Cyberpsychology, Behavior, and Social Networking
Volume 26, Number 7, 2023

DOI: 10.1089/cyber.2022.0206

An Analysis of Temporal Trends in Anti-Asian Hate and Counter-Hate on Twitter During the COVID-19 Pandemic

Brittany Wheeler, MS,[1] Seong Jung, BS,[2] Deborah L. Hall, PhD,[1]
Monika Purohit, MS,[3] and Yasin Silva, PhD[3]

Abstract

Recent studies have documented increases in anti-Asian hate throughout the COVID-19 pandemic. Yet relatively little is known about how anti-Asian content on social media, as well as positive messages to combat the hate, have varied over time. In this study, we investigated temporal changes in the frequency of anti-Asian and counter-hate messages on Twitter during the first 16 months of the COVID-19 pandemic. Using the Twitter Data Collection Application Programming Interface, we queried all tweets from January 30, 2020 to April 30, 2021 that contained specific anti-Asian (e.g., *#chinavirus, #kungflu)* and counter-hate (e.g., *#hateisavirus)* keywords. From this initial data set, we extracted a random subset of 1,000 Twitter users who had used one or more anti-Asian or counter-hate keywords. For each of these users, we calculated the total number of anti-Asian and counter-hate keywords posted each month. Latent growth curve analysis revealed that the frequency of anti-Asian keywords fluctuated over time in a curvilinear pattern, increasing steadily in the early months and then decreasing in the later months of our data collection. In contrast, the frequency of counter-hate keywords remained low for several months and then increased in a linear manner. Significant between-user variability in both anti-Asian and counter-hate content was observed, highlighting individual differences in the generation of hate and counter-hate messages within our sample. Together, these findings begin to shed light on longitudinal patterns of hate and counter-hate on social media during the COVID-19 pandemic.

Keywords: Twitter, quantitative research, COVID-19, anti-Asian, counter-hate, latent growth curve modeling

Introduction

The COVID-19 pandemic has had detrimental and far-reaching effects on a global scale, yet it has uniquely impacted individuals of Asian descent. The marked increase in anti-Asian hate, violence, and xenophobia throughout the pandemic—owing to the origins of SARS-CoV-2 in Wuhan, Hubei Providence of China—has been well-documented. Within the United States, for instance, prejudice targeting Asian Americans and Pacific Islanders (AAPIs) has risen in both in-person contexts[1] as well as online spaces.[2–7] Similar trends globally have led the United Nations to caution against ''a pandemic of hate.''[8]

Although anti-Asian hate in the context of COVID-19 is a recent phenomenon, there has been extensive work demonstrating the negative impacts of racism on its targets.[9] For instance, previous research has found that Asians targeted by racially motivated harassment are at greater risk for poorer mental and physical health outcomes, including depression, anxiety, chronic stress, and chronic disease.[10–12] In fact, during the first few months of the pandemic (i.e., January–March 2020), there was a 39 percent increase in Asian Americans who were identified as experiencing severe anxiety through Mental Health America's online mental health screening tool.[13,14] Speaking on the effects of racism online, research by Yang and colleagues[15] indicated that Asian

[1]School of Social and Behavioral Sciences and [2]School of Mathematical and Natural Sciences, Arizona State University, Glendale, Arizona, USA.
[3]Department of Computer Science, Loyola University Chicago, Chicago, Illinois, USA.

Americans who encountered discrimination in their passive use of social media during the COVID-19 pandemic reported lower subjective well-being. Of note, this finding was mediated by increased worry about encountering discrimination again.

Rather than focus on the psychological outcomes of racially motivated attacks, this research seeks to shed light on temporal trends in anti-Asian and counter-hate content on social media, the understanding of which may offer insights about other hate campaigns online. That is, a crucial question that has yet to receive sufficient empirical attention is how anti-Asian hate, as well as positive messages to combat the hate, have varied in online spaces over time throughout the pandemic.

One of the few efforts to explore anti-Asian *and* counter-hate messages on social media during the pandemic comes from recent work by He and colleagues,[4] who developed a machine learning model to classify anti-Asian hate, counter-hate, and neutral (irrelevant) content in a large corpus of Twitter data. In addition to generating a labeled dataset and performing a range of linguistic and social network analyses, the researchers also provided a brief descriptive overview of an observed ''ebb and flow of hate and counter-speech'' over a 14-month span. Specifically, these researchers found large initial spikes of anti-Asian activity during the early stages of the pandemic that then decreased at a steady rate. In contrast, there were large spikes in counter-hate activity following violent in-person attacks against Asian Americans (e.g., the Atlanta spa shootings). Other researchers found similar bursts of activity in anti-Asian and counter-hate content[16,17]; however, because the assessment of temporal trends was not a primary focus, crucial insights about the evolution of anti-Asian hate and counter-hate can be gained from additional longitudinal analyses.

In this study, we used latent growth curve analysis to investigate temporal changes in the frequency of anti-Asian and counter-hate messages on Twitter throughout the first 16 months of the COVID-19 pandemic—a longer time frame than most included in previous studies. Whereas other studies have evaluated trends pertaining to sentiment,[17,18] geographic location,[19] and moral beliefs,[20] we are unaware of any prior studies that have used latent growth curve analysis to evaluate patterns in the frequency of this content during the pandemic. That is, we believe this methodology can provide invaluable insights for modeling between-user differences within the context of within-user changes, further illuminating how trends in the use of certain keywords change over time.[21]

We predicted that the frequency of both anti-Asian and counter-hate messages would vary considerably over time. Specifically, we hypothesized that the frequency of anti-Asian content would fluctuate in a curvilinear pattern, given the descriptive patterns reported in previous research,[4,16,17] evolving public health circumstances (e.g., lockdowns, social distancing recommendations), the highly political nature of responses to the pandemic,[16] and a shifting political landscape.[16,22] In contrast, we were unsure which of two alternative hypotheses might be supported in our investigation of counter-hate messages. On one hand, the frequency of counter-hate messages might also fluctuate in a curvilinear pattern, in response to shifts in the public health and political landscape. On the other hand, counter-hate messages might steadily increase over time, in response to the increased prevalence and salience of anti-Asian hate in both online and offline spaces.

Materials and Methods

As part of a broader data collection effort investigating anti-Asian prejudice on Twitter during the COVID-19 pandemic[23] (Wheeler B, et al. Technical Report: Global Prevalence Patterns of Anti-Asian Prejudice on Twitter During the COVID-19 Pandemic. Loyola eCommons; in review, https://ecommons.luc.edu/cs_facpubs/324/), we used the Twitter Data Collection Application Programming Interface (API)[a] to query tweets containing either anti-Asian or counter-hate (i.e., anti-prejudice) keywords. Specifically, we queried all publicly available tweets posted between January 30, 2020—when the World Health Organization declared the spread of COVID-19 a global health issue—and April 30, 2021—the last day before the start of AAPI Heritage Month (the following year), when positive AAPI messages might increase independent of COVID-19. Because all data were collected from publicly available accounts—and thus did not include any identifiable private information—the study did not meet the criteria for human subjects research requiring IRB review.[24]

For each date in this timeframe, we obtained a count of the number of times 12 specific anti-Asian hashtags and keywords (*#batsoup/batsoup, #chinavirus/chinavirus, #gobacktochina/gobacktochina, #chinesevirus/chinesevirus, #chineseplague/chineseplague, #gook/gook, #chinaliedpeopledied/chinaliedpeopledied, #kungflu/kungflu, #wuflu/wuflu, #chingchong/chingchong, #makechinapay/makechinapay, #ccpvirus/ccpvirus*) and five counter-hate hashtags and keywords (*#hateisavirus/hateisavirus, #Iamnotavirus/Iamnotavirus, #racismisavirus/racismisavirus, #washthehate/washthehate, #stopasianhate/stopasianhate*) appeared in the Twitter feeds of publicly available accounts. Versions of each designated keyword with and without a preceding hashtag were included in the frequency count. We selected these keywords based on relevant literature,[4] news publications,[25–27] and social media posts discussing anti-Asian attitudes during the early months of the pandemic.

A total of 13,008,053 tweets were queried from 3,298,940 distinct users. An initial dataset was created containing the number (count) of each anti-Asian and counter-hate keyword for each date across the 16-month timeframe.[b] From this initial dataset, we extracted a random subset of 1,000 users who had used one or more anti-Asian or counter-hate keyword using the *sample()* R function.[28] This function gathers a random sample of user ID numbers without duplicates, where the probability of a user being selected in the sample is proportional to the remaining users.[28] The sample size ($N = 1,000$) was chosen based on simulation studies[29–31] demonstrating adequate statistical power when evaluating linear and quadratic trends across 16 time points. A count reflecting the number of times each individual used an anti-Asian or counter-hate keyword was then tallied for each of the 16 months of data collection.

As shown in Figure 1, the total number of anti-Asian keywords (among all users in the sample) ranged from 0 to 46 in a given month, with the highest number of anti-Asian keywords occurring in March 2020. The total number of counter-hate keywords (among all users in the sample) ranged from 0 to 60, with the highest number of counter-hate keywords occurring in March 2021. Moreover, at the level of individual users, the cumulative total number of anti-Asian

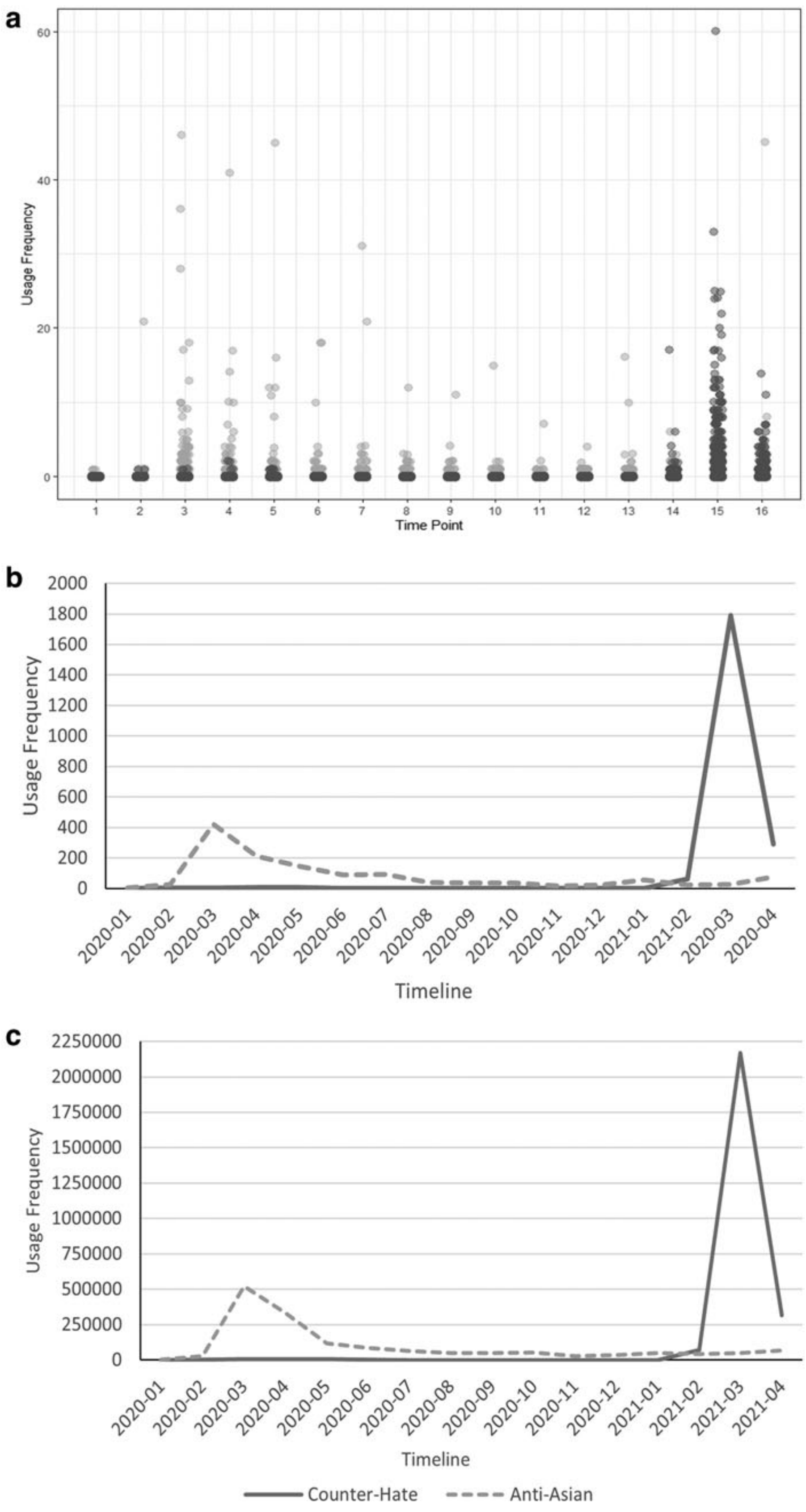

FIG. 1. Frequency of anti-Asian and counter-hate keywords for the random sample of Twitter users **(a, b)** and the full dataset **(c)**. **(a)** The frequency of anti-Asian and counter-hate keywords for a random sample of Twitter users ($N = 1{,}000$). Each point in this figure represents an individual user's count of anti-Asian or counter-hate keywords for a given month, with the *gray* points representing tweets containing anti-Asian keywords and the *black* points representing counter-hate keywords. **(b)** Represents this same information contained within **(a)** in the form of a line graph for comparison with the full dataset. The *line* represents the sum of keywords used for each month for the random sample of Twitter users. **(c)** Frequency of anti-Asian and counter-hate keywords for the full dataset ($N = 3{,}298{,}940$). The *line* represents the sum of keywords used for each month for the full dataset.

keywords across the 16-month data collection period ranged from 0 to 142, whereas the total number of counter-hate keywords ranged from 0 to 62. Compared with the full dataset, the random sample of Twitter users showed comparable user frequencies (Fig. 1a–c), providing evidence of the representativeness of this subsample.

Analytical plan

A series of latent growth curve models were performed using Mplus 8.5[32] to investigate changes in anti-Asian and counter-hate activity over time. For all models, the frequency of keyword use at each time point was specified as a count variable with a negative binomial distribution and was

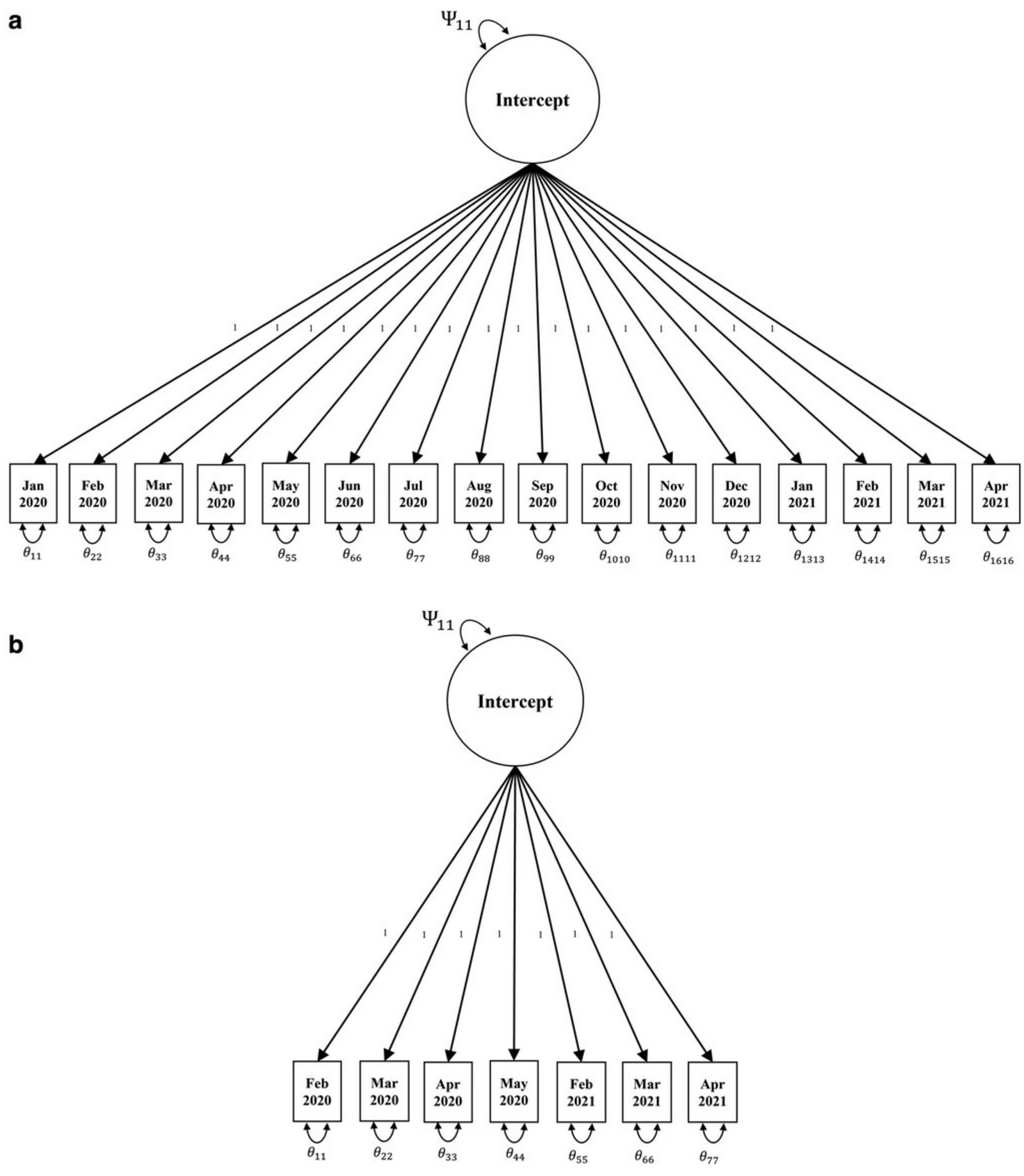

FIG. 2. Path diagram of the intercept-only models for anti-Asian **(a)** and counter-hate **(b)** keyword use. All loadings for the latent intercept are fixed to one. Time points in the counter-hate model for months with counts of zero do not appear in the diagram.

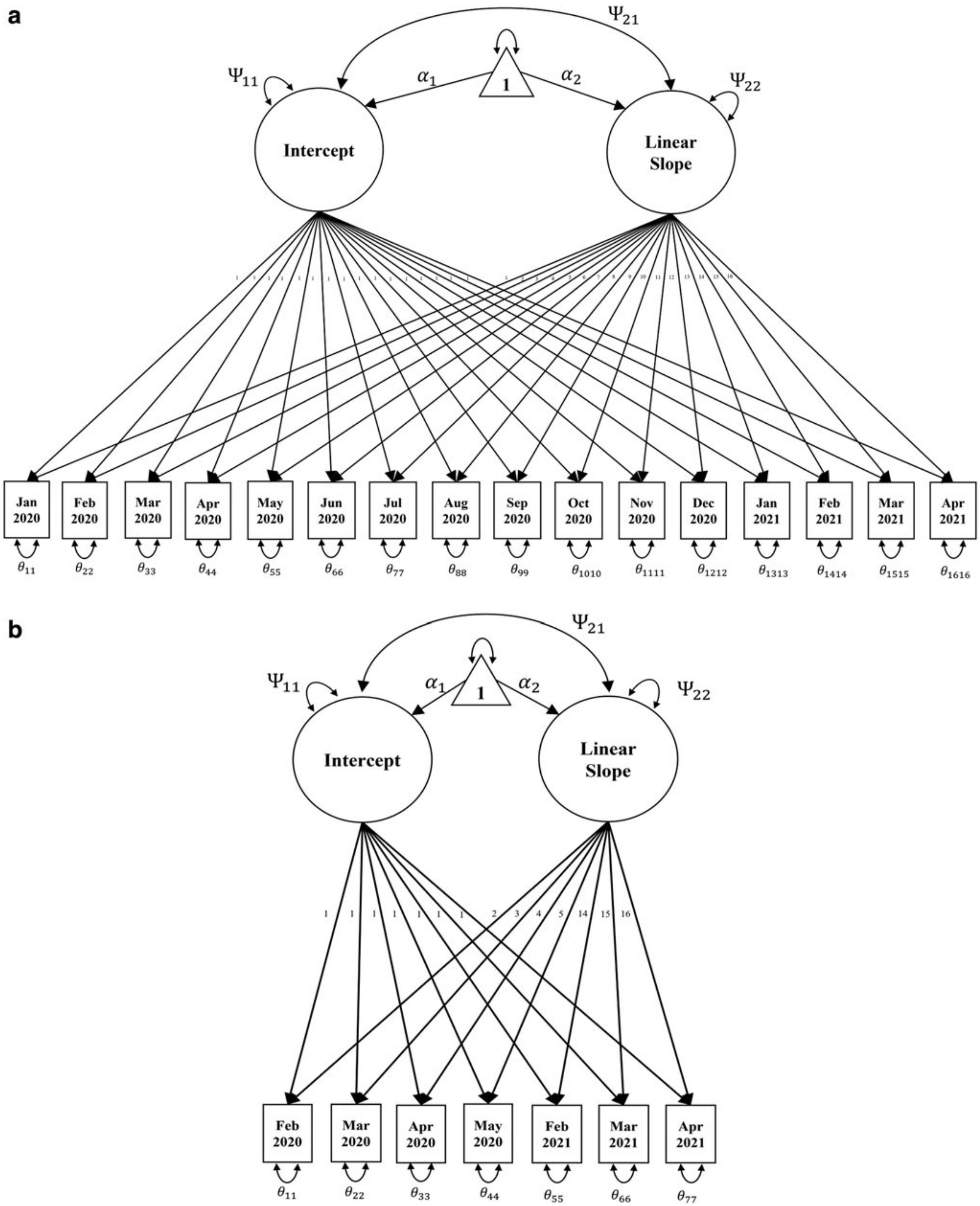

FIG. 3. Path diagram of the linear growth curve models for anti-Asian **(a)** and counter-hate **(b)** keyword use. All loadings for the latent intercept were fixed to one and loadings for the linear slope were set to represent 1-month increases. The intercept was fixed at the first time point for which there was a nonzero keyword count. Time points in the counter-hate model for months with counts of zero do not appear in the diagram but were accounted for in the statistical model by fixing the loadings to reflect this gap in time.

estimated using maximum likelihood estimation. Specifically, for our (separate) analyses of anti-Asian and counter-hate frequencies, we tested three models. The first model (Fig. 2) was an intercept-only model, which assumes that users showed no change in their frequency of (anti-Asian or counter-hate) keyword use over time. The second model was a linear growth model (Fig. 3), which assumes that users showed linear increases or decreases in their anti-Asian or counter-hate keyword use over time, with the intercept of the model centered at the first time point for which there was a nonzero keyword count.[c]

The third model (Fig. 4) was a quadratic growth model, which assumes that users can have a quadratic (i.e., curvilinear) increase or decrease in anti-Asian or counter-hate keyword use over time. To more easily identify differences between the linear and quadratic growth models and to prevent the correlation between these two latent variables from being too large, the intercepts of the quadratic growth models were set to a timepoint midway through the data collection period (i.e., September 2020 for the anti-Asian model and May 2020 for the counter-hate model).[d] Because the data consisted of counts, the difference between the −2 log-likelihood (*LL*) values was used to compare the fit between models. In addition, because the coefficients produced by Mplus were in a log metric, the values were exponentiated before interpretation.

Results

Anti-Asian keyword use

Whereas the linear (Δ $-2LL = 46.85$, $df = 3$, $p < 0.001$) and quadratic (Δ $-2LL = 437.06$, $df = 7$, $p < 0.001$) growth models showed significantly better fit than the intercept-only model, the quadratic growth model fit the data significantly better than the linear growth model (Δ $-2LL = 483.91$, $df = 4$, $p < 0.001$). Therefore, we moved forward with the interpretation of the quadratic growth model only. As shown in Figure 5, the frequency of anti-Asian keywords quickly rose in the first few months and then declined over time, with the curvilinear pattern supported by the significance of the quadratic slope ($\Psi_3 = 1.03$, $SE = 1.02$, $p < 0.001$).

Significant covariances between the intercept and the linear slope ($\Psi_{21} = 1.12$, $p = 0.016$), between the intercept and the quadratic slope ($\Psi_{32} = -0.96$, $p < 0.001$), and between the linear slope and the quadratic slope ($\Psi_{31} = -1.00$, $p = 0.025$) were found, indicating that greater anti-Asian keyword use at the model's intercept (September 2020) was associated with a slower rate of deceleration and confirming the superior fit of the quadratic model over the intercept-only and linear growth models. Finally, there was evidence of significant between-user variability in the frequency of anti-Asian keyword use in September 2020 ($\Psi_{11} = 57.63$, $SE = 1.76$, $p < 0.001$), between-user differences in (linear) rates of change ($\Psi_{22} = 1.04$, $SE = 1.01$, $p < 0.001$), and between-user differences in (quadratic) rates of acceleration ($\Psi_{33} = 1.00$, $SE = 1.00$, $p = 0.001$) over time. This variability between users is also reflected in Figure 5, as some users showed positive quadratic trends, whereas others showed negative quadratic trends.

Counter-hate keyword use

The linear growth model fit the data significantly better than the intercept-only model (Δ $-2LL = 26.94$, $df = 3$, $p < 0.001$). Of note, the quadratic model for counter-hate keyword use did not converge, even after increasing the number of iterations, suggesting that a quadratic trend was not a good fit for the data.[33] Therefore, only the results of the linear model were interpreted. In the linear growth model, there were no significant covariances between the intercept and the linear slope ($\Psi_{21} = 0.99$, ns), indicating no relation between individuals' frequency of counter-hate keywords in February 2020 (i.e., the intercept of the linear model) and their rate of change throughout the data collection period.

The linear slope ($\alpha_2 = 1.47$, $SE = 1.00$, $p < 0.001$) reflected that with each 1-month increase in time, the model predicted a corresponding increase of 1.47 counter-hate keywords, on average. Whereas there was no significant between-user variability in the frequency of counter-hate keyword use in February 2020 ($\Psi_{11} = 1.02$, $SE = 1.38$, ns), there were, however, between-user differences in the (linear) rate of change over time ($\Psi_{22} = 1.01$, $SE = 1.00$, $p < 0.001$; Fig. 6).

Discussion

We performed latent growth curve analysis to investigate temporal changