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How Did #StopAsianHate and #BlackLivesMatter React to Each Other after the Atlanta Shootings: An Analysis of Twitter Hashtag Networks

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The Atlanta Spa shootings interrogate the model minority myth of Asian Americans and their positionality in U.S. racial politics. Whereas recent nationwide surveys report broad support for Black Lives Matter among them, many studies have also portrayed Afro-Asian historical relationships as contentious. The main question in the current study is how the #StopAsianHate activism had reacted to the #BlackLivesMatter movement and vice versa on Twitter in terms of a shared sense of linked fate. To this end, we sought to examine hashtags and semantic networks with the data from March 2 to April 26, 2021. The tweets addressing #StopAsianHate without #BlackLivesMatter were characterized primarily by narratives about anti-Asian hate crimes and by South-Korean band BTS's fanbase ARMY's voices but with minimal concern regarding the trial of former police officer Derek Chauvin in the case of George Floyd's murder. In contrast, the tweets exclusively containing #BlackLivesMatter delivered messages on anti-Asian violence in response to the Atlanta tragedy although the degree and betweenness centralities of #asianlivesmatter had diminished as public attention was shifted to the trial. The overall evidence seems to suggest that hashtag activism, unlike offline rallies since the shootings, could be caught within the boundaries of imagined communities due to tagged interactions, engendering tension between social identity and collective identity.

Keywords: #StopAsianHate, #BlackLivesMatter, Twitter, semantic network

A shooting spree in Atlanta in March 2021 interrogates the model minority myth of Asian Americans that has worked as a "melancholic mechanism" (Eng & Han, 2019) of effacing a long history of discrimination and exclusion against them in America. Where do these minorities then fit in U.S. racial politics with the backdrop of anti-Asian hate crimes amidst the COVID-19 pandemic (Hua & Junn, 2021)? The chair of Asian Americans and Pacific Islanders (AAPI) Progressive Action, Tung Nguyen, brought up the fundamental issue during an interview, "Do we go ahead as a single Asian American movement to address anti-Asian racism? Or is anti-Asian racism both part of a bigger wave of racism, and the solution is beyond just what Asian Americans care about or should do?" (Kaur, 2021, p. 33).

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The nationwide surveys indicate increased positive attitude toward Black Lives Matter (BLM) over the two years before the death of George Floyd in 2020 (Cohn & Quealy, 2020) and particularly overall broad support among Asian Americans afterward until 2021 (Horowitz, 2021; Thomas & Horowitz, 2020). Nonetheless, not a few studies have documented the recent trajectories of contentious relationships between African Americans and Asian Americans (Kuo, 2018; Liu, 2018). Since part of the latter's indifference to the BLM movement is attributable to a sense of belonging to the United States regardless of different identities and citizenship status (Yellow Horse, Kuo, Seaton, & Vargas, 2021), their belief in "linked fate" (Dawson, 1994) with Black Americans and the other groups of color is then deemed to enhance cross-racial coalitions in the era of post-Civil rights movements.

Social media provide a new medium for online hashtag activism but with weaknesses such as low-cost slacktivism, "liquid organizing" (Gerbaudo, 2012), and "tactical freeze" (Tufekci, 2017). Although social media platforms are inherently designed for spontaneous and live interactions in response to real-life events, admittedly the use of hashtags not only creates mutual awareness and spreads ideas but also enhances a sense of togetherness in online communication networks as "affective publics" (Bonilla & Rosa, 2015; Dawson, 2020; Yang, 2016). When "hashtag-based story telling" (Wang & Zhou, 2021, p. 2) effectively reshapes public opinions and sentiments, hashtag activism as "connective action" (Bennett & Segerberg, 2012) often successfully coevolves with real-life social movements, as demonstrated by the #BlackLivesMatter (Mislán & Dache-Gerbino, 2018; Peng, Budak, & Romero, 2019; Schneider, 2020; Tillery, 2019; Williamson, Trump, & Einstein, 2018). Black Lives Matter has successfully developed great "narrative capacity," which refers to the movement's capability to appeal to the broader public by persuasively framing stories on its own terms (Tufekci, 2017, pp. 193–209).

The primary question in the present study is whether and to what extent the Stop Asian Hate activism has paved the ground for Asian-Black solidarity via social media, where computer-mediated communications and interaction rituals operate in considerably different contexts and norms. It cannot be ruled out that tagging around #StopAsianHate and #BlackLivesMatter may each create their own parochial communities polarized over racial and political issues. We thus sought to examine Twitter hashtags and their networks during the period from March 2 to April 26, 2021, which covers both the day of the Atlanta shootings (March 16) and the day of the guilty verdict of former police officer Derek Chauvin charged in the case of George Floyd's murder (April 20). In terms of social identity and collective identity as a driver of collective action and its outcomes (Priante, Ehrenhard, van den Broek, & Need, 2018), our conjecture is that the former tends to be dominant over the latter insofar as online interactions, on the basis of digital tags associated with racial and other categories in personalized experiences and messages, fail to redraw the us-and-them boundaries.

Literature Review

In the wake of increasing anti-Asian hate crimes over the last couple of years (Ruiz, Edwards, & Lopez, 2021), the tragedy in Atlanta fueled sporadic campaigns initiated at the beginning of 2021 by virally spreading messages as well as videos of physical attacks against elderly Asians in public spaces. Influencers in the fashion industry, business leaders, politicians, and advocate groups joined to voice their concerns to raise awareness using #StopAsianHate with other hashtags on social media (Walters

& Morales, 2021). A growing number of laypeople continued to post their personal experiences of racism, participate in online donations, and share information about offline gatherings, as commonly observed in a typical case of online activism. A complex context has arisen with anti-Asian sentiments associated with "Chinese virus," as tweeted by Trump (Hswen et al., 2021) on the one hand and with an intensifying backlash to the BLM movement during his presidency following a widening counter-discourse signified by #AllLivesMatter (Gallagher, Reagan, Danforth, & Dodds, 2018; Torkelson & Hartmann, 2021) on the other. As to BLM, the #StopAsianHate activism brings up the question of the positionality of Asian Americans as fragile citizens with double standards in the racial politics of America polarized by the White-Black binary (Hua & Junn, 2021).

According to a survey in June and September 2020, Asian Americans are far more likely to show positive attitudes toward the BLM movement than non-Hispanic Whites. The overall patterns of support are very similar between Asian Americans and Hispanic and Latino groups, but the degree of their support has remained more consistent from 75% to 69% compared with the other two groups (Figure 1 in Thomas & Horowitz, 2020). The most recent survey result in September 2021 shows that 29% of Asian Americans still strongly support, and 39% somewhat support BLM (Horowitz, 2021). Despite encouraging cases of Afro-Asian solidarity in the long history of race relations in America (Chang, 2020; Hope, 2019), there have been even antagonistic incidents between Asian Americans and Black communities (Kuo, 2018; Liu, 2018). A prototypical example can be found in disputed views on the conviction of Peter Liang in 2016, the officer who fatally shot an unarmed Black man: One group of Asian Americans for the centering of Black lives and the other group against it. Nationwide rallies and protests mainly organized by Chinese Americans reflected growing disagreement within the Asian American communities (Liu, 2018). A larger cleavage was reproduced in social media, such as #Asian4BlackLivesMatter versus #SavePeterLiang. The pro-Liang groups positioned themselves politically within their communities by creating a narrative of victimization online (Kuo, 2018).

While minority groups of color have been divided in the racial politics that defines America, with a back door open for Asian Americans to slip in under invisible privileges (Warren & Twine, 1997), certain distinctions between Black Americans and other non-Black minorities have increased in demographic characteristics and multiracial identification (Lee & Bean, 2012). In spite of an in-between social status and the ambivalent identities of Asian Americans regarding pro-Whiteness and anti-Blackness, it turned out that those who support BLM among Asian Americans are more likely to perceive anti-Black discrimination by virtue of sharing linked fate not only with other Asian Americans but also with other non-White groups (Merseth, 2018), as predicted by the model of common in-group identity (Gaertner, Mann, Murrell, & Dovidio, 1989). In a similar vein, knowledge and explicit acknowledgment of racism in the United States tend to lower Asian Americans' indifference to BLM, regardless of nativity (Yellow Horse et al., 2021). Under the circumstances, a "pan-ethnic linked fate" (Li & Nicholson, 2021, p. 9) could overcome social, cultural, and political cleavages along the lines of ethnicity and race, especially in the era of BLM against White supremacy.

Advances in online platforms such as social media and social network services, represented by Twitter and Facebook, respectively, have paved an innovative pathway to generate public opinions and sentiments of self-organizing networked citizens faster than ever, which is otherwise not attainable, and to consequently transform the landscape of politics (Harlow, 2013; Lane, Kim, Lee, Weeks, & Kwak, 2017; Shirky, 2010; Wilson, 2011). Nevertheless, a body of scholarship has addressed the limits of online activism in bringing about real social and political change (Lewis, Gray, & Meierhenrich, 2014). Being episodically oriented (Zulli, 2020), social media platforms induce online users to immediately react to offline issues and events (e.g., Twitter's "what's happening"). Specifically, hashtags via social media tend to quickly gain huge popularity and dissipate from public prominence afterward (Anderson, Toor, Olmstead, Rainie, & Smith, 2018). However, it has been also documented that recurrently emerging discourses around particular topics often enable the shifting of public discourse, thereby constituting counter-publics (Jackson, Bailey, & Foucault Welles, 2020; Lynch, 2011) as alternative political arenas for underrepresented and marginalized groups of people. Online activism further amplifies offline protests beyond the hashtags by widely bridging localized online communities across geographical boundaries, as is the case with the nationwide propagation of the BLM movement (Freelon, McIlwain, & Clark, 2016).

A large volume of literature to date has been indeed devoted to empirical investigations on the #BlackLivesMatter activism via Twitter. It can be grouped into four broad categories in terms of research method and analytical strategy: Qualitative content analysis of tweets or hashtags (Bonilla & Rosa, 2015; Carney, 2016; Edrington & Lee, 2018; Ince, Rojas, & Davis, 2017; Jackson & Foucault Welles, 2016; Ray, Brown, Fraistat, & Summers, 2017; Tillery, 2019) including topic modeling (Badaoui, 2021), qualitative research using interviews with participants (Mundt, Ross, & Burnett, 2018), analysis of retweet networks and Web hyperlinks (Freelon et al., 2016; Stewart, Arif, Nied, Spiro, & Starbird, 2017), and analysis of semantic hashtag networks or topical graphs (Dacon & Tang, 2021; Gallagher et al., 2018). In contrast, there are a few empirical studies on the #StopAsianHate movement. Fan, Yu, and Gilliland (2021) categorize the top hashtags into three domains constituting social movement, advocating action, influencing narrative change, and building identity, and further into sub-domains (e.g., specific advocate, general advocate). They find that the #StopAsianHate activism primarily rests on general slogans and AAPI influencers although shared identities look multidimensional (e.g., related to event, place, racial inequality). It also shows another limitation, particularly in terms of the diversity of participants. Lee and Jang (2021) examined the daily change in topics on Twitter for only seven days following the Atlanta shootings. It turned out that the consistent top three topics were community building for anti-Asian violence, stopping racism against Asians, and urging actions for and from AAPI. Cao, Lee, Sun, and De Gagne (2022) found five topics underlying the #StopAsianHate narratives such as "Asian hate is not new" and "increase the visibility of the AAPI community" (pp. 4–7), suggesting implications of each theme for practitioners and policy makers. Xie, Liu, and Cheng (2023) qualitatively explored narratives presented on Twitter through the lens of social justice practices and underscored the importance of a reflection strategy for sustainable movements.

Regarding Asian-Black solidarity after the rise of the BLM movement, most studies are based on qualitative or survey methods including survey experiment (Arora & Stout, 2019; Hope, 2019; Kuo, 2018; Liu, 2018; Merseth, 2018; Yellow Horse et al., 2021). Exceptionally, Guo and Liu (2022) examine the main topics of tweets in #BlackLivesMatter and #StopAsianHate and the correlation between two issue networks using the quadratic assignment procedure. Concluding that the agenda-setting effect of both activisms considerably increased after a certain period of time, they also suggest that the two movements, in spite of several shared topics, are probably situated in different social networks and contexts. Tong, Li, Li, Bei, and Zhang (2022) is another study focusing on the commonalities and differences between hashtags associated with each slogan. According to the topic modeling results, there are four common topics on Twitter such as fighting to stop racism, expressing negative and positive emotions, calling for participation in offline activities, and building up the community. However, in these two studies, the data for each movement cover different time spans, 2020 and 2021, respectively.

Our research question is centered on whether and to what extent the #StopAsianHate and #BlackLivesMatter activism showed the potential for Asian-Black solidarity via social media after the Atlanta shootings. Online users' interactions based on tags as cognitive and affective signifiers of social causes and values might lead to the echo chamber effect (Lai, 2022, Ch. 10), as like-minded users take up competing battles of memes with heightened parochialism. If this is the case, online publics tend to be more polarized with racialized hashtags and restricted narratives than their offline counterparts (e.g., a series of rallies like the Black and Asian Solidarity 5K in New York's Union Square on March 21, 2021). Unlike previous qualitative studies on the #StopAsianHate movement (Cao et al., 2022; Fan et al., 2021; Lee & Jang, 2021; Xie et al., 2023) and the ones employing topic modeling for comparisons of online public spheres led by the two movements (Guo & Liu, 2022; Tong et al., 2022), the current article is interested in semantic networks generated by Twitter users, where hashtags as nodes represent indices for classifying individual tweets into emergent narratives. With the data of hashtags and their co-occurrence networks, we examine descriptive statistics of the tweets containing #StopAsianHate and #BlackLivesMatter, dominant issues in the tweets addressing #StopAsianHate, #BlackLivesMatter, and both, and finally structural properties of each network. Based on the assembled evidence, we seek to draw conclusions on yet another pitfall of hashtag activism beyond the common focus on a positive or negative relationship between online and offline activism.

Data and Method

We collected the Twitter data from March 2 to April 26, 2021 (as explained in detail later), that contained #BlackLivesMatter and #BLM as well as #StopAsianHate using an open-source Python library named Twint (Zacharias & Poldi, 2020). Without using Twitter's API, this scraping tool enables the downloading of tweets searched by certain criteria such as users, topics, and hashtags across any designated period of time. Our focus was on original posts and hence we did not consider retweets for hashtag network analysis. Figure 1 graphs the number of tweets per day in March, where the blue line represents #StopAsianHate and the red one represents #BlackLivesMatter and #BLM. The latter group of tweets belongs to either #BlackLivesMatter, #BLM, or both since we merged two data files independently collected from these distinctive hashtags into one without duplicates. Tweets on #StopAsianHate skyrocketed on March 17, then declined quickly for the next four days with some sporadic high peaks. In contrast, the volume of the #BLM tweets moved through small-scaled ups and downs, but its average obviously was bigger than that of #StopAsianHate before the shooting day. As illustrated in Figure 2, Twitter users spontaneously responded to the news that the former police officer was found guilty of the murder of George Floyd, but the volume of tweets plummeted even during the same day. Meanwhile, there were quite minor fluctuations around small numbers of tweets per day on #StopAsianHate during the entire month. In this way, hashtags related to specific events tend to emerge almost instantaneously and then fade from public attention. It appears that the dynamics of both #StopAsianHate and #BlackLivesMatter (and #BLM) were not exceptional.

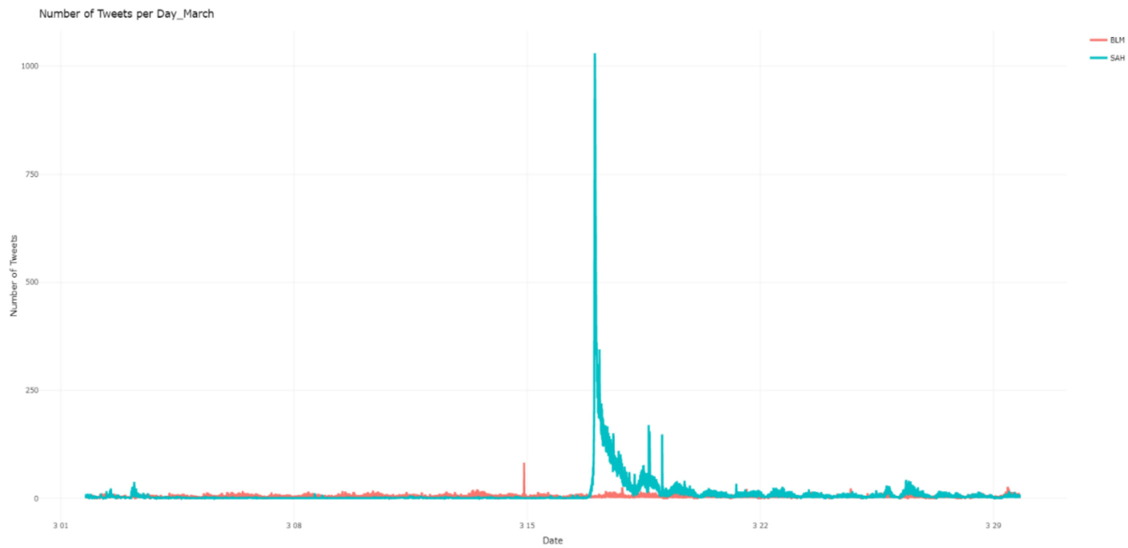

Figure 1. Number of tweets per day in March (Coordinated Universal Time [UTC] − 06).

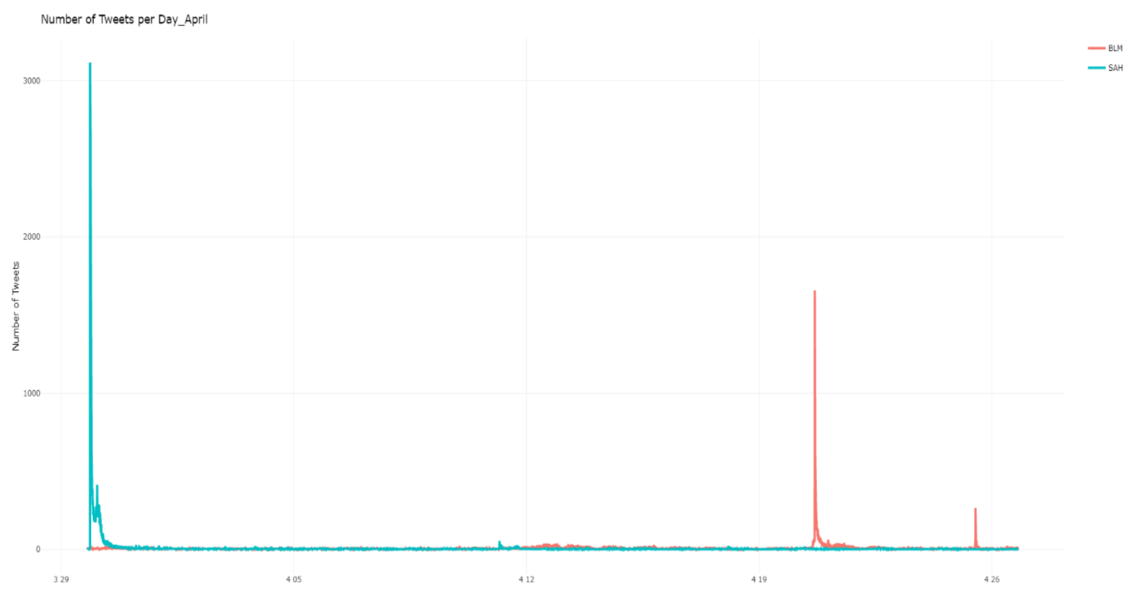

Figure 2. Number of tweets per day in April (UTC − 06).

To zoom in on temporal changes in the key signifiers centered around the three master hashtags, our analysis rested on eight periods of seven days in Table 1. We reconfirmed the current time window after considering Twitter users’ reactions to racial injustice issues related to key incidents during the two months, such as an elderly Asian man left brain dead from injuries after being assaulted in Oakland (P2), President Biden's calling out the rise in hate crimes against Asian Americans during the pandemic (P2), an elderly Asian woman who fought back a man who assaulted her on a San Francisco street (P3), Barack Obama's first tweet on the shooting rampage (P3), Sandra Oh's speech urging people to stand together for #stopasianhate (P3), an Asian American official's military scars under his shirts shown on anti-Asian hate at town meeting (P4), a building security guard who closed the door, not helping an elderly Asian woman under attack (P5), a #StopAsianHate tweet by the South Korean band BTS (P5), a young Black man fatally shot by a police officer in Minnesota (P6), an attack on an Asian man in New York, who collected cans after losing his job during the pandemic (P8), and the president's tweet on passing the COVID-19 Hate Crimes Act (P8).

Table 1. Division of Time Periods (UTC + 0).

P1	P2	P3	P4
3.2~3.8	3.9~3.15	3.16~3.22	3.23~3.29
P5	P6	P7	P8
3.30~4.5	4.6~4.12	4.13~4.19	4.20~4.26

We divided all tweets of each period into three groups after filtering out the tweets including #AllLivesMatter to focus on the nature of online Asian-Black solidarity: One addressing exclusively #StopAsianHate (Group S hereafter); another for #BlackLivesMatter or #BLM (Group B); and the other containing both #StopAsianHate and #BlackLivesMatter or #BLM (Group SB). First, we examined the major characteristics of tweets containing #StopAsianHate, #BlackLivesMatter, and #BLM. Next, we continued to identify the dominant issues of tweets tagging #StopAsianHate only, #BlackLivesMatter or #BLM only, and both. The intersection set of tweets was particularly important to assess its unique nature. In this way, our approach was more advantageous than focusing on each master hashtag alone as we could find similarities and differences in the online public sphere across the three distinctive subsets. Semantic network analysis intends to examine the structure of texts based on the shared meanings of symbols. Linkages in a semantic network represent associations among concepts or ideas embedded in broader narratives (Doerfel, 1998). Lastly, we investigated the key structural properties of each semantic network of hashtags such as density, community, and two measures of centrality. Beyond simply counting the frequency of hashtags, we sought to consider the latent structure in which they were embedded without sensitivity to their repeated patterns across tweets. Informed by Shim, Park, and Wilding (2015), we considered that degree centrality shows which hashtags have more linkages to adjacent ones than the others (i.e., repetitive narratives at the local level), whereas betweenness centrality indicates which ones play the role of bridging other hashtags more often (i.e., boundary spanning narratives at the global level). In this manner, we were concerned with not only the diversity of narratives and the number of cohesive subgroups but also which hashtags are central in different aspects.

Results

Table 2 summarizes the number of tweets and some characteristics of retweets. Right after the shootings, the number of tweets that mentioned #StopAsianHate exceeded 300,000 for seven days (P3). As seen from the table, there is another gigantic peak of a similar size in the fifth period triggered by a tweet the BTS posted on March 30, 2021, that condemned anti-Asian hate crimes and violence. This particular tweet was shared surprisingly more than a million times. Overall, the average frequency of retweeting in Group S is considerably higher than that in Group B, all the time including even the periods in which the tweets on #StopAsianHate are vastly outnumbered by those on #BlackLivesMatter or #BLM. The #StopAsianHate retweets also show the more severe fluctuations around the mean in terms of the coefficient of variation (CV) except for only the second period.

Table 2. Descriptive Statistics of Tweets and Retweets.

		Group S	Group B	Group SB
P1	Number of tweets	11,685	32,814	94
	Retweet means (max)	5.42 (16,592)	1.62 (2,744)	1.03 (28)
	Retweet CV	34.04	14.22	3.20
P2	Number of tweets	4,060	41,979	147
	Retweet means (max)	7.74 (3,436)	3.18 (18,000)	0.76 (11)
	Retweet CV	10.31	30.77	1.92
P3	Number of tweets	330,685	32,465	4,191
	Retweet means (max)	10.06 (108,049)	2.85 (20,476)	6.04 (12,825)
	Retweet CV	44.27	40.97	33.13
P4	Number of tweets	51,947	31,194	2,152
	Retweet means (max)	7.76 (56,183)	2.07 (1,157)	2.04 (620)
	Retweet CV	39.06	10.04	10.26
P5	Number of tweets	279,329	37,062	1,991
	Retweet means (max)	8.00 (1,022,953)	3.00 (8,290)	1.62 (235)
	Retweet CV	243.39	25.84	6.11
P6	Number of tweets	19,646	50,972	1,155
	Retweet means (max)	6.16 (48,295)	5.09 (10,649)	1.22 (145)
	Retweet CV	56.90	22.13	5.18
P7	Number of tweets	12,420	74,492	1,217
	Retweet means (max)	10.09 (16,481)	3.00 (5,304)	8.47 (3,425)
	Retweet CV	21.67	18.53	16.61
P8	Number of tweets	12,026	142,587	1,247
	Retweet means (max)	28.58 (68,310)	3.00 (9,435)	1.06 (124)
	Retweet CV	30.46	21.79	5.02

Table 3 presents the list of the top 15 hashtags of each group in March to avoid complexity (see Appendix 1[1] for how to treat hashtag synonyms and Appendix 2[2] for the top 30 list in each period of seven days). In Group S, it turned out that there are many hashtags calling attention to hate crimes

[1] https://tinyurl.com/28ymapxe
[2] https://tinyurl.com/y5ftskz4

against Asians, but the names of the shooter or Asian victims rarely circulate as a form of hashtag. Noticeably, the frequency of #bighitprotectyourartist is similar to that of #atlanta. As seen from Appendix 2 [3], several hashtags in the top 30 list (e.g., #noracismmedia ranked second, #bayern3_rassismus ranked 30th) related to the BTS in the first period originated from the incident in which a radio station host in Germany compared the BTS with COVID-19 on air. Only #blacklivesmatters and #justiceforgeorge ranked 21st and 22nd, respectively, during the second period (Appendix 2[4]). In Group B, we observed some hashtags in the top list such as #biden (and #bidenharris), #lgbtq, and #ethiopia, which implies that tweets in this group were widely concerned with political, minority, and international issues (e.g., genocide in Ethiopia, war crimes, human rights violations) as well as racism-related ones (e.g., #breonnataylor, #sayhername in memory of the death of an African woman fatally shot by police officers in Louisville). It is especially notable that #asianlivesmatter is one of the most frequently used hashtags in both Group B and SB apart from our targeted hashtags. Overall, most hashtags in Group SB seem to show patterns in common with a mixture of the top hashtags in Group B and Group S. Nevertheless, White supremacy (e.g., #whitesupremacy, #endwhitesupremacy) is mentioned in Group SB only. Along with these tags and others (e.g., #solidarity, #stopwhiteterrorism within the top 30 list), Asians and Blacks are depicted as common sufferers in the post-racial era although the number of tweets in Group SB is comparatively smaller (e.g., only 94 tweets in P1).

Table 3. The Top 15 Hashtags by Group in March.

	Group S	Freq	Group B	Freq	Group SB	Freq
1	stopasianhate	409,575	blacklivesmatter	87,744	stopasianhate	6,828
2	asiansarehuman	109,935	blm	58,866	blacklivesmatter	5,154
3	racismisnotcomedy	61,089	biden	4,828	blm	1,071
4	stopaapihate	26,731	georgefloyd	4,522	stopasianhatecrimes	1,070
5	stopasianhatecrimes	26,636	lgbtq	3,512	asianlivesmatter	801
6	racismisntcomedy	10,622	ethiopia	3,382	stopracism	576
7	asianlivesmatter	10,211	freesenegal	2,747	stopappihate	570
8	protectasianlives	9,626	asianlivesmatter	2,739	asiansarehuman	214
9	stopasianracism	8,400	tigraygenocide	2,698	lgbtq	125
10	appi	3,258	eritrea	2,657	whitesupremacy	114
11	noracisminmedia	2,495	tigray	2,656	racism	114
12	saynotoracism	2,202	standwithtigray	2,636	endracism	100
13	toppsracist	1,856	amhara	2,634	appi	88
14	atlanta	1,834	breonnataylor	2,340	racismisnotcomedy	86
15	bighitprotectyourartistis	1,813	endsars	2,172	stopthehate	85

As seen from Table 4, the tweets in Group S appear to cover varying narrative sources—from China's alleged responsibility for the COVID-19 pandemic (e.g., #bannon) through protests in Myanmar to even an Asian's cat attacked by two Brooklyn women (e.g., #justiceforponzu). Whereas trial-related tagging

[3] https://tinyurl.com/y5ftskz4
[4] https://tinyurl.com/y5ftskz4

is less prevalent, some BTS-related hashtags continue to remain on the top list in April, following the previous month (e.g., #racismisnotcomedy, #megaculiao, #weloveyoubts, #elracismonoescomedia as a multitude of responses to an anti-BTS parody sketch in a Chilean comedy show on April 10 in P6). In contrast, a considerable number of the top-ranked hashtags in Group B remarked on George Floyd or Derek Chauvin. Some other Black victims of police violence during the same period are frequently mentioned such as Daunte Wright and Ma'Khia Bryant. In support of institutional change (e.g., #defundthepolice), the Twitter users in Group B seemed to associate similar incidents with arranged symbolic meanings representing structural racism against Black and African Americans in the United States. When Derek Chauvin was found guilty on April 20, 2021, and after (P8), Group SB in particular prioritized sharing stories of racial injustice and racism toward the Black population by tagging not only #georgefloyd but also #justice, #stopracism, and others (Appendix 2[5]). In Group SB (and B as well), more hashtags are presented about building shared identities with the #StopAsianHate activism in March, but hashtags on White supremacy remain outside the top 15 list in April. It should be mentioned here that we found some hashtags presented by a single and same user (e.g., #echopark, #bluecheck in Group SB). For this reason, other hashtags frequently co-occurring with them are possibly overrepresented, and #BlackLivesMatter and #StopAsianHate cannot be exceptional.

Table 4. The Top 15 Hashtags by Group in April.

	Group S	Freq	Group B	Freq	Group SB	Freq
1	stopasianhate	329,912	blacklivesmatter	217,222	stopasianhate	5,688
2	stopaapihate	221,161	blm	108,262	blacklivesmatter	4,336
3	stopasianhatecrimes	77,933	georgefloyd	23,723	blm	2,017
4	racismisnotcomedy	5,363	justiceforgeorgefloyd	16,194	stopappihate	464
5	asianlivesmatter	3,411	dauntewright	16,029	stopasianhatecrimes	464
6	justiceforponzu	1,432	derekchauvintrial	12,708	georgefloyd	210
7	asiansarehuman	1,369	derekchauvin	7,641	echopark	201
8	bts	1,340	remembermynoah	7,235	bluecheck	201
9	appi	1,227	noahsarmy	6,760	asianlivesmatter	198
10	whatshappeninginmyanmar	1,210	week44	6,642	stopracism	171
11	tachaspeaks	1,144	georgefloydtrial	6,365	biden	164
12	megaculiao	1,082	thenoahdonohoefoundation	5,828	covid19	149
13	weloveyoubts	1,076	makhiabryant	5,058	echoparkriseup	136
14	elracismonoescomedia	1,023	defundthepolice	4,963	justice	122
15	bannon	750	justicefordauntewright	4,877	derekchauvin	106

Next, we temporally analyzed major network measures of co-occurrence hashtags to examine characteristics and patterns in similarities and differences across the three groups. A summary of network measures is presented in Tables 5 through 7. The densities of Group SB rank consistently the highest throughout the whole period, which implies that its symbolic networks are the most cohesive with the highest degree of

[5] https://tinyurl.com/y5ftskz4

hashtag connectedness at the global level. Although the ratio of the number of hashtags to the number of tweets tends to decrease whenever Twitter users focus more on specific episodes by immediately reacting to them (e.g., Group S in P5 and Group B in P8 reflecting overwhelming responses to a BTS tweet and the guilty verdict of Derek Chauvin, respectively), Group S seems to have the overall lower narrative capacities than Group B in terms of variability of hashtags per tweet. When considered together with the average of retweets and its variations from Table 2, Group S seems more likely to generate and share a fewer number of hashtags than Group B. Additionally, we extracted cohesive groups from the hashtag network for each period per group by using the Louvain method of community detection, as presented in Tables 5 through 7. It is expected that a more disintegrated network tends to have a higher ratio of the number of communities to the number of hashtags (i.e., the inverse of the average number of nodes across clusters). Since Group B shows the lowest ratios during the entire period, subgroups of hashtag networks exclusively addressing #BlackLivesMatter or #BLM are inferred to be less segmented than those of the other two networks.

Table 5. Summary of Measures for Hashtag Networks of Group S.

	P1	P2	P3	P4	P5	P6	P7	P8
Density	.023	.012	.0030	.0036	.0075	.0070	.0057	.011
# of tweets	11,685	4,060	330,685	51,947	279,329	19,646	12,420	12,026
# of hashtags	2,477	1,605	21,898	10,384	12,463	5,493	4,800	4,227
# of hashtags / # of tweets	.21	.40	.066	.20	.045	.28	.39	.35
# of clusters (modularity)	44 (.49)	62 (.53)	735 (.39)	197 (.49)	505 (.33)	133 (.52)	106 (.60)	199 (.49)
# of clusters / # of hashtags	.018	.039	.034	.019	.041	.024	.022	.047

Table 6. Summary of Measures for Hashtag Networks of Group B.

	P1	P2	P3	P4	P5	P6	P7	P8
Density	.0028	.0024	.0023	.0025	.0025	.0023	.0020	.0017
# of tweets	32,814	41,979	32,465	31,194	37,062	50,972	74,492	142,587
# of hashtags	19,789	21,202	19,986	18,946	19,712	20,805	26,511	33,100
# of hashtags / # of tweets	.60	.51	.62	.61	.53	.41	.36	.23
# of clusters (modularity)	99 (.55)	98 (.51)	91 (.53)	113 (.54)	108 (.52)	271 (.50)	132 (.47)	396 (.43)
# of clusters / # of hashtags	.0050	.0046	.0046	.0060	.0055	.013	.0050	.012

Table 7. Summary of Measures for Hashtag Networks of Group SB.

	P1	P2	P3	P4	P5	P6	P7	P8
Density	.13	.17	.012	.019	.024	.042	.020	.046
# of tweets	94	147	4,191	2,152	1,991	1,155	1,217	1,247

# of hashtags	142	241	2,628	1,836	1,703	1,370	1,694	1,361
# of hashtags / # of tweets	1.51	1.64	.63	.85	.86	1.19	1.39	1.09
# of clusters (modularity)	10 (.40)	7 (.44)	35 (.37)	35 (.46)	29 (.51)	27 (.46)	35 (.49)	25 (.48)
# of clusters / # of hashtags	.070	.029	.013	.019	.017	.020	.021	.018

We present two network centrality measures in Tables 8 through 10 and Tables 11 through 13, with particular focus on the critical period for each movement due to space limits (see Appendix 3[6] about both centrality measures of the top 30 hashtags varying every week and Appendix 4[7] about some exemplary tweets per group). First, for Group S in the third period of March (P3) right after the shootings, even #Atlanta does not seem to be as prominent as the listed hashtags concerning BTS (e.g., #racismisnotcomedy, #bighitprotectyourartists, #apologize_to_bts). Some hashtags with high levels of degree centrality including BTS-related ones are locally recurrent without expanding narratives outward. In terms of betweenness centrality, just a few (e.g., #stopasianhatecrimes, #stopaapihate) except #stopasianhate apparently bridge the rest of hashtags across localized communities, which holds true for the other periods after P3, as in Appendix 3.[8] On the other hand, the top hashtags in Group B show more divergent patterns in terms of degree and betweenness: Some with high degree centrality and low betweenness centrality (e.g., #resist, #motivation, #grassroots) and others with low degree centrality and high betweenness centrality (e.g., #covid19, #racism, #antifa, #blacktwitter, #stopasianhatecrimes), as further seen from Appendix 3.[9] Notably, at least in the third period, #asianlivesmatter with high degrees of both centralities seems to play a significant role of circulating symbolic meanings not only in Group B but also in Group SB. It is not shown here, but we also find that #whitesupremacy serves as a common narrative in peripheral parts of the semantic networks of Group SB over a relatively long period from P3 to P5 (see Appendix 3[10]).

Table 8. Hashtags of Group S by Degree and Betweenness Centralities in March (P3).

	Hashtag	Degree	Hashtag	Betweenness
1	stopasianhate	15.52	stopasianhate	.95
2	asiansarehuman	7.57	stopasianhatecrimes	.0121
3	racismisnotcomedy	4.62	stopaapihate	.0118
4	stopasianhatecrimes	2.16	asiansarehuman	.0053
5	stopaapihate	1.96	racismisnotcomedy	.0043
6	asianlivesmatter	1.12	asianlivesmatter	.0029
7	racismisntcomedy	1.00	atlanta	.0014

[6] https://tinyurl.com/339m62y7
[7] https://tinyurl.com/32fm3zss
[8] https://tinyurl.com/339m62y7
[9] https://tinyurl.com/339m62y7
[10] https://tinyurl.com/339m62y7

8	bighitprotectyourartists	0.38	covid19	.0014
9	apologize_to_bts	0.31	stpatricksday	.0012
10	atlanta	0.30	aapi	.0007
11	covid19	0.29	love	.0005
12	bighitdoaction	0.28	stopracism	.00045
13	aapi	0.27	racism	.00043
14	toppsracist	0.26	asian	.00042
15	stopracism	0.19	snydercut	.00042

Table 9. Hashtags of Group B by Degree and Betweenness Centralities in March (P3).

	Hashtag	Degree	Hashtag	Betweenness
1	blacklivesmatter	3.36	blacklivesmatter	.59
2	blm	2.24	blm	.40
3	lgbtq	0.45	asianlivesmatter	.0107
4	resist	0.40	covid19	.0073
5	biden	0.39	racism	.0065
6	fbr	0.36	antifa	.0049
7	asianlivesmatter	0.35	blacktwitter	.0046
8	motivation	0.31	lgbtq	.00375
9	grassroots	0.30	biden	.00341
10	noh8	0.30	georgefloyd	.00246
11	covid19	0.30	stopasianhatecrimes	.00230
12	tweetuk	0.29	love	.00220
13	worldsspotlight	0.29	usa	.00192
14	weekdayuk	0.29	black	.00188
15	weekenduk	0.29	saytheirnames	.00187

Table 10. Hashtags of Group SB by Degree and Betweenness Centralities in March (P3).

	Hashtag	Degree	Hashtag	Betweenness
1	stopasianhate	4.71	stopasianhate	.60
2	blacklivesmatter	3.67	blacklivesmatter	.29
3	blm	1.37	blm	.07
4	asianlivesmatter	0.74	asianlivesmatter	.0075
5	stopasianhatecrimes	0.66	stopaapihate	.0066
6	stopaapihate	0.64	stopasianhatecrimes	.0057
7	asiansarehuman	0.39	atlanta	.0015
8	stopracism	0.25	asiansarehuman	.0014
9	biden	0.20	covid19	.00098
10	atlanta	0.18	racism	.00089
11	racismisnotcomedy	0.17	stophate	.00085
12	racism	0.14	stopracism	.00081
13	stophate	0.13	lgbtq	.00076
14	lgbtq	0.13	biden	.00069
15	endracism	0.12	stopthehate	.00067

In the eighth period of April (P8), some hashtags of Group S on the top seem to play the role of local hubs (e.g., #bannon, #drlimengyan1), while others (e.g., #covid19, #asianlivesmatter) are more likely to serve as global connectors across the network. However, there are no hashtags connotating solidaristic reactions to racial injustice faced by Black people except #weargeorgefloyd and

#makhiabryant even during the week when the trial of Derek Chauvin was held. As to Group B, hashtags such as #georgefloyd and #justiceforgeorgefloyd are predominantly salient to integrating narratives. During the previous weeks, as presented in Appendix 3,[11] the hashtags related to specific names of victims (e.g., #breonnataylor, #daunterwright) play the same role as a hub across the entire network, which means that the users in Group B put them together with #BlackLivesMatter to construct collective identities. As popular concerns eventually move toward fighting racism and anti-Black violence (e.g., #policebrutality), the betweenness centrality of #asianlivesmatter tends to decrease slower than its degree centrality from P4 through P7. In Group SB, as is the case with its top central hashtags in P3, fairly consistent rank orders continue to be shown in P8 across the two centrality measures. The hashtags associated with #BlackLivesMatter on one side and with #StopAsianHate on the other side are copresent even in P8 when the trial was the center of public attention. Some symbolic lexicons (e.g., #stopasianhatecrimes, #georgefloyd) remain salient in this Twitter community until the last period: They can be regarded as fairly central either locally or globally given their rankings of centrality scores. Besides, it is hardly evidenced that some hashtags conveying a common fate in March (e.g., #endwhitesupremacy, #solidarity) have moved out of peripheral regions toward more central positions in the semantic networks (Appendix 3[12]).

Table 11. Hashtags of Group S by Degree and Betweenness Centralities in April (P8).

	Hashtag	Degree	Hashtag	Betweenness
1	stopasianhate	6.92	stopasianhate	.96
2	stopasianhatecrimes	2.26	stopaapihate	.0093
3	stopaapihate	2.25	stopasianhatecrimes	.0080
4	bannon	1.74	covid19	.0026
5	drlimengyan1	1.71	aapi	.0013
6	闫丽梦(Yan Li-meng)	1.69	asianlivesmatter	.00115
7	limengyan	1.53	asian	.00092
8	郭文贵(Guo Wengui)	1.50	oscars	.00075
9	yanlimeng	1.46	justiceforponzu	.00056
10	stop	1.16	racism	.00046
11	justiceforponzu	.55	asianamerican	.00035
12	covid19	.42	china	.00034
13	ethnicity	.22	stopracism	.00025
14	ccp	.21	viral	.00022
15	unrestrictedbioweapon	.20	usa	.00020

[11] https://tinyurl.com/339m62y7
[12] https://tinyurl.com/339m62y7

Table 12. Hashtags of Group B by Degree and Betweenness Centralities in April (P8).

	Hashtag	Degree	Hashtag	Betweenness
1	blacklivesmatter	6.21	blacklivesmatter	.60
2	blm	3.15	blm	.36
3	georgefloyd	1.56	georgefloyd	.027
4	remembermynoah	1.21	justiceforgeorgefloyd	.0095
5	noahsarmy	1.15	derekchauvintrial	.0053
6	week44	1.13	derekchauvin	.0053
7	justiceforgeorgefloyd	0.97	makhiabryant	.0044
8	thenoahdonohoefoundation	0.86	justice	.0044
9	derekchauvintrial	0.75	antifa	.0041
10	derekchauvin	0.64	georgefloydtrial	.0041
11	georgefloydtrial	0.56	blacktwitter	.0040
12	makhiabryant	0.51	racism	.0036
13	derekchauvinisguilty	0.40	covid19	.00303
14	justice	0.37	policereformnow	.00243
15	guilty	0.35	biden	.00234

Table 13. Hashtags of Group SB by Degree and Betweenness Centralities in April (P8).

	Hashtag	Degree	Hashtag	Betweenness
1	stopasianhate	5.03	stopasianhate	.57
2	blacklivesmatter	4.16	blacklivesmatter	.27
3	blm	2.59	blm	.0942
4	stopasianhatecrimes	1.50	stopasianhatecrimes	.0036
5	racists	1.19	stopaapihate	.0033
6	justice	1.14	racism	.0030
7	georgefloyd	1.09	justiceforgeorgefloyd	.0026
8	covid19	1.08	georgefloyd	.0026
9	love	1.04	love	.00257
10	stopracism	1.03	justice	.00253
11	justiceforgeorgefloyd	0.97	lgbtq	.00239
12	equality	0.93	biden	.00233
13	nojusticenopeace	0.90	covid19	.00209
14	endracism	0.88	stopracism	.00184
15	protest	0.87	asianlivesmatter	.00119

Discussion and Conclusions

Our main findings can be summarized as follows. First, the tweets addressing #StopAsianHate without #BlackLivesMatter (Group S) in March were characterized by narratives regarding anti-Asian hate crimes and ARMY's voices. BTS-related hashtags were outstandingly frequent even right after the Atlanta shootings, which implies a lack of incorporating hashtags on the tragedy into a master slogan. It can be also inferred that the original tweets posted by influencers were largely shared since the average number of retweets and the overall volatility are considerably higher than those in Group B. The tweets in April apparently embraced more diverse issues, while some hashtags on the top (e.g., #bannon, #drlimengyan1) were put against the blame on China for the COVID-19 pandemic. However, there were few responses to not only the recurring violence against Black Americans but also the guilty verdict of Derek Chauvin. According to results about node centrality, #StopAsianHate, not surprisingly, was an outstanding hub in the entire network, while most BTS-related hashtags (except #racismisnotcomedy) were at best local hubs because hashtags in other far communities did not seem to rely heavily on them.

Next, the tweets exclusively containing #BlackLivesMatter (Group B) expressed condemnation of anti-Asian hate crimes (e.g., #asianlivesmatter) immediately after the shootings in March. The users in this group seemed to give their deep condolences to the Asian victims by replacing the first letters of a master slogan with "Asian" and also showed a broad and high involvement in social and political issues (e.g., #bidenharris, #lgbtq) in addition to anti-Black violence (e.g., #dauntewright, #makhiabryant). They seemed to amplify narratives of the BLM movement by listing specific names of victims together with their master hashtag even long after the death of George Floyd. Notably, the semantic network in this group consisted of less segmented communities although the number of hashtags relative to the number of tweets was higher than that in Group S. In terms of degree and betweenness centrality, some hashtags (e.g., #resist, #grassroots) that serve more as local connectors and others (e.g., #racism, #antifa, #blacktwitter) that bridge local communities together seem to constitute richer narratives. In April, both centralities of #asianlivesmatter considerably reduced after public concern was shifted to the trial.

Lastly, the number of tweets with both #StopAsianHate and #BlackLivesMatter was, not surprisingly, the smallest in the third group (Group SB). Some top hashtags in common with Group B urged attention to the tragedy of the Atlanta shootings in support of the emerging #StopAsianHate activism. There existed not only hashtags addressing anti-Black and anti-Asian violence as local connectors but also narratives about solidarity against White supremacy after the shootings although the latter stories gradually moved toward peripheral parts of the network and eventually disappeared after the day of guilty verdict of Derek Chauvin. The overall findings from Group SB seem to indicate a lack of the spillover or reciprocity effect on solidarity on Twitter between the two movements, which is largely consistent with the conclusions from existing studies on the #StopAsianHate activism (Fan et al., 2021; Guo & Liu, 2022). It may be a long while before narrative, institutional, and disruptive capacities are developed (Tufekci, 2017) beyond the successful creation of declarative slogans and endorsement by celebrities (Freelon, Marwick, & Kreiss, 2020).

The present study has several limitations, however. First of all, we observed some cases in Group SB in which hashtags were juxtaposed in bulk either by the same users or by online bots. This type of issue with Twitter data has been aptly addressed by Jackson and colleagues (2020). Consequently, the unique features of hashtags in Group SB and their networks might be biased to some extent. We guess that those cases of tweets were probably posted to take advantage of the popularity of both #BlackLivesMatter and #StopAsianHate. Second, the demographics of Twitter users could not be correctly identified so it was substantially hard to investigate how they were significantly associated with distinguished features of semantic networks by group. To take an extreme example, there remains the chance that other groups of color rather than Asian Americans constitute a majority of active users who supported #StopAsianHate for some periods of time. Third, it was nearly impossible with hashtags alone to sufficiently compare topical narratives by group. Creating new hashtags and disseminating new messages might be easier for the BTS fans as a smart mob. For a better understanding of stories in social networking site (SNS) communities, non-tagged messages should be analyzed although a certain weakness is unavoidable in the method of data collection based on hashtags (e.g., Guo & Liu, 2022; Tong et al., 2022). Last but not least, we failed to analyze varying repertoires and frames of collective action emerging from hashtags on a strictly theoretical basis.

Our tentative conclusions await further refinement in future research. Above all, it remains to be investigated with the data of the following periods whether or not the #StopAsianHate activism attains sustainability while constructing shared identities with other minorities of color including Black Americans. It is also worthwhile to rigorously examine either the configuration between "information driver" and "information generator" in each group of user networks (Wang & Zhou, 2021) or the co-evolutionary dynamics of those two hashtag activisms from the perspective of the social movement spillover (e.g., Zhou & Yang, 2021). Although the current study does not comprehensively capture the online dynamics of both movements, what is observed from our two-month data at the incipient stage seems to stand in contrast to positive public opinion among Asian communities toward BLM and a linked fate as "we-ness" shared offline with BLM through mutual cooperation in local rallies of varying scales over the last couple of years. We conjecture that the #StopAsianHate activism has been led primarily by influencers as "thinkers" and also that its main hashtags are yet to be fully evolved enough to provide multifaceted narratives compared with those in the #BlackLivesMatter activism (Fan et al., 2021; Guo & Liu, 2022). In the era of social media, slacktivism, spontaneity, and episodical orientation are often blamed as drawbacks of hashtag activism for social and political change. The key implication of the present study rather lies in its weakness in solidarity across digital communities based on racialized experiences, which seems partly attributable to tagging-based interactions as online participatory culture and limited narrative capacities of generating reciprocal "collective effervescence" in a Durkheimian notion.

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