Article

Social Media + Society
October-December 2022: 1–12
Article reuse guidelines:
sagepub.com/journals-permissions
DOI: 10.1177/20563051221146182
journals.sagepub.com/home/sms

From #BlackLivesMatter to #StopAsianHate: Examining Network Agenda-Setting Effects of Hashtag Activism on Twitter

Jing Guo[1] and Shujun Liu[2]

Abstract

With large, representative, and comparable data scraped from Twitter, this study tries to provide comprehensive understanding of the salient topics under #BlackLivesMatter and #StopAsianHate online movements. Employing semi-supervised Latent Dirichlet allocation topic modeling, five topics have been extracted from 3-month tweets data after George Floyd's death in 2020. Six topics have been extracted from 3-month tweets data after the Atlantic spa shooting tragedy in 2021. Both movements reflected salient topics on the tragedy that just took place during the data collection period. In addition, general violence, collective actions, community support, and criticism on White racism are all identified as important issues of the counter-racism discourse flooded on social media. In addition, our study explores the network agenda-setting effects of hashtag activisms. The results show that issue networks of the first 2 weeks' counter-racism discourses after the crime could not set network agenda for the next 2 weeks' discourses. However, the network agenda-setting effects became significant after the first 2 weeks and stayed stable as time went on. In addition, we do not find a significant relationship between issue networks of the two movements under study. It counter-argues any assumption that one counter-racism movement online could trigger similar movements among different groups.

Keywords

hashtag activism, Twitter, BlackLivesMatter, StopAsianHate, network agenda-setting

Hate speech is an unfortunately common occurrence in cyber space which often links to religion and racism (George, 2017) and in some cases culminates in severe threats and harm to individuals and communities (Calvert, 1997). Previous studies (Ringrose, 2018; S. Sharma, 2013; Siapera, 2019; Wahl-Jorgensen, 2019) have accused Twitter of propagating racism, populism, and stereotypes on minorities with circulation of gifs, memes, and strategic uses of humor, arguing that the affordances of social media platforms have facilitated increasing "ideological silos" and "echo chambers" (Ott, 2017).

However, researchers also showed that the rising number of tweets were in fact defending vulnerable minorities, which enabled the formation and circulation of anti-racist and anti-Islamophobic in a wider public sphere (Dawes, 2017; Jackson & Foucault, 2015). For example, the #stop Islam hashtag trended Twitter after ISIS (Islamic State of Iraq and Syria) took credit for Brussels terror attack in 2016, with a growing debate around whether there was an association between Islam and terrorism. It was noticeable that there were rising numbers of tweets actually defending Muslims and absolving them from responsibility for the attacks (Poole et al., 2021). In Poole et al.'s (2021) study on #stop Islam hashtag, the emotional expression against anti-Islam discourses was conceptualized as counter-narratives, pointing to the importance of constructing alternative narratives against online hate. They argued that although Twitter takes an active role in constituting hatred discourses, there are also activist groups subtly re-shaping the affordances of platforms in countering hate campaigns (Feigenbaum, 2014; Treré, 2019).

This study investigates two major anti-racism hashtag activism cases on Twitter (i.e., #BlackLivesMatter [BLM]

[1]The Chinese University of Hong Kong, Hong Kong
[2]Cardiff University, UK

Corresponding Author:
Shujun Liu, School of Social Science, Cardiff University, sbarc|spark, Maindy Road, Cardiff CF24 4HQ, UK.
Email: Shujun-Liu@Outlook.com

and #StopAsianHate [SAH]). Hashtag activism refers to the online movement where large numbers of postings appear under a common hashtag with a social or political claim (Yang, 2016). For example, in the case of BLM, anti-racism-related postings flooded in networked spaces, rendering the posters a narrative form and agency to perform the activist discourses (Campbell, 1998). In this study, we empirically examined two hashtag activism cases of BLM and SAH trended on Twitter since 2020 in a comparative manner with network agenda-setting (NAS) theory. In particular, we went beyond the legacy agenda-setting effects of traditional media on the public and focused on the inter agenda-setting effects among hashtag activism cases in social media. Being different from previous agenda-setting studies regarding issues and attributes, the object of this study targets on attributed network. By such efforts, we hope to explore how the anti-racism hashtag activisms have been constructed, progressed, and inter-connected.

Agenda-setting theory has seen continuous evolvement since the pioneering 1968 Chapel Hill study (McCombs & Shaw, 1972). From the first-level agenda-setting effects (objects agenda) to second-level agenda-setting (attributes agenda), the theoretical focus has been expanded to capture the details of audience' understanding of the world (McCombes et al., 2000). The elements of the world image investigated to date are objects and attributes, which are disconnected elements of the whole. However, in reality, the outside world could be presented in a person's mind in an integrated form rather than separated objects. Guo and McCombs (2011) introduced third-level agenda-setting to advance agenda-setting theory by examining whether news media are capable of transferring the relationships, or the connections, between the elements of an agenda. Following this line of research, this study tried to further empirically examine and expand third-level agenda-setting theory in social media settings. Practically, the study also aims to help the public to understand more about how the underprivileged group inter-connect and mobilize each other in countering hate campaigns.

BLM and SAH Movements

Entering 2020 the era that COVID-19 pandemic spread globally, social injustice has been intensified worldwide. Activists have fueled their energy in implementing online and offline protests, defending community rights while promoting mutual aid and solidarity (Aouragh, 2019). Knitting social relations across ethnicity play a fundamental role in a time of strong resurgence of racism under COVID-19 pandemic (Pleyer, 2020). Since 2020, two hashtag activism cases against racism stood out. BLM trended on Twitter after the murder of George Floyd, a 46-year-old African American man killed by a White police officer in Minneapolis on 26 May 2020. It triggered an international wave of protests against racism and police violence. SAH online activism broke out after a gunman's killing eight Asian people at three Atlanta-area spas on 16 March 2021. The gun killing had sparked fears among advocacy groups that the Anti-Asian hate crimes would be racially motivated.

Both cases caused campaigns online and offline against racism and hatred. Right after George Floyd's death, tweets fighting against racism flooded under BLM, making the movement returned to national headlines and gained international attention. Similarly, the crime at Atlanta triggered tsunami of SAH on Twitter overnight. In terms of time order, the sudden return of BLM popularity on Twitter happened 10 months before the rising trend of SAH. Since both campaigns were for counter-racism ends, it is logical to explore whether BLM movement on Twitter could influence and set the agenda for SAH movement.

However, it is also key to view both cases distinctively as racism in the United States is a historical problem with complex social, economic, political, and cultural reasons (Bacon, 2011; Kim, 2007; Roger, 2002). As Altman (2015) argues, Black Lives Matter movement engages in bringing attention to police killings and abuse of African Americans which reflects the continuous struggle for human equality among African Americans in the United States. Discrimination against Black people in the United States is a historical hate gaze with the affective politics of fear (Ahmed, 2014). According to statistics from *The Guardian* (2021), numbers of people killed by police in the United States amounted 207 and 266 in year 2015 and 2016 separately. Therefore, Black Lives Matter movement has been focusing on police abuse of African Americans, while addressing some similar issues related with previous Black liberation movements, such that Black people are seen as criminals, and Black bodies are seen as expendable and frightened (Clayton, 2018).

Put differently, SAH movement broadly refers to Asian Americans' struggle against the discrimination they had been subject to. Unlike African Americans' struggles, the Asian American movements started much later in 1960s (Wei, 1993). Studies have found that Asian Americans are still seen as "forever foreigners" (Okihiro, 2014; Xu & Lee, 2013). Being viewed as clumsy and lacking appropriate skills, Asian Americans were left out in the socialization process of the US society (Fiske et al., 2002). Therefore, differing from Black Americans' struggle against slavery and police violence, Asian Americans' calling for justice is more originated from their dissatisfaction of being recognized as "others" (Li & Nicholson, 2021). Today, Asian Americans have achieved higher rankings in governments, big corporations, and universities. Is it the time to optimistically think that Asian Americans appear to be assimilating into the US mainstream society? The answer is negative. The swift surge of anti-Asian racism during the COVID-19 pandemic has exposed the marginalized and conditional status of Asian Americans by labeling Asians as "yellow peril" and "unAmericanness" (Li & Nicholson, 2021). Under the COVID-19 pandemic, a non-profit organization "Stop AAPI Hate" was created to support

Asians who were attacked physically or psychologically for being accused as the origin of the corona virus. In this study, SAH hashtag activism refers to the anti-Asian violence rallies with social media supports held across the United States and other countries in 2021 in response to racism against Asian Americans. Many of which occurred in the wake of series of shootings in Georgia in March 2021.

Bearing similarities and differences, the growing public attention to and engagement in these two hashtag activism cases provide opportunity to have an inquiry on the relationship between the two cases. First, in this study, we capture the salient issues (topics) under both hashtags. Second, the study also explores the network agenda-setting effect by examining the correlations of topic networks within each hashtag but between different time periods. More importantly, we further examine whether the BLM movement has set the salient network agenda for SAH movement.

There are several rationales under the above research purposes. First, both cases are counter-racism social media campaigns after the COVID-19 outbreak, which may share similar salient issues. Second, the sudden return of BLM happened 10 months before the rising trend of SAH which satisfied the premise of temporal causal relationship of agenda-setting effect. Third, Twitter, as the social media platform being used by both mass media and individuals in transferring information, acts as an effective channel of information delivery and agenda-setting (Conway et al., 2015). Once BLM has set the agenda for Twitter community, the effects would possibly be transferred to the online discourses covering a similar event, such as SAH. Thus, this study drew on the network agenda-setting theory in investigating how social media could facilitate the network agenda-setting between counter-racism hashtag activism campaigns.

Agenda-Setting Theory

Agenda-setting research concentrates on the relationship between media content and audience perception. Traditionally, agenda-setting theory argues that news media play a critical role in setting the governments' agenda and influencing the pictures in the public's mind (McCombs, 2004). Tracing back to Walter Lippmann's (1922) *Public Opinion*, the news media help bridge the perceived world reality in audience's mind and the portrayed environment (p. 3).

Numerous empirical studies have examined the "images" in media and that in people's minds in different countries since the groundbreaking 1968 Chapel Hill study (McCombs & Shaw, 1972). The commonly adopted approach to study agenda-setting is formed by two levels of analysis. The first level analyzes the transfer of object salience. Objects are conceptualized as anything that can be described, characterized, and shaped through text, such as political figures, issues, countries, or organizations (T. Zhang et al., 2017). The second-level agenda-setting studies the exchange of attributes of the issue, suggesting that the attributes or meanings that are attached to objects can be transferred as well (Kiousis et al., 2015; McCombs, 2004), including cognitive attributes (e.g., frames) and affective attributes (e.g., tone or sentiment).

According to the agenda-setting theory, the mass media play a normative role in generating consensus among different social groups by highlighting a few issues (Chan & Lee, 2014). The media agenda is operationalized as the issues highlighted by the media while the public agenda is what the citizens to contemplate and deliberate (McCombs & Shaw, 1972). As a causal relationship between the media agenda and public agenda, the time order is clearly defined that media agenda comes first.

The growing interest in agenda-setting scholarship among mass communication researchers resulted in substantial development of the theory. Guo and McCombs (2011) introduced the third-level analysis, NAS, which examines the transference of networked relationships among objects and/or attributes. The NAS model argues that the news media not only can tell the audience what to think and how to think about certain objects, it is also capable in demonstrating how these objects or attributes are connected. In other words, the objects network suggests to what extent they would be perceived and recalled together.

The NAS model incorporates the concept of cognitive mapping proposed by some psychologists and philosophers (e.g., Armstrong, 1973; Barsalou et al., 1998), arguing that people's mental representations could be operated in pictures and diagrams. The mental model of "cognitive mapping" suggests that human brain has the spatial and networked thinking ability to process "scripts" or "schema" (Guo & McCombs, 2011). In other words, after media exposure, audiences could map out the salient objects and attributes in their mind in the form of a network structure in which one unit of information is connected to numerous other nodes (Anderson, 1983). By activating and reactivating certain information, the media is capable in creating and strengthening the connection between constructs in the audience's memory (H. T. Chen et al., 2020). For example, on the topic of counter-racism, if a media outlet or social media post reports crime and immigration recurrently, the audience will be likely to retrieve the connection between the two issues.

Research on the third-level agenda-setting is emerging (H. T. Chen et al., 2020; Neil et al., 2018; Wanta & Alkazemi, 2018). The first NAS study found that the interrelationships among the political candidates' attributes emphasized by news media had a significant correlation with the public's perception of the candidates (Guo & McCombs, 2011). Studies examining the object-based network can also be found (e.g., Kiousis et al., 2015; Neil et al., 2018; T. Zhang et al., 2017). For instance, Vu et al.'s (2014) study found that news media bundled issue objects that could set the agenda for the interrelationships salient in the public's mind. H. T. Chen et al. (2020) combined content analyses of news stories and the survey data in Hong Kong to examine selective exposure and network agenda-setting, finding that the network agenda of like-minded media was significantly associated with respondents' opinion repertoires for those who involved in selective exposure.

Studies on agenda-setting effects were also conducted in social media settings. For example, Vargo's (2011) first- and second-level agenda-setting analyses on Twitter data suggest that traditional newscasts and newspaper articles can predict the total amount of Twitter posts an issue receives. This finding was triangulated by Parmelee and Bichard's (2012) interview with Twitter users. Later, Vargo et al. (2014) applied a big Twitter dataset to examine the vertical (top-down) and horizontal media agendas during the 2012 US presidential election. From the network analysis perspective, this study showed how issues about the election were talked about in relationship to each other and compared the agenda-setting effects on Obama supporters and Romney supporters. Being different from their previous studies on the 2008 US election (Vargo, 2011), the testing of agenda-setting is not simply "How often was issue 'X' mentioned during period 'Y,'" but in terms of the interconnections and relationships among issues inside of an agenda. The development of NAS model goes beyond the individual measurement of issue saliences with a focus on the issue linkages.

Reviewing the existing literatures, the NAS model has been examined between different types of media outlets. However, little attention has been paid to the NAS effects on social media in constructing hashtag activisms. We believe it is an important area to explore given that it potentially reflects social media's capability in forming users' opinion repertoire and fueling online activisms. In this study, the issue network agenda was defined as how the issues under one hashtag relate to each other. If the agenda could be set effectively, a significant correlation will be found between the issue network agenda of A and B.

In digital spaces, the public agenda is not only influenced by the agenda set by media accounts, but also by all user-generated content. Taking a holistic approach, we first exposure the salient topics under BLM and SAH. Second, we hypothesize that in both cases, the general issue network (including both media posts and user-generated content) could set agenda for the network of what was going to be talked about in due course. To be specific, if we divided the time period of BLM movement by every 2 weeks (unit), social media content during the N unit will set network agenda on the content during ($N+1$) unit (e.g., issue network agenda of tweets right after George Floyd's death could possibly set network agenda on the next 2 weeks' discourses under BLM). Therefore, we propose the following research question and hypothesis:

> *RQ1*. What are the major topics of tweets under BLM and SAH?

> *H1*. There exists a network agenda-setting effect of social media hashtag content in an ongoing process.

In addition, this study tried to offer a fresh perspective to investigate the chronological changes of network agenda-setting effects. As the focus of public discussion and users' attention usually become fragmented after a wave of concentrated discussions on certain topics online (Webster, 2014; Webster & Ksiazek, 2012), we assume that the issue network of hashtag activism will be changed and reshaped during the movement in due course. Thus, it is possible that the network agenda-setting effects within each case (i.e., BLM and SAH) became weaker as time went on. We propose the second hypothesis:

> *H2*. The network agenda-setting effect proposed in H1 became weaker as time went on.

More importantly, we compare the network agenda-setting effects of BLM on SAH to uncover to what extent their issue networks are related to or differ from each other. This helps to reflect the characteristics of the two counter-racism hashtag activism cases and indicate whether or not social media could breed networked connections between online activism movements. We propose the second research question:

> *RQ2*. Is there a significant relationship between the increased salience of issue networks under BLM and SAH?

Methods

Data Collection

This study applies computational methods in collecting and analyzing tweets under BLM posted after George Floyd's death in 2020 and tweets under SAH posted after the 2021 murder in Atlanta spas. Public tweets under BLM from 26 May 2020 to 26 August 2020 (3 months data after George Floyd's death) and tweets under SAH from 16 March 2021 to 16 June 2021 (3 months data after the gun killing in Atlanta) were retrieved by using the library Twint. Twint is an advanced Twitter scraping tool written in Python and allows for scraping tweets without using Twitter's API. In simple terms, it is a function similar to scraping through Twitter's standard web interface (Caren, 2020). Being unique from Twitter scraping API, Twint has no limit of downloading tweets, it can download almost all the tweets using different parameters like hashtags, usernames, and topics (H. Sharma, 2020). Retweets and replies were excluded to make the data focus on original posting. The reason of including tweets of 3-month period is that this study aimed at comparing the network agenda-setting effects in different time periods. In total, we obtained 7,057,548 tweets under #BlackLivesMatter

(BLM data) and 822,088 tweets under #StopAsianHate (SAH data).

After collecting the whole datasets, we further filtered the tweets data to focus on the active Twitter accounts. This also helped to filter out some social bots and spam accounts to have a more accurate analysis of hashtag activism discourse. Therefore, we referred to previous studies (e.g., Hong et al., 2013; Y. Zhang et al., 2013) and only included the tweets from users who have posted at least 10 tweets under the target hashtags (i.e., BLM, SAH) during the 3 months for further analyses. Thus, the final sample size for analysis is 1,441,748 for BLM and 92,118 for SAH.

Topic Modeling

To examine the third-level agenda-setting, we first investigate the salient issues under the two hashtags (RQ1). These issues were operationalized as main topics of tweets. After data cleaning and text processing through (1) removing punctuation, numbers, special characters, stop words and repeated tweets, (2) applying tokenization, and (3) lemmatization with R package Quanteda (Benoit et al., 2018), topic modeling techniques were used to extract the topic of each tweet. Topic modeling is widely used in natural language processing to gain insights about the text data. There are different methods of topic modeling, among which Latent Dirichlet Allocation (LDA) is one of the most widely used methods (Kumar & Paul, 2016). By LDA, corpus can be processed and classified into patterns to project the features of higher dimensional space onto a lower-dimensional space. In this study, R package seeded-LDA (Lu et al., 2011) was first used to automatically set one most relevant topic to each tweet. In the first stage, we have tried setting different numbers of topics (from 10 to 5) to run LDA. After checking the assigned topics manually to finalize the most interpretable topics, we found that only depending on automatic topic modeling could not provide distinctive and interpretable topic results, as the most frequently mentioned keywords in each topic were overlapped and scattered. Despite this, the automatic method helped produce the most salient tokens in clusters.

In the second stage, the authors manually checked the randomly selected 500 automatic LDA results for both BLM and SAH datasets to better capture the major topics and corresponding keywords. We also reviewed news coverage of both movements at the time to know the process and key events of the two cases. This process made us concluded five major topics under BLM and six topics under SAH.

In the next stage, a dictionary was created to further test our manual topic classification and automatically assign each tweet a most relevant topic. Based on the previous automatic LDA results, we combined the keywords been identified and what we knew about major issues of the two cases from mass media to construct two separate dictionaries. The dictionaries comprise keywords on different topics for both datasets respectively and enable us to further conduct semi-supervised topic modeling using R package seeded-LDA (dictionary details could be found in online Appendix). Semi-supervised topic modeling is a useful technique to guide the computational topic classification process when the automatic retrieved topics were overlapping and did not make much sense. In this way, we used the dictionary to set some seed words to guide the model to converge around those terms in certain direction (Wang et al., 2012). For tweets with no specific meaning or could not be categorized to any topic, the results will be "NA" and "others." We filtered out these confounding tweets and finalize 1,248,087 tweets under BLM while 77,955 tweets under SAH with assigned topics.

Social Network Analysis

The next step is to operationalize the network of salient issues. Based on the semi-supervised LDA coding, topics being mentioned by the same Twitter account are considered as implicitly linked (Vargo et al., 2014). The datasets were converted to adjacency (i.e., co-occurrence) matrices to reflect network issue agendas. Each row and column represent a topic in the network. Each cell in the matrix reports the number of times the two topics were mentioned concurrently. For example, the matrix cell associated with topic "actions" and "violence against black people" is 37,752, which means that the two issues were mentioned 37,752 times by the same poster during the study period.

To test H1 and H2, we split the BLM and SAH datasets into six sub-datasets. Each sub-dataset comprises tweets for 2 weeks. For example, sub-dataset BLM1 refers to tweets posted during the first 2 weeks after Floyd's death, BLM2 refers to tweets posted during the third and fourth weeks after Floyd's death. As the last step in network analysis, the networks of the sub-datasets were then compared by utilizing the quadratic assignment procedure (QAP) via R package SNA's qaptest function (Butts, 2008). QAP addresses the strength and specification of ties from one network to another and calculates a correlation coefficient (Simpson, 2001). Employing QAP, the null-hypothesis is that the test-statistic of association equals the expected value under permutation distribution (Hubert, 1986). In other words, QAP tests whether there is no similar pattern between the elements of the different variables (Dekker et al., 2003). QAP was found to be superior and unbiased to ordinary least squares analysis in testing hypothesis in regression models based on dyadic data, especially in network analysis as data on network variables is typically represented in the form of a square matrix (Krackhardt, 1988).

Degrees of centrality were also measured for each topic to show the significance of different issues, which refers to the number of connections between a node (a topic in the analysis here) and all the other nodes in the network (Wasserman & Faust, 1994). To test H1 and H2 (the NAS effect within

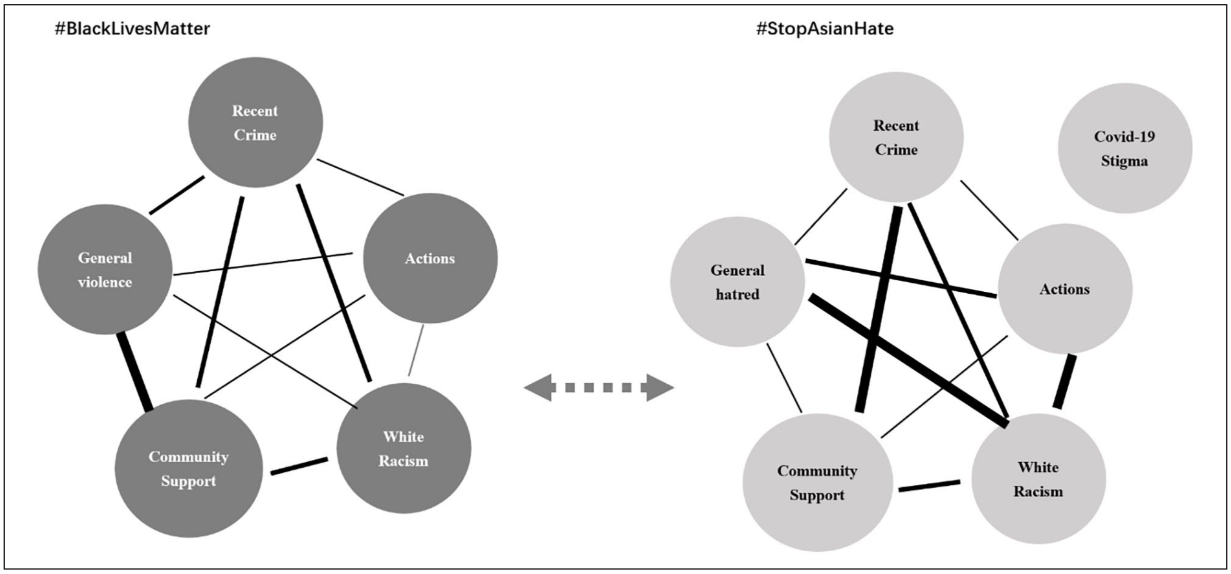

Figure 1. Network agenda-setting effects between #BlackLivesMatter and #StopAsianHate.
Edge size indicates times of co-occurrence between the two topics posted by the same tweeter during the study period.

one hashtag across time), QAP correlation tests were performed to compare the network matrices of topics extracted between sub-datasets BLM1 and BLM2, BLM2 and BLM3, BLM3 and BLM4, BLM4 and BLM5, and BLM5 and BLM6. Same tests were conducted between sub-datasets of SAH data to see if the results could be replicated.

To answer RQ2 (the NAS effect between the two hashtags), which tests the issue network correlation between BLM and SAH, the QAP test was conducted to test the correlations between the BLM dataset and the SAH dataset of the 3 months. It is worth noting that the data size for these two cases is unbalanced, which reflects the actual popularity differences between the two hashtags. We did not employ data processing technique to deal with it, because QAP Test investigates the correlation between two networks in terms of both the direction and the strength of tendency and change in scale of tweets. Therefore, the unbalanced sample size does not influence the value correlation directly.

To make the networks comparable, we further conceptualized the topics retrieved by semi-supervised LDA topic modeling and found that the extracted topics under both hashtags are similar but with one major difference (details provided in the results session). We found that both datasets reflected salient topics of specific recent crime (Topic 1), general hate and violence (Topic 2), actions (Topic 3), community support (Topic 4), and criticism against White racism (Topic 5). However, the SAH data provides one more distinguished topic, namely COVID-19 stigma (Topic 6). The results echoed with Ziems et al.'s (2020) study that the pro-Asian counter-hate tweets were largely COVID-19-related. Therefore, the QAP test between BLM data and SAH data were only conducted among tweets assigned for Topics 1–5. In other words, COVID-19 stigma-related tweets in SAH data were filtered out before the QAP test in answering RQ2. Figure 1 provided an example of the QAP test structure. As visualized in Figure 1, node (tweets issue) on the topic of COVID-19 in SAH dataset was removed. What QAP tested was the correlation between both networks each with 5 nodes and 10 edges.

Results

Based on the semi-supervised LDA topic modeling results, five salient topics under BLM and six salient topics under SAH were extracted. For BLM data, the salient topics include (1) recent crime against Black people (i.e., George Floyd's death), (2) general violence against Black people (including some historic cases, such as the death of Tamir Martin in 2014, death of Philando Castile in 2016, and death of Breonna Taylor in 2020), (3) collective actions by Black people (including petition, protests, and lawsuits), (4) community support, and (5) criticism against the White racism. Figure 2 indicates the change of popularity on each topic with 2 weeks as a unit.

For SAH data, the salient topics include (1) recent crime against Asian people (i.e., Atlantic spa shooting), (2) general hatred against Asian people, (3) collective actions by Asian people, (4) community support (such as Asian Americans/Pacific Islanders community), and (5) criticism against the White racism. Figure 3 visualized the distributions of SAH tweets on each topic during different time periods.

Comparing the salient topics extracted from tweets under two hashtags, both similarities and differences were clearly reflected. As for similarities, tweets under both hashtags frequently mentioned the recent crimes (Topic 1), especially during the first week after the crime took place. In this study,

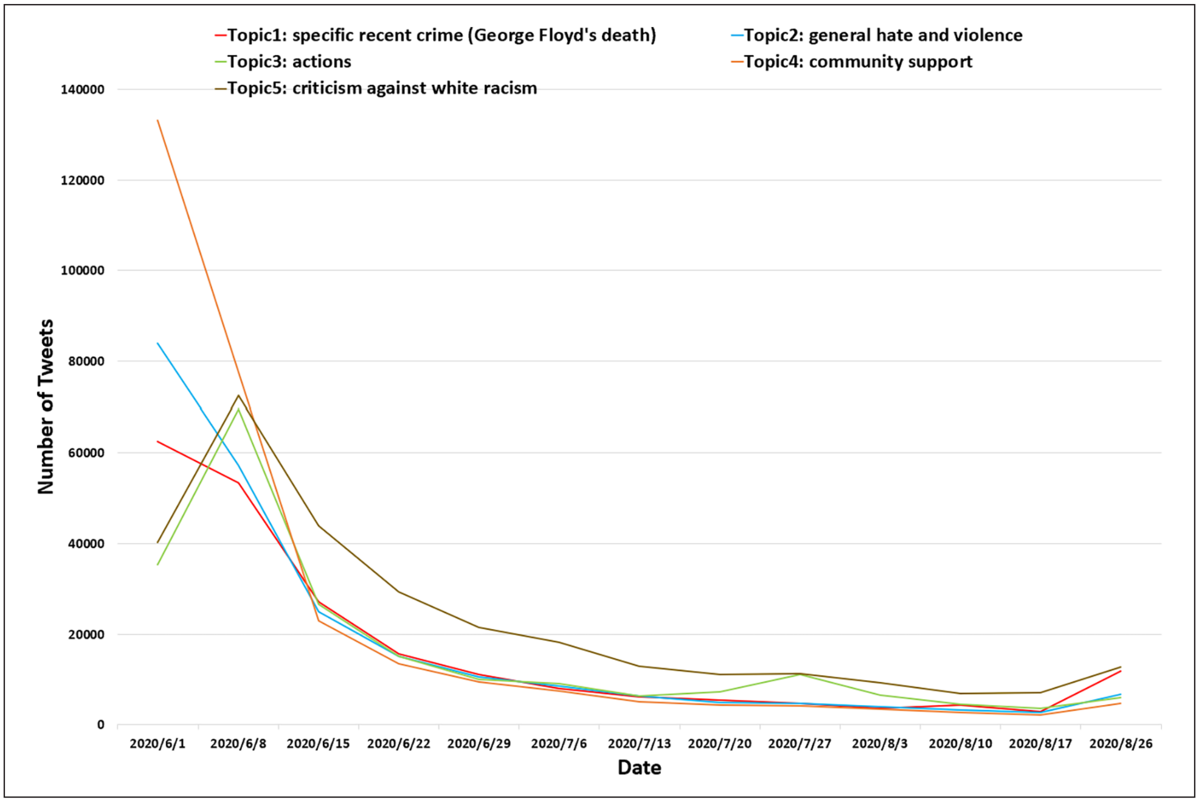

Figure 2. Topic distribution of #BlackLivesMatter tweets per week.

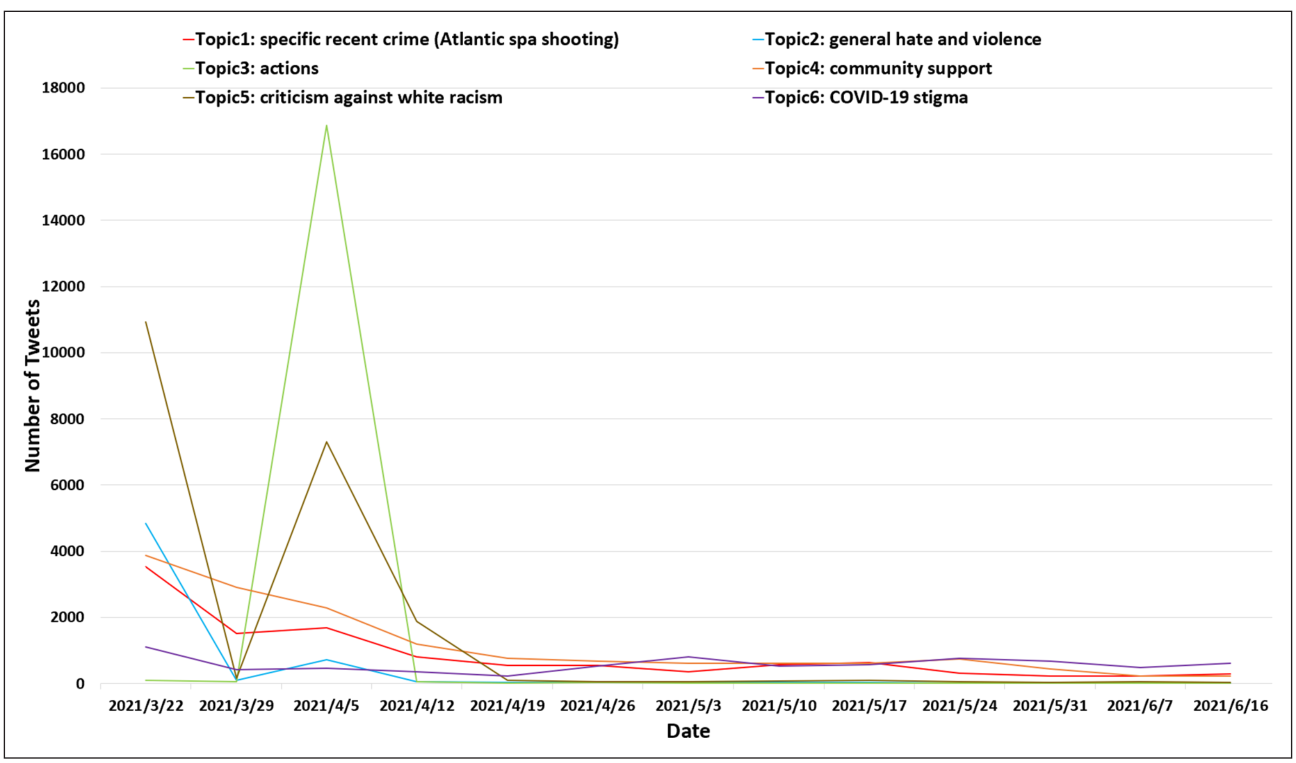

Figure 3. Topic distribution of #StopAsianHate per week.

the tipping points (George Floyd's death and Atlantic spa shooting) were taken as the starting point for our data collection. However, the "recent crime" topic lost popularity dramatically after the first 2 weeks. It was noticeable that the Twitter users frequently talked about general violence or hatred against the under privileged groups (Topic 2) and called for community support (Topic 4) when the "recent crime" ranked as a hot topic. In addition, after the crimes took place, more tweets began to focus on real activist actions (Topic 3) and criticizing the historical White racism (Topic 5). As was shown in Figures 2 and 3, Topics 3 and 5 both saw an increase during the first 2 weeks after George Floyd's death and the Atlantic spa shooting.

As for differences, the most obvious dimension is the popularity of the topics. Apparently, BLM triggered larger amount of social media discussions on Twitter. Based on the data we collected, during 3 months after George Floyd's death, there were more than 7 million original tweets posted with BLM. However, during the same time length after Atlantic spa shooting, number of tweets mentioning SAH did not reached 1 million. One possible reason could be that platform diversity in counter-Asian hate campaigns is higher than that in BLM movement. Since many Asian Americans are immigrants from Asian countries, it is more common for them to use multiple social media platforms like WeChat, Weibo, LINE, and KakaoTalk except for Facebook and Twitter in their counter-hate discussions. Therefore, the issue network on Twitter is supposed to be more scattered then BLM.

In addition to the tweets amount under two hashtags, other differences also emerged. The BLM tweets frequently talked about Black people's death under police violence. Large numbers of tweets called for justice against police brutality. The findings were in line with previous literatures saying that the BlackLivesMatter movement has been focusing on police abuse of African Americans (Altman, 2015; Clayton, 2018). For SAH tweets, the main focus was on the ideological discrimination against Asian people. Asian people were trying to make their voice heard and what they cared most was that the Western people used comedies to make fun of Asians, calling Asians the origins of COVID-19 virus (Topic 6). Asian's counter-racism discourse was more ideological focused in showing anger against the racism comedy shows. However, Black people's counter-racism discourse was more of the life and death matter. Interestingly, although with an Asian focus, the SAH tweets hashtag frequently mentioned BLM to show unity and alliance with the Black people. In the first topic extracted from SAH tweets, the keywords included "black" and "women," showing alliance with other vulnerable groups in Asians' hashtag activism campaigns.

The next step examined the network agenda-setting effects. We created two issue networks based on tweets' topics of the two datasets. Degree centralities captures the centrality or importance of topics being measured by the number of ties that a node has. As visualized in Figure 1, a tie meant a single co-occurrence between the two topics from the same tweeter. For BLM data, degree centralities were recorded as 326,374 (Topic 1), 361,704 (Topic 2), 289,840 (Topic 3), 358,604 (Topic 4), and 306,450 (Topic 5) while for the 6 extracted topics of SAH data, the degree centrality records were 9,142 (Topic 1), 8,544 (Topic 2), 7,938 (Topic 3), 10,510 (Topic 4), 11,978 (Topic 5), and 6,088 (Topic 6).

Table 1. Chronological Changes of NAS Effects on #BlackLivesMatter and #StopAsianHate Tweets.

	IV	DV	Coefficient	*p* value
#BlackLivesMatter	BLM1	BLM2	.11	.30
	BLM2	BLM3	.98	.006**
	BLM3	BLM4	.97	.02*
	BLM4	BLM5	.90	.01*
	BLM5	BLM6	.84	.04*
#StopAsianHate	SAH1	SAH2	.35	.10
	SAH2	SAH3	.97	.003**
	SAH3	SAH4	.96	.001***
	SAH4	SAH5	.90	.002**
	SAH5	SAH6	.84	.009**

IV: Independent variable; DV: Dependent variable.
QAP tests were conducted between issue networks with different time periods using R SNA package. BLM1 (tweets under #BlackLivesMatter hashtag from 26 May to 10 June 2020, N = 731,510); BLM2 (from 11 to 25 June 2020, N = 219,239); BLM3 (from 26 June to 10 July 2020, N = 105,717); BLM4 (from 11 to 25 July 2020, N = 72,186); BLM5 (from 26 July to 9 August 2020, N = 55,347); BLM6 (from 10 to 26 August 2020, N = 64,088). SAH1 (tweets under SAH hashtag from 16 to 30 March 2021, N = 55,291); SAH2 (from 1 to 14 April 2021, N = 8,475); SAH3 (from 15 to 30 April 2021, N = 4,417); SAH4 (from 1 to 14 May 2021, N = 3,564); SAH5 (from 15 to 30 May 2021, N = 3,875); SAH6 (from 31 May 2021 to 16 June 2021, N = 2,333).
*$p < .05$; **$p < .01$; ***$p < .001$.

