Following Biden	55.18%	20.25%	16.91%	3.64%	1.23%	2.79%

Asian immigrant Mohammad Anwar going to spend any time in jail?"

5) Negative Opinion: Representing 5.43% of the Twitter users in our study population, this topic expresses negative opinion against the #StopAsianHate and #StopAAPIHate movement, including encouraging tension between Black and Asian communities, inciting anti-Asian sentiment, and justifying that hate is not the reason for the attacks.

6) Policy: Accounting for 1.56% users, the tweets of this topic explicitly demand for policy change or make references to specific laws. For instance, there are tweets that refer to gun control: "In the aftermath of the anti-Asian attacks in Atlanta, just a reminder: Waiting period for an abortion in GA: 24-h waiting period for a gun in GA: none."

C. Public Opinion Varies Across User Characteristics

We conduct logistic regression to examine the predictive effect of user characteristics and the state-level rate of racial bias-motivated hate crimes on the choice of level-1 and level-2 topics. The results of logistic regression of six level-1 topics are summarized in Table V. Each column represents a logistic regression model. The complete logistic regression outputs for level-1 and level-2 topics are further presented in the Supplementary Material.

1) Women Are More Likely to State Direct Support and Demand for Policy Change: The majority tweets of men and women are about showing support. However, there are some nuanced differences. The 55.84% tweets of women are about direct support, while this topic only accounts for 46.18% of the tweets by men. By conducting logistic regression (summarized in Table V), we find that women retweet more direct supportive tweets ($B = -0.27, \mathrm{SE} = 0.02, p < .001, \mathrm{OR} = 0.76, and 95\%\mathrm{CI} = [0.73, 0.79]$), more tweets that explicitly demand for policy change ($B = -0.23, \mathrm{SE} = 0.08, p < .01, \mathrm{OR} = 0.79, and 95\%\mathrm{CI} = [0.68, 0.93]$), fewer news ($B = 0.30, \mathrm{SE} = 0.03, p < .001, \mathrm{OR} = 1.35, and 95\%\mathrm{CI} = [1.28, 1.42]$), fewer negative tweets against #StopAsianHate and #StopAAPIHate ($B = 0.14, \mathrm{SE} = 0.04, p < .01, \mathrm{OR} = 1.15, and 95\%\mathrm{CI} = [1.05, 1.25]$), and fewer discussions about double standard ($B = 0.28, \mathrm{SE} = 0.04, p < .001, \mathrm{OR} = 1.32, and 95\%\mathrm{CI} = [1.23, 1.42]$) than males.

2) Men Discuss in a More General Way, While Women Talk About More Specific Issues: Men are more likely to retweet general supportive statement ($B = 0.16, \mathrm{SE} = 0.03, p < .001, \mathrm{OR} = 1.17, and 95\%\mathrm{CI} = [1.12, 1.25]$), tweets about political figures' ($B = 0.20, \mathrm{SE} = 0.06, p < .01, \mathrm{OR} = 1.28, and 95\%\mathrm{CI} = [1.08, 1.38]$) or celebrity's support ($B = 0.38, \mathrm{SE} = 0.05, p < .001, \mathrm{OR} = 1.46, and 95\%\mathrm{CI} = [1.32, 1.60]$), and tweets supporting "All

TABLE V
LOGISTIC REGRESSION OUTPUTS FOR THE OPINION TOWARD THE #STOPASIANHATE AND #STOPAAPIHATE MOVEMENT AGAINST DEMOGRAPHICS AND OTHER VARIABLES OF INTEREST

Independent variable	Support (1)	News (2)	Denouncement (3)	Double standard (4)	Negative opinion (5)	Policy (6)
Male	-0.27*** (0.02)	0.30*** (0.03)	0.01 (0.03)	0.28*** (0.04)	0.14** (0.04)	-0.23** (0.08)
Age (years)	-0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)	-0.00 (0.00)	-0.01*** (0.00)	0.01** (0.00)
White	-0.25*** (0.02)	0.06 (0.03)	0.27*** (0.03)	0.17*** (0.05)	-0.06 (0.06)	0.84*** (0.11)
Black	-0.46*** (0.03)	-0.34*** (0.04)	0.02 (0.04)	0.72*** (0.05)	1.10*** (0.06)	0.36* (0.15)
Hispanic	-0.12 (0.08)	0.01 (0.10)	0.22* (0.11)	0.02 (0.16)	-0.23 (0.22)	0.84** (0.30)
Following Trump	-0.59*** (0.04)	0.51*** (0.05)	0.09 (0.05)	0.22** (0.07)	0.61*** (0.08)	-0.19 (0.17)
Following Biden	0.24*** (0.03)	-0.01 (0.04)	0.07 (0.04)	-0.81*** (0.07)	-1.26*** (0.12)	0.56*** (0.09)
Hate crimes	0.16 (0.10)	-0.02 (0.13)	0.23 (0.14)	-0.06 (0.19)	-1.80*** (0.27)	0.22 (0.38)
N				46,085		

Note. * $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$. Each model includes control variables (see Supplemental Materials). Table entries are coefficients (standard errors).

lives matter" ($B = 0.99, \text{SE} = 0.15, p < .001, \text{OR} = 2.53, and 95\%\text{CI} = [2.01, 3.63]$) (Table A. 10, see the Supplementary Material). However, women tend to show support by retweeting tweets about more specific issues such as resources ($B = -0.54, \text{SE} = 0.04, p < .001, \text{OR} = 0.58, and 95\%\text{CI} = [0.54, 0.63]$) and stories about the victims ($B = -0.50, \text{SE} = 0.10, p < .001, \text{OR} = 0.61, and 95\%\text{CI} = [0.50, 0.73]$). For denouncement (Table A. 12, see the Supplementary Material), men retweet more general discussion about anti-Asian racism ($B = 0.15, \text{SE} = 0.07, p < .05, \text{OR} = 1.16, and 95\%\text{CI} = [1.01, 1.34]$), while women talk about western imperialism ($B = -0.53, \text{SE} = 0.18, p < .01, \text{OR} = 0.59, and 95\%\text{CI} = [0.41, 0.84]$), Asian fetishization ($B = -0.89, \text{SE} = 0.27, p < .01, \text{OR} = 0.41, and 95\%\text{CI} = [0.24, 0.69]$), and issues about White family with Asian members ($B = -0.54, \text{SE} = 0.24, p < .05, \text{OR} = 0.58, and 95\%\text{CI} = [0.36, 0.94]$). Interestingly, we also find significant difference for discussion about college admission, where men pay more attention ($B = 1.13, \text{SE} = 0.29, p < .001, \text{OR} = 3.10, and 95\%\text{CI} = [1.75, 5.42]$). For news (Table A. 11, see the Supplementary Material), women retweet the tweets that share personal experience involving harm or racism ($B = -0.44, \text{SE} = 0.06, p < .001, \text{OR} = 0.64, and 95\%\text{CI} = [0.58, 0.72]$), while men retweet the anti-Asian harm news that is written by media ($B = 0.28, \text{SE} = 0.05, p < .001, \text{OR} = 1.32, and 95\%\text{CI} = [1.20, 1.45]$).

3) Older Adults Retweet More News, Denouncement, and Demand for Policy Change: If the age is to increase by one year, the adult is 1.01 times more likely to retweet news ($B = 0.01, \text{SE} = 0.00, p < .001, \text{OR} = 1.01, and 95\%\text{CI} = [1.01, 1.01]$), 1.01 times more likely to retweet make denouncement ($B = 0.01, \text{SE} = 0.00, p < .001, \text{OR} = 1.01, and 95\%\text{CI} = [1.01, 1.01]$), and 1.01 times more likely to retweet tweets seeking policy change ($B = 0.01$, SE = 0.00, p <.01, OR = 1.01,$and 95\%\text{CI} = [1.00, 1.01]$). Take the "18–29" and "65+" age groups as an example, news-related tweets account for 27.01% for "65+," and however, they only account for 15.31% for "18–29." The 20.45% tweets of "65+" make denouncement, while only 12.96% tweets of "18–29" are related to denouncement. The younger adults are more likely to retweet direct support ($B = -0.01, \text{SE} = 0.00, p < .001, \text{OR} = 0.99, and 95\%\text{CI} = [0.99, 0.99]$) and express negative opinion ($B = -0.01, \text{SE} = 0.00, p < .001, \text{OR} = 0.99, and 95\%\text{CI} = [0.99, 0.99]$).

4) Older Adults Tend to Denounce Political Figures and Groups: Of all the level-2 topics of "Denouncement" (Table A. 12, see the Supplementary Material), age is found to have a significant effect on the choice of topics that denounce specific political figures and groups. The older the adults are, the more likely, they denounce Donald Trump ($B = 0.03, \text{SE} = 0.00, p < .001, \text{OR} = 1.03, and 95\%\text{CI} = [1.02, 1.04]$), Republican ($B = 0.02, \text{SE} = 0.00, p < .001, \text{OR} = 1.02, and 95\%\text{CI} = [1.02, 1.03]$), and Democratic parties ($B = 0.05, \text{SE} = 0.01, p < .001, \text{OR} = 1.05, and 95\%\text{CI} = [1.04, 1.05]$).

5) Race/Ethnicity Shows Significant Effect on the Choice of Topics: Using Asian as the reference group, we find that White adults are less likely to state direct support tweets ($B = -0.25, \text{SE} = 0.02, p < .001, \text{OR} = 0.78, and 95\%\text{CI} = [0.74, 0.81]$), more likely to retweet denouncement ($B = 0.27, \text{SE} = 0.03, p < .001, \text{OR} = 1.31, and 95\%\text{CI} = [1.22, 1.39]$), double standard related tweets ($B = 0.17, \text{SE} = 0.05, p < .001, \text{OR} = 1.19, and 95\%\text{CI} = [1.08, 1.30]$), and demand for policy change ($B = 0.84, \text{SE} = 0.11, p < .001, \text{OR} = 2.32, and 95\%\text{CI} = [1.86, 2.89]$).

Black adults are less likely to state direct support tweets ($B = -0.46, \text{SE} = 0.03, p < .001, \text{OR} = 0.63, and 95\%\text{CI} = [0.59, 0.67]$) and retweet news ($B = -0.34, \text{SE} = 0.04, p < .001, \text{OR} = 0.71, and 95\%\text{CI} = [0.66, 0.77]$). They are more likely to express negative opinion ($B = 1.10, \mathrm{SE} = 0.06, p < .001, \mathrm{OR} = 3.00, and 95\%\mathrm{CI} = [2.66, 3.39]$), discuss double standard ($B = 0.72, \mathrm{SE} = 0.05, p < .001, \mathrm{OR} = 2.05, and 95\%\mathrm{CI} = [1.86, 2.27]$), and demand for policy change ($B = 0.36, \mathrm{SE} = 0.15, p < .05, \mathrm{OR} = 1.43, and 95\%\mathrm{CI} = [1.07, 1.92]$).

`Hispanic` adults are only found to be more likely to retweet denouncement ($B = 0.22, \mathrm{SE} = 0.11, p < .05, \mathrm{OR} = 1.25, and 95\%\mathrm{CI} = [1.00, 1.54]$) and demand for policy change ($B = 0.84, \mathrm{SE} = 0.30, p < .01, \mathrm{OR} = 2.32, and 95\%\mathrm{CI} = [1.30, 4.18]$).

6) Different Race/Ethnicity Groups Tend to Defend Themselves When Discussing #StopAsianHate and #StopAAPIHate: `Black` community is more likely to discuss solidarity between them and `Asian` community ($B = 0.89, \mathrm{SE} = 0.10, p < .001, \mathrm{OR} = 2.44, and 95\%\mathrm{CI} = [1.99, 2.94]$) (Table A. 10, see the Supplementary Material). When it comes to double standard (Table A. 13, see the Supplementary Material), they focus on the topics that `Black` adults and `Asian` adults are treated differently ($B = 1.24, \mathrm{SE} = 0.29, p < .001, \mathrm{OR} = 3.46, and 95\%\mathrm{CI} = [1.95, 6.11]$). In addition, they tend to retweet tweets that criticize white supremacy ($B = 0.63, \mathrm{SE} = 0.10, p < .001, \mathrm{OR} = 1.88, and 95\%\mathrm{CI} = [1.54, 2.27]$) (Table A. 12, see the Supplementary Material). On the contrary, `White` adults are more likely to retweet tweets that attribute the anti-Asian crimes to `Black` community instead of white supremacy ($B = 0.69, \mathrm{SE} = 0.31, p < .05, \mathrm{OR} = 1.99, and 95\%\mathrm{CI} = [1.11, 3.63]$).

7) Political Divides Extend to the Choice of Topics: Following Trump and following Biden are both found to have significant effect on direct support, negative opinion, and double standard. Compared to people who do not follow Biden, those who follow Biden are more likely to show direct support ($B = 0.24, \mathrm{SE} = 0.03, p < .001, \mathrm{OR} = 1.27, and 95\%\mathrm{CI} = [1.20, 1.34]$) but less likely to express negative opinion ($B = -1.26, \mathrm{SE} = 0.12, p < .001, \mathrm{OR} = 0.28, and 95\%\mathrm{CI} = [0.23, 0.36]$) and talk about double standard ($B = -0.81, \mathrm{SE} = 0.07, p < .001, \mathrm{OR} = 0.44, and 95\%\mathrm{CI} = [0.39, 0.51]$). By contrast, compared to people who do not follow Trump, those who follow Trump are less likely to show direct support ($B = -0.59, \mathrm{SE} = 0.04, p < .001, \mathrm{OR} = 0.55, and 95\%\mathrm{CI} = [0.51, 0.60]$) but more likely to express negative opinion ($B = 0.61, \mathrm{SE} = 0.08, p < .001, \mathrm{OR} = 1.84, and 95\%\mathrm{CI} = [1.56, 2.16]$) and talk about double standard ($B = 0.22, \mathrm{SE} = 0.07, p < .01, \mathrm{OR} = 1.25, and 95\%\mathrm{CI} = [1.08, 1.43]$).

8) Disagreements Lie in Five Subtopics Between Biden's and Trump's Followers: For Trump followers, they are more likely to retweet the opinion that `Black` is to be blamed for the anti-Asian crimes ($B = 1.13, \mathrm{SE} = 0.24, p < .001, \mathrm{OR} = 3.10, and 95\%\mathrm{CI} = [1.93, 4.95]$), denounce the anti-Asian racism within college admission ($B = 0.76, \mathrm{SE} = 0.33, p < .05, \mathrm{OR} = 2.14, and 95\%\mathrm{CI} = [1.11, 4.10]$) (Table A. 12, see the Supplementary Material), support "All lives matter" ($B = 0.23, \mathrm{SE} = 0.03, p < .001, \mathrm{OR} = 1.26, and 95\%\mathrm{CI} = [1.20, 1.34]$) (Table A. 10), and retweet news about `Black` targeting `Asian` ($B = 0.94, \mathrm{SE} = 0.11, p < .001, \mathrm{OR} = 2.56, and 95\%\mathrm{CI} = [2.10, 3.16]$), but less likely to retweet news about personal experience ($B = -0.94, \mathrm{SE} = 0.13, p < .001, \mathrm{OR} = 0.39, and 95\%\mathrm{CI} = [0.30, 0.50]$) (Table A. 11), compared to those who do not follow Trump. Following Biden has opposite effect on these five topics against following Trump.

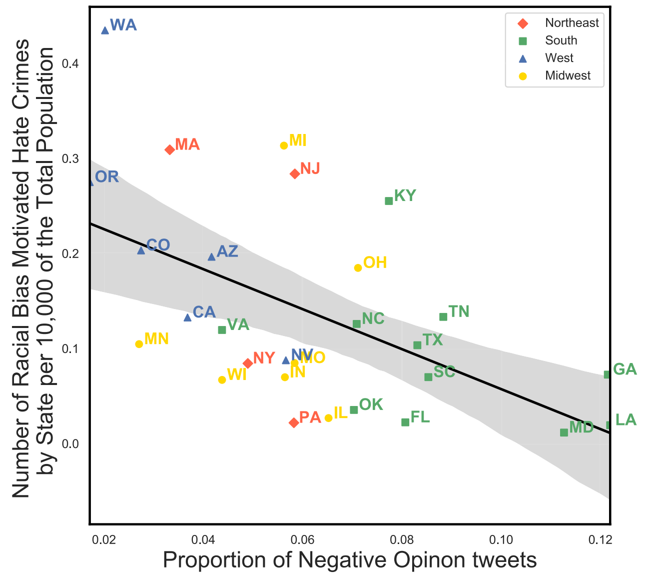


Fig. 3. Number of racial bias-motivated hate crimes by state per 10 000 of the total population versus proportion of negative opinion tweets.

D. Hate Crimes and Public Opinion Toward #StopAsianHate and #StopAAPIHate

1) Negative Opinion Is the Weakest in the States With Most Hate Crimes: The number of racial bias-motivated hate crimes per 10 000 of the total population by state is negatively associated with the likelihood of expressing negative opinion ($B = -1.80, \mathrm{SE} = 0.27, p < .001, \mathrm{OR} = 0.16, and 95\%\mathrm{CI} = [0.10, 0.28]$). We further explore the relationship between hate crimes and topics of the tweets in Fig. 3, where we color the states according to their geographic region. The states of the south are in the bottom-right corner. The clusters of the south, west, and midwest northeast in Fig. 3 suggest a common opinion toward anti-Asian hate crimes among spatially proximal populations.

E. Retweet Network

To investigate the retweet activity, we build a directed retweet network, where nodes represent Twitter users and edges represent retweet relationships. If user i retweets a tweet of a user j, we add an edge going from node i to node j. The direction of an edge points to the user that is retweeted. In our study, the retweet network consists of 41 611 nodes and 40 915 edges. For each node, we calculate its in-degree, which is the number of its in-going links and represents the number of different Twitter users that have retweeted at least one of her/his tweets. The users with a large in-degree are considered to be influencers. The top ten influencers are shown in Table VI. To preserve users' privacy, we have anonymized the screen names with code names. Each influencer may post tweets of different level-1 topics.

TABLE VI
TOP TEN INFLUENCERS OF THE RETWEET NETWORK

Screen name	In-degree	# of `Followers` change (%)	Occupation	Top Topic
Reporter 1	1,175	60,618 –>62,397 (2.93)	Reporter	Support
Unknown 1	1,085	1,032 –>1,057 (2.42)	NA	Double standard
Comedian 1	960	1,574 –>1,943 (23.44)	Comedian	Support
Professor 1	958	475 –>1,268 (166.95)	Professor	Support
Politician 1	643	76,314 –>86,832 (13.78)	Politician	News
Politician 2	629	1,604,795 –>1,614,121 (0.58)	Politician	Support
Union organizer 1	588	6,111 –>6,522 (6.73)	Union organizer	Support
Journalist 1	568	777,469 –>807,086 (3.81)	Journalist	News
Reporter 2	552	31,894 –>32,239 (1.08)	Reporter	Double standard
Reporter 3	526	13,899 –>23,425 (68.54)	Reporter	News

In Table VI, we list the level-1 topic with the most retweets. Among the top topics of the top ten influencers, five are about "Support," three are about "News," and the other two are about "Double standard." The majority of these influencers are Asian-American reporters, journalists, or politicians. The tweets of Asian-Americans may receive more attention from the general public compared to others. Two Asian-Americans of the top ten influencers—Professor 1 and Reporter 3—gained proportionally more followers during the study period.

VI. CONCLUSION AND DISCUSSION

The public opinion toward the #StopAsianHate and #StopAAPIHate movement of 46 058 Twitter users across 30 states in USA ranging from March 18, 2021 to April 11, 2021 are collected and analyzed. Among them, 51.56% show direct support, 18.38% retweet news about anti-Asian crimes, 14.69% denounce anti-Asian racism, 8.37% discuss issues about double standard, 1.56% explicitly demand for policy change, and 5.43% express negative opinion against the #StopAsianHate and #StopAAPIHate movement (Table IV).

The #StopAsianHate and #StopAAPIHate movement is more likely to attract participation from women and younger adults. A similar pattern is observed in the #BlackLivesMatter movement [18]. The percentages of `Asian` and `Black` communities in our study population are greater than those in the general Twitter population. Moreover, most users are active in other online movements related to racial or social issues.

We observe that public opinion varies across user characteristics including gender, age, race/ethnicity, as well as political affiliation. Women are more likely to state direct support and demand for policy change than men. They focus on specific issues, while men tend to discuss in a more general way. Older adults retweet more news, denouncement, and demand for policy change. Of all the level-2 topics of "denouncement," older adults tend to denounce political figures and groups. Different race/ethnicity groups respond to topics about #StopAsianHate and #StopAAPIHate differently and tend to defend themselves in the discussions. The `Black` and `White` communities point to each other as the ones to be blamed for the anti-Asian hate crimes. The creation of a strong movement identity leads to a backlash [43]. In our study, it is observed that when the `Black` community criticizes white supremacy for the Atlanta attack, the `White` community resists by retweeting tweets that attribute the anti-Asian crimes to the `Black` community. For instance, one of the most retweeted references is the report of *Criminal Victimization, 2018* by the Bureau of Justice Statistics, where the data show that `Blacks` are the major offenders of the violent incidents against `Asian` community [45]. The previous study suggests that `Whites` perceive their whiteness as a negative attribute that now puts them at a perceptual disadvantage in society and think that their whiteness should not to be used as a marker of liability for continuing racial hate against minorities [46]. With respect to political affiliation, we find that political divides extend to the choice of topics in the #StopAsianHate and #StopAAPIHate movement, with Biden followers more likely to show direct support but less likely to express negative opinion or discuss double standard.

Furthermore, the rate of racial bias-motivated hate crimes has a significant effect on negative opinion. In the places with the highest racial bias-motivated hate crime rate, the negative opinion is the weakest. It is suggested that when individuals are targeted because of their race or ethnicity, they are likely to experience a host of negative emotions that are qualitatively distinct from those experienced following nonbiased criminal victimization [47]. People who have not encountered hate crimes might express negative opinions because they do not have the related experience, along with the negative emotions, thus making it harder for them to understand the seriousness of hate crimes. We further find that spatially proximal populations may share a common attitude toward anti-Asian crimes. To increase awareness and have a better understanding of racial bias-motivated hate crimes, hate crime education programs can be deployed [48].

Based on the analysis of the retweet network, we identify the top ten influencers. The majority of the top influencers are Asian-Americans. Four of them are reporters or journalists, and two of them are politicians. The level-1 topics of their tweets that are retweeted most are "Support," "News," and "Double standard."

Our study does not include the relevant tweets that were retweeted for fewer than 20 times. The states that are less populated are not selected in the study population in order to provide a reliable state-level analysis. In addition, it is worth investigating the public opinions in other countries on the #StopAsianHate and #StopAAPIHate movement.

To the best of our knowledge, this is the first large-scale social media-based study to understand public opinion toward the #StopAsianHate and #StopAAPIHate movement. We hope that our work can provide insights and promote research on anti-Asian hate crimes and ultimately help address such a serious societal issue for the common benefits of all communities. Future work could investigate the relationship between culture and public opinion. The echo chamber effect of the #StopAsianHate and #StopAAPIHate movement may be analyzed for different groups as well.

References

[1] V. Taylor and N. E. Whittier, "Collective identity in social movement communities: Lesbian feminist mobilization," in *Frontiers in Social Movement Theory*, A. D. Morris and C. M. Mueller, Eds. Yale Univ. Press, 1992, pp. 104–129.

[2] G. Yang, "Narrative agency in hashtag activism: The case of# blacklivesmatter," *Media Commun.*, vol. 4, no. 4, p. 13, 2016.

[3] D. Freelon, C. D. McIlwain, and M. Clark, "Beyond the hashtags: #ferguson, #blacklivesmatter, and the online struggle for offline justice," Center Media Social Impact, Amer. Univ., Forthcoming, Washington, DC, USA, Tech. Rep., 2016.

[4] R. J. Gallagher, A. J. Reagan, C. M. Danforth, and P. S. Dodds, "Divergent discourse between protests and counter-protests:# BlackLivesMatter and# AllLivesMatter," *PLoS ONE*, vol. 13, no. 4, Apr. 2018, Art. no. e0195644.

[5] R. Ray, M. Brown, N. Fraistat, and E. Summers, "Ferguson and the death of Michael Brown on Twitter: #BlackLivesMatter, #TCOT, and the evolution of collective identities," *Ethnic Racial Stud.*, vol. 40, no. 11, pp. 1797–1813, Sep. 2017.

[6] S. R. DiBrito, C. M. Lopez, C. Jones, and A. Mathur, "Reducing implicit bias: Association of women surgeons #HeForShe task force best practice recommendations," *J. Amer. College Surgeons*, vol. 228, no. 3, pp. 303–309, Mar. 2019.

[7] S. Jaffe, "The collective power of #MeToo," *Dissent*, vol. 65, no. 2, pp. 80–87, 2018.

[8] R. Jagsi *et al.*, "Sexual harassment in medicine-# metoo," *New England J. Med.*, vol. 378, no. 3, pp. 209–211, 2018.

[9] D. Zarkov and K. Davis, "Ambiguities and dilemmas around# metoo: #forhow long and # whereto?" *Eur. J. Women's Stud.*, vol. 25, no. 1, pp. 3–9, Feb. 2018.

[10] V. Duong, P. Pham, R. Bose, and J. Luo, "#MeToo on campus: Studying college sexual assault at scale using data reported on social media," 2020, *arXiv:2001.05970*.

[11] R. Jeung, A. Y. Horse, T. Popovic, and R. Lim, "Stop aapi hate national report," *Stop AAPI Hate*, 2021.

[12] A. R. Gover, S. B. Harper, and L. Langton, "Anti-asian hate crime during the COVID-19 pandemic: Exploring the reproduction of inequality," *Amer. J. Criminal Justice*, vol. 45, no. 4, pp. 647–667, Aug. 2020.

[13] H. Tessler, M. Choi, and G. Kao, "The anxiety of being Asian american: Hate crimes and negative biases during the COVID-19 pandemic," *Amer. J. Criminal Justice*, vol. 45, no. 4, pp. 636–646, Aug. 2020.

[14] A. N. Ancheta, *Race, Rights, and the Asian American Experience*. New Brunswick, NJ, USA: Rutgers Univ. Press, 2006.

[15] A. Saw, A. Y. Horse, and R. Jeung, "Stop AAPI hate mental health report," Stop AAPI Hate Coalition, San Francisco, CA, USA, Tech. Rep., 2021.

[16] L. Tan, S. Ponnam, P. Gillham, B. Edwards, and E. Johnson, "Analyzing the impact of social media on social movements: A computational study on Twitter and the occupy wall street movement," in *Proc. IEEE/ACM Int. Conf. Adv. Social Netw. Anal. Mining*, Aug. 2013, pp. 1259–1266.

[17] T. Bonilla and A. B. Tillery, "Which identity frames boost support for and mobilization in the #BlackLivesMatter movement? An experimental test," *Amer. Political Sci. Rev.*, vol. 114, no. 4, pp. 947–962, Nov. 2020.

[18] A. Olteanu, I. Weber, and D. Gatica-Perez, "Characterizing the demographics behind the #BlackLivesMatter movement," 2015, *arXiv:1512.05671*.

[19] A. Reyes-Menendez, J. R. Saura, and S. B. Thomas, "Exploring key indicators of social identity in the #MeToo era: Using discourse analysis in UGC," *Int. J. Inf. Manage.*, vol. 54, Oct. 2020, Art. no. 102129.

[20] L. Fan, H. Yu, and A. J. Gilliland, "#StopAsianHate: Archiving and analyzing Twitter discourse in the wake of the 2021 Atlanta spa shootings," *Proc. Assoc. Inf. Sci. Technol.*, vol. 58, no. 1, pp. 440–444, Oct. 2021.

[21] E. Tran, "#Stopasianhate: A critical discourse analysis of anti-asian racism during the COVID-19 pandemic in online Canadian news media," *Student Res. Proc.*, vol. 6, no. 1, 2021.

[22] E. M. Cody, A. J. Reagan, L. Mitchell, P. S. Dodds, and C. M. Danforth, "Climate change sentiment on Twitter: An unsolicited public opinion poll," *PLoS ONE*, vol. 10, no. 8, Aug. 2015, Art. no. e0136092.

[23] A. Karami, L. S. Bennett, and X. He, "Mining public opinion about economic issues: Twitter and the U.S. presidential election," *Int. J. Strategic Decis. Sci.*, vol. 9, no. 1, pp. 18–28, Jan. 2018.

[24] Y. Wang, J. Luo, and X. Zhang, "When follow is just one click away: Understanding Twitter follow behavior in the 2016 us presidential election," in *Proc. Int. Conf. Social Informat.* Cham, Switzerland: Springer, 2017, pp. 409–425.

[25] D. S. Kim and J. W. Kim, "Public opinion sensing and trend analysis on social media: A study on nuclear power on Twitter," *Int. J. Multimedia Ubiquitous Eng.*, vol. 9, no. 11, pp. 373–384, Nov. 2014.

[26] S. W. H. Kwok, S. K. Vadde, and G. Wang, "Tweet topics and sentiments relating to COVID-19 vaccination among Australian Twitter users: Machine learning analysis," *J. Med. Internet Res.*, vol. 23, no. 5, May 2021, Art. no. e26953.

[27] H. Lyu *et al.*, "Social media study of public opinions on potential COVID-19 vaccines: Informing dissent, disparities, and dissemination," *Intell. Med.*, Aug. 2021.

[28] X. Zhang, Y. Wang, H. Lyu, Y. Zhang, Y. Liu, and J. Luo, "The influence of COVID-19 on the well-being of people: Big data methods for capturing the well-being of working adults and protective factors nationwide," *Frontiers Psychol.*, vol. 12, p. 2327, Jun. 2021.

[29] Y. Zhang *et al.*, "Monitoring depression trends on Twitter during the COVID-19 pandemic: Observational study," *JMIR Infodemiology*, vol. 1, no. 1, p. e26769, 2021.

[30] N. Yeung, J. Lai, and J. Luo, "Face off: Polarized public opinions on personal face mask usage during the COVID-19 pandemic," in *Proc. IEEE Int. Conf. Big Data (Big Data)*, Dec. 2020, pp. 4802–4810.

[31] S. N. Saleh, C. U. Lehmann, S. A. McDonald, M. A. Basit, and R. J. Medford, "Understanding public perception of coronavirus disease 2019 (COVID-19) social distancing on Twitter," *Infection Control Hospital Epidemiol.*, vol. 42, no. 2, pp. 131–138, Feb. 2021.

[32] H. Lyu, L. Chen, Y. Wang, and J. Luo, "Sense and sensibility: Characterizing social media users regarding the use of controversial terms for COVID-19," *IEEE Trans. Big Data*, vol. 7, no. 6, pp. 952–960, Dec. 2021.

[33] Z. Xiong, P. Li, H. Lyu, and J. Luo, "Social media opinions on working from home in the united states during the COVID-19 pandemic: Observational study," *JMIR Med. Informat.*, vol. 9, no. 7, Jul. 2021, Art. no. e29195.

[34] *Hate Crime Statistics, 2019*, Federal Bur. Invest., United States Department of Justice, Washington, DC, USA, 2020.

[35] S.-G. Jung, J. An, H. Kwak, J. Salminen, and B. J. Jansen, "Assessing the accuracy of four popular face recognition tools for inferring gender, age, and race," in *Proc. 12th Int. AAAI Conf. Web social media*, 2018, pp. 1–4.

[36] P. G. Efthimion, S. Payne, and N. Proferes, "Supervised machine learning bot detection techniques to identify social Twitter bots," *SMU Data Sci. Rev.*, vol. 1, no. 2, p. 5, 2018.

[37] S. I. Serengil and A. Ozpinar, "LightFace: A hybrid deep face recognition framework," in *Proc. Innov. Intell. Syst. Appl. Conf. (ASYU)*, Oct. 2020, pp. 23–27.

[38] *2015–2019 American Community Survey 5-Year*, U.S. Census Bureau, Suitland-Silver Hill, MA, USA, 2020.

[39] S. Bergsma and B. Van Durme, "Using conceptual class attributes to characterize social media users," in *Proc. 51st Annu. Meeting Assoc. Comput. Linguistics*, 2013, pp. 710–720.

[40] D. M. Blei, A. Y. Ng, and M. I. Jordan, "Latent Dirichlet allocation," *J. Mach. Learn. Res.*, vol. 3, pp. 993–1022, Jan. 2003.

[41] M. Bastian, S. Heymann, and M. Jacomy, "Gephi: An open source software for exploring and manipulating networks," in *Proc. Int. AAAI Conf. Web Social Media*, vol. 3, no. 1, pp. 361–362, 2009.

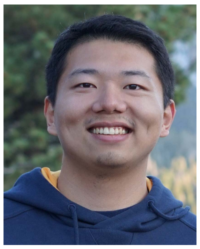
[42] S. Wojcik and A. Hughes, "Sizing up Twitter users," *Pew Res. Center Internet Technol.*, vol. 24, pp. 1–23, Apr. 2019.

[43] F. Polletta and J. M. Jasper, "Collective identity and social movements," *Annu. Rev. Sociol.*, vol. 27, no. 1, pp. 283–305, 2001.

[44] B. Xie and P. T. Jaeger, "Older adults and political participation on the internet: A cross-cultural comparison of the USA and China," *J. Cross-Cultural Gerontol.*, vol. 23, no. 1, pp. 1–15, Mar. 2008.

[45] R. E. Morgan and B. Oudekerk, "Criminal victimization, 2018," *Bur. Justice Statist.*, vol. 253043, pp. 1–53, Sep. 2019.

[46] R. L. Jackson and S. M. Heckman, "Perceptions of white identity and white liability: An analysis of white Student responses to a college campus racial hate crime," *J. Commun.*, vol. 52, no. 2, pp. 434–450, Jun. 2002.
[47] K. Craig-Henderson and L. R. Sloan, "After the hate: Helping psychologists help victims of racist hate crime," *Clin. Psychol., Sci. Pract.*, vol. 10, no. 4, pp. 481–490, 2003.
[48] J. F. Anderson, L. Dyson, and W. Brooks Jr, "Preventing hate crime and profiling hate crime offenders," *Western J. Black Stud.*, vol. 26, no. 3, p. 140, 2002.



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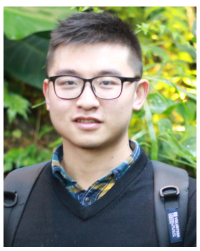

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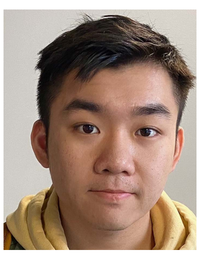

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