Table 1 detailed results of QAP tests between different time periods. The results showed similar patterns that the first 2 weeks after the tipping point (recent crimes) could not set network agenda for the next 2 weeks' tweets (BLM: $B = .11$, $p > .05$; SAH: $B = .35$, $p > .05$). However, the network agenda-setting effects became significant as time went on. Dividing the 3-month period under study to six equal time periods, results show that although the first period's network agenda could not significantly affect the second period's network agenda, the correlation became significant upon the second period. As shown in Table 1, the network agenda of Period 2 significantly predicted the network agenda of Period 3 (BLM: $B = .98$, $p < .01$; SAH: $B = .97$, $p < .01$). The network agenda-setting effects were also significant between Periods 3 and 4, 4 and 5, and 5 and 6. Therefore, H1 was partially supported. A slight but continuous decrease of the coefficients was also captured in both datasets. Thus, H2 was supported.

Examining the network agenda-setting effects of BLM on SAH, QAP test showed non-significant results ($B = -.13$, $p = .63$), implying that tweets under BLM failed to set the network agenda for tweets under SAH. RQ2 was answered.

There could be several possible reasons underlying this result. First, as was mentioned above, SAH movement was mostly supported by immigrants from Asian countries, it was more common for them to use multiple social media platforms except for Twitter to conduct counter-hate discussions. Therefore, the networks of discourses on one single platform could be scattered and only present one part of the whole picture.

Second, although QAP test is based on correlation which could not be influenced by tweets numbers, number of edges between different topics could be largely affected if one author tweeted quite many times on various topics. Thus, as we have approximately 15 times of tweets in BLM data compared with the SAH data under analysis, the issue network structure of BLM tweets should be more sensitive to individual influence, especially the very active tweeters.

Third and most importantly, our findings implied that although the counter-racism discourses on Twitter share similarities and mutual concerns, the issue networks of different movements (e.g., movements by African Americans and Asian Americans) are different in nature. As was reflected by Figure 1, the BLM issue network has most links between Topic 2 (general crime) and Topic 4 (community support). It also showed large numbers of links between Topic 1 (recent crime) and other topics (i.e., general violence, community support, White racism). However, SAH issue network presented large numbers of edges between Topic 2 (general hatred) and Topic 5 (White racism), as well as Topic 3 (actions) and Topic 5 (White racism) while the BLM issue network did not show such patterns. The findings showed different logics among discourses under the two hashtags. The BLM network underlined that George Floyd's death and historic violence against Black people are most salient topics which bear the capability in triggering further discussions. However, the SAH network reflected that the SAH movement focused more on general hatred and racism against Asian community which required more community support. Therefore, although the rising trend of BLM happened 10 months earlier than the rising popularity of SAH movement, it did not trigger similar network agenda for Asian people's movements.

Discussion

While social media has been criticized for spreading hatred and racism (George, 2017; Ringrose, 2018), researchers began to recognize that the counter-racism discourses are with growing prevalence on social media platforms. With large, representative and comparable data scraped from Twitter, this study tried to provide comprehensive understanding of the salient topics under two hashtag activism cases (i.e., BLM and SAH), which were considered as two of the most important recent counter-racism campaigns on Twitter. By semi-supervised LDA topic modeling methods, five topics were extracted from 3-month tweets data under BLM after George Floyd's death while six topics were extracted from 3-month tweets data under SAH after the Atlantic spa shooting tragedy. Our findings illustrated that for both counter-racism cases, the sudden tragedies happened to vulnerable groups bear capability in triggering discussions online. Both online movements reflected salient topic on the crime just took place during the data collection period. In addition, general violence or hatred, actions, community support, and criticisms against White racism were all proved as important issues of the counter-racism discourse on social media. Our results echoed with Jackson and Foucault's (2016) study on #Ferguson that the use of the hashtag #Ferguson at the center of a counter public network has provoked and shaped public debates about race, policing, governance, and justice.

In addition to the descriptive findings, our study tried to explore the network agenda-setting effects of hashtag activisms on social media. We contend that counter-publics created by marginalized groups could be identified as the networked public sphere (Benkler, 2008). By testing the NAS effects, it could answer part of the questions as how hashtag activisms trigger and impact online discussions in an ongoing process. It also helped us to understand whether different hashtag activisms could be significantly correlated with each other and mobilize further actions. Our results showed that issue networks of the first 2 weeks' discourse after the crime could not set network agenda for the next 2 weeks' discourses. However, the network agenda-setting effects became significant from the third and fourth weeks and stayed stable as time went on. As we found replicated results based on data of two hashtags, the patterns were proved to be robust and reliable. A possible reason could be that the breaking event like George Floyd's death and Atlantic shooting compounded the network agenda of both movements. After discussions on the breaking news lost popularity, the network agenda of hashtag activism became stable and able to set continuous effects for the ongoing counter-racism discourses. Findings of this study added to the NAS theory especially in the context of social media. Traditional agenda-setting theory stays valid in print or broadcasting media. However, as digital media news content is interactive with fluctuated popularity, the NAS effects also seem to be unstable, especially when some breaking news burst out.

We did not find a significant relationship between BLM and SAH issue networks. The finding could be explained according to previous literature that in the United States, racism against Black people and Asian people are structured in different social contexts (Bacon, 2011; Kim, 2007; Roger, 2002). Therefore, although both communities are considered as vulnerable and has been unfairly treated by the American mainstream society for long, the major concerns and underlying mechanisms of the counter-racism discourses between Africans and Asians are different. It counter-argues the assumption that one counter-racism movement online could trigger similar movements among different groups. For tweets under BLM and SAH, although sharing some similar salient topics, it does not necessarily mean both discourses formed in similar network structure.

The network agenda-setting studies pioneered by Guo and McCombs (2011) presented evidence that news media is capable of transferring the salience of the relationships, or the connections, between attribute agendas. Other studies (e.g., Z. Chen et al., 2019) were interested in whether the network agenda-setting effects on social media is from a top-down approach (from influencer to individual), or actually bottom-up (from grassroots to influencers). Instead of examining whether the social media influencers could set issue network agenda to the public, we are typically interested in how the collective efforts by both mass media accounts and individuals during an online movement could carry-on and influence similar collective actions. Thus, in our study, attention was paid to the agenda of issue relationship covered in social media on counter-racism campaigns. This enables us to draw a holistic perspective in comparing network agenda between online social movements and provides a novel perspective in network agenda study.

In addition, this study also contributed to the literature by investigating the chronological changes of issue network agenda-setting effects. The power of network agenda-setting effects does not stay stable as time goes on and may turn insignificant in some circumstances. The findings drive us to pay more attention to how the networked online audiences may become scattered in their attention and become immune to similar discourses.

The results could not be interpreted without limitations. First, we only scraped 3-month data and took the tweets posted by active tweeters under analysis. This may reduce the generalizability of our results. Future researcher could try to explore the NAS effects in a longer period to examine the ongoing trends. Second, as tweets are short in nature, LDA is not the most ideal method to extract topics. Although the authors combined manual checking and semi-supervised LDA to boost accuracy, it is still recommended to further advance the machine learning process. Third, the operationalization of tweets issue networks is adapted from Vargo et al. (2014). The method only adds an edge between the topics mentioned by a same tweeter. It limits the scope of the network operationalization. Last but not least, we should acknowledge the social bot and spam accounts in Twitter may affect the topic modeling results. We tried to attenuate the problem by only including tweets posted by active posters (who tweeted at least 10 times under the hashtag) for analysis. However, it is not a sufficient method to fully detect and rule out the irrelevant tweets.

Despite the limitations, our study was an initial attempt in examining the third-level agenda-setting effects of social media hashtag activism. Based on data collected under two counter-racism discourses on Twitter, we provide a comparable and comprehensive understanding of how such discourses were constructed on social media. Practically, the extracted topics for BLM and SAH help the academia as well as the public to know what the major appeals and demands of the vulnerable groups are. For activists who wish to leverage the breaking news as an opportunity to mobilize an online movement, it is very important for them to realize what specific issues the community may care about and how these issues are connected. This may help in fueling a continuous public attention and discussion to finally make policy change.

Theoretically, our study offers a fresh perspective to understand chronological changes of network agenda-setting effects of hashtag activism, especially after the sudden rise of topic popularity triggered by certain news event. Our findings suggested that anti-racism discourses are multi-dimensional with various structures. One hashtag activism may not possibly frame the issue networks of upcoming events on social media.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

ORCID iDs

Jing Guo https://orcid.org/0000-0001-8707-1124
Shujun Liu https://orcid.org/0000-0002-9374-7036

Supplemental Material

Supplemental material for this article is available online.

References

Ahmed, S. (2014). *The cultural politics of emotion* (2nd ed.). Edinburgh University Press.

Altman, A. (2015, April 9). Black Lives Matter: A new civil rights movement is turning a protest cry into a political force. *Time Magazine*. http://time.com/time-person-of-the-year-2015-runner-up-black-lives-matter/

Anderson, J. R. (1983). *The architecture of cognition*. Harvard University Press.

Aouragh, M. (2019). "White privilege" and shortcuts to anti-racism. *Race & Class*, *61*(2), 3–26. https://doi.org/10.1177/0306396819874629

Armstrong, D. M. (1973). *Belief, truth and knowledge*. Cambridge University Press.

Bacon, J. (2011). Declarations of independence: African American abolitionists and the struggle for racial and rhetorical self-determination. In M. Lacy & K. Ono (Eds.), *Critical rhetorics of race* (pp. 139–158). New York University Press.

Barsalou, L. W., Huttenlocher, J., & Lamberts, K. (1998). Basing categorization on individuals and events. *Cognitive Psychology*, *36*(3), 203–272. https://doi.org/10.1006/cogp.1998.0687

Benkler, Y. (2008). *The wealth of networks*. Yale University Press.
Benoit, K., Watanabe, K., Wang, H., Nulty, P., Obeng, A., Müller, S., & Matsuo, A. (2018). Quanteda: An R package for the quantitative analysis of textual data. *Journal of Open Source Software*, *3*(30), Article 774. https://doi.org/10.21105/joss.00774
Butts, C. T. (2008). Social network analysis with SNA. *Journal of Statistical Software*, *24*, 1–51.
Calvert, C. (1997). Hate speech and its harms: A communication theory perspective. *Journal of Communication*, *47*(1), 4–19. https://doi.org/10.18637/jss.v024.i06
Campbell, K. K. (1998). The discursive performance of femininity: Hating Hillary. *Rhetoric & Public Affairs*, *1*(1), 1–20. http://doi.org/10.1353/rap.2010.0172
Caren, N. (2020). *Scraping twitter with twint*. https://nealcaren.org/lessons/twint//
Chan, M., & Lee, F. L. (2014). Selective exposure and agenda setting: Exploring the impact of partisan media exposure on agenda diversity and political participation. *Asian Journal of Communication*, *24*(4), 301–314. https://doi.org/10.1080/01292986.2014.903424
Chen, H. T., Guo, L., & Su, C. C. (2020). Network agenda setting, partisan selective exposure, and opinion repertoire: The effects of pro-and counter-attitudinal media in Hong Kong. *Journal of Communication*, *70*(1), 35–59. https://doi.org/10.1093/joc/jqz042
Chen, Z., Su, C. C., & Chen, A. (2019). Top-down or bottom-up? A network agenda-setting study of Chinese nationalism on social media. *Journal of Broadcasting & Electronic Media*, *63*(3), 512–533. https://doi.org/10.1080/08838151.2019.1653104
Clayton, D. M. (2018). Black lives matter and the civil rights movement: A comparative analysis of two social movements in the United States. *Journal of Black Studies*, *49*(5), 448–480. https://doi.org/10.1177/0021934718764099
Conway, B. A., Kenski, K., & Wang, D. (2015). The rise of Twitter in the political campaign: Searching for intermedia agenda-setting effects in the presidential primary. *Journal of Computer-Mediated Communication*, *20*(4), 363–380. https://doi.org/10.1111/jcc4.12124
Dawes, S. (2017). #JeSuisCharlie, #JeNeSuisPasCharlie and ad hoc publics. In G. Titley, D. Freedman, G. Khiabany, & A. Mondon (Eds.), *After Charlie Hebdo* (pp. 180–191). Zed Books.
Dekker, D., Krackhardt, D., & Snijders, T. (2003). Multicollinearity robust QAP for multiple regression. North American Association for Computational Social and Organization Sciences (NAACSOS) Conferences, Pittsburgh, PA, USA.
Feigenbaum, A. (2014). Resistant matters: Tents, tear gas and the "other media" of occupy. *Communication and Critical/Cultural Studies*, *11*(1), 15–24. https://doi.org/10.1080/14791420.2013.828383
Fiske, S. T., Cuddy, A. J. C., Glick, P., & Xu, J. (2002). A model of (often mixed) stereotype content: Competence and warmth respectively follow from perceived status and competition. *Journal of Personality and Social Psychology*, *82*(6), 878–902. https://doi.org/10.1037/0022-3514.82.6.878
George, C. (2017). Hate spin: The twin political strategies of religious incitement and offence-taking. *Communication Theory*, *27*(2), 156–175. https://doi.org/10.1111/comt.12111
The Guardian. (2021). The counted people killed by police in the US. *The Guardian*. https://www.theguardian.com/us-news/ng-interactive/2015/jun/01/the-counted-police-killings-us-database
Guo, L., & McCombs, M. (2011, May). *Network agenda setting: A third level of media effects* [Paper presentation]. Annual ICA conference, Boston, MA.
Hong, L., Doumith, A. S., & Davison, B. D. (2013). Co-factorization machines: Modeling user interests and predicting individual decisions in twitter. In *Proceedings of the sixth ACM international conference on web search and data mining*. New York: ACM.
Hubert, L. (1986). *Assignment methods in combinational data analysis* (Vol. 73). CRC Press.
Jackson, S. J., & Foucault, W. B. (2015). Hijacking #myNYPD: Social media dissent and networked counterpublics. *Journal of Communication*, *65*(6), 932–952. https://doi.org/10.1111/jcom.12185
Jackson, S. J., & Foucault, W. B. (2016). #Ferguson is everywhere: Initiators in emerging counterpublic networks. *Information, Communication & Society*, *19*(3), 397–418.
Kim, Y. Y. (2007). Ideology, identity, and intercultural communication: An analysis of differing academic conceptions of cultural identity. *Journal of Intercultural Communication Research*, *36*(3), 237–253. https://doi.org/10.1080/1369118X.2015.1106571
Kiousis, S., Kim, J. Y., Ragas, M., Wheat, G., Kochhar, S., Svensson, E., & Miles, M. (2015). Exploring new frontiers of agenda building during the 2012 US presidential election preconvention period. *Journalism Studies*, *16*(3), 363–382. https://doi.org/10.1080/1461670X.2014.906930
Krackhardt, D. (1988). Predicting with networks: Nonparametric multiple regression analysis of dyadic data. *Social Networks*, *10*(4), 359–381. https://doi.org/10.1016/0378-8733(88)90004-4
Kumar, A., & Paul, A. (2016). *Mastering text Mining with R*. Packt Publishing Ltd.
Li, Y., & Nicholson, H. L. (2021). When "model minorities" become "yellow peril"—Othering and the racialization of Asian Americans in the covid pandemic. *Sociology Compass*, *15*(2), Article e12849. https://doi.org/10.1111/soc4.12849
Lippmann, W. (1922). *Public opinion*. Macmillan.
Lu, B., Ott, M., Cardie, C., & Tsou, B. K. (2011). Multi-aspect sentiment analysis with topic models. In M. Spiliopoulou, H. Wang, D. J. Cook, J. Pei, W. Wang, O. R. Zaiane, & X. Wu (Eds.), *Proceedings of the 11th IEEE international conference on data mining workshops* (pp. 81–88), Washington, DC, USA.
McCombes, M., Lopez-Escobar, E., & Llamas, J. P. (2000). Setting the agenda of attributes in the 1996 Spanish general election. *Journal of Communication*, *50*(2), 77–92. https://doi.org/10.1111/j.1460-2466.2000.tb02842.x
McCombs, M. (2004). *Setting the agenda: The mass media and public opinion*. Polity Press.
McCombs, M. E., & Shaw, D. L. (1972). The agenda-setting function of mass media. *Public Opinion Quarterly*, *36*, 176–187. https://doi.org/10.1086/267990
Neil, J., Schweickart, T., Zhang, T., Lukito, J., Kim, J. Y., Golan, G., & Kiousis, S. (2018). The dash for gas: Examining third-level agenda-building and fracking in the United Kingdom. *Journalism Studies*, *19*(2), 182–208. https://doi.org/10.1080/1461670X.2016.1181528

Okihiro, G. Y. (2014). *Margins and mainstreams: Asians in American history and culture*. University of Washington Press.

Ott, B. L. (2017). The age of Twitter: Donald J. Trump and the politics of debasement. *Critical Studies in Media Communication*, *34*(1), 59–68. https://doi.org/10.1080/15295036.2016.1266686

Parmelee, J. H., & Bichard, S. L. (2012). *Politics and the Twitter Revolution: How tweets influence the relationship between political leaders and the public*. Lexington Books.

Pleyers, G. (2020). The pandemic is a battlefield. Social movements in the COVID-19 lockdown. *Journal of Civil Society*, *16*(4), 295–312. https://doi.org/10.1080/17448689.2020.1794398

Poole, E., Giraud, E. H., & de Quincey, E. (2021). Tactical interventions in online hate speech: The case of #stopIslam. *New Media & Society*, *23*(6), 1415–1442. https://doi.org/10.1177/1461444820903319

Ringrose, J. (2018). Digital feminist pedagogy and post-truth misogyny. *Teaching in Higher Education*, *23*(5), 647–656. https://doi.org/10.1080/13562517.2018.1467162

Roger, B. (2002). Race, ethnicity and culture. In M. Holborn (Ed.), *New directions in sociology*. Causeway. https://www.academia.edu/21837504/Race_Ethnicity_and_Culture

Sharma, H. (2020, September). *Complete tutorial on twint: Twitter scraping without Twitter's API*. https://analyticsindiamag.com/complete-tutorial-on-twint-twitter-scraping-without-twitters-api/

Sharma, S. (2013). Black Twitter? Racial hashtags, networks and contagion. *New Formations*, *78*, 46–64. https://doi.org/10.3898/NewF.78.02.2013

Siapera, E. (2019). Organised and ambient digital racism: Multidirectional flows in the Irish digital sphere. *Open Library of Humanities*, *5*(1), Article 13. https://doi.org/10.16995/olh.405

Simpson, W. (2001, March). *The quadratic assignment procedure (QAP)* [Paper presentation]. Stata Users Group Meeting, Boston, MA.

Treré, E. (2019). *Hybrid media activism: Ecologies, imaginaries, algorithms*. Routledge.

Vargo, C. (2011, August). *Twitter as public salience: An agenda-setting analysis* [Paper presentation]. AEJMC Annual Conference, St. Louis, MO.

Vargo, C. J., Guo, L., Mccombs, M., & Shaw, D. L. (2014). Network issue agendas on twitter during the 2012 U.S. presidential election. *Journal of Communication*, *64*(2), 296–316. https://doi.org/10.1111/jcom.12089

Vu, H. T., Guo, L., & McCombs, M. E. (2014). Exploring "the world outside and the pictures in our heads": A network agenda-setting study. *Journalism & Mass Communication Quarterly*, *91*(4), 669–686. https://doi.org/10.1177/1077699014550090

Wahl-Jorgensen, K. (2019). *Emotions, media and politics*. Polity Press.

Wang, D., Thint, M., & Al-Rubaie, A. (2012). Semi-supervised latent Dirichlet allocation and its application for document classification. In *2012 IEEE/WIC/ACM International Conferences on Web Intelligence and Intelligent Agent Technology* (Vol. 3, pp. 306–310). IEEE. https: doi.org/10.1109/WI-IAT.2012.211

Wanta, W., & Alkazemi, M. (2018). Journalism as agenda setting. *Journalism*, *19*, 189–204.

Wasserman, S., & Faust, K. (1994). *Social network analysis: Methods and applications*. Cambridge University Press.

Webster, J. G. (2014). *The marketplace of attention: How audiences take shape in a digital age*. MIT Press.

Webster, J. G., & Ksiazek, T. B. (2012). The dynamics of audience fragmentation: Public attention in an age of digital media. *Journal of Communication*, *62*(1), 39–56. https://doi.org/10.1111/j.1460-2466.2011.01616.x

Wei, W. (1993). *The Asian American Movement*. Temple University Press.

Xu, J., & Lee, J. C. (2013). The marginalized "Model" minority: An empirical examination of the racial triangulation of Asian Americans. *Social Forces*, *91*(4), 1363–1397. https://doi.org/10.1093/sf/sot049

Yang, G. (2016). Narrative agency in hashtag activism: The case of #BlackLivesMatter. *Media and Communication*, *4*(4), 13–17. http://doi.org/10.17645/mac.v4i4.692

Zhang, T., Kim, J. Y., Mohr, T. L., Myslik, B. A., Khalitova, L., Golan, G. J., & Kiousis, S. (2017). Agenda-building role of state-owned media around the world: 2014 Hong Kong protest case. *Journal of Public Relations Research*, *29*(5), 238–254. https://doi.org/10.1080/1062726X.2017.1396988

Zhang, Y., Chen, W., & Yin, Z. (2013). Collaborative filtering with social regularization for TV program recommendation. *Knowledge-Based Systems*, *54*, 310–317. https://doi.org/10.1016/j.knosys.2013.09.018

Ziems, C., He, B., Soni, S., & Kumar, S. (2020). *Racism is a virus: Anti-Asian hate and counterhate in social media during the Covid-19 crisis*. arXiv preprint arXiv:2005.12423. https://doi.org/10.48550/arXiv.2005.12423

Author Biographies

Jing Guo is a doctoral student at the School of Journalism and Communication, The Chinese University of Hong Kong. Her research centers on political communication and health communication with a focus on the role of social media.

Shujun Liu (PhD, Tsinghua University) is a research associate of the School of Social Science at Cardiff University. Her research interests include political communication, digital society, and journalism practice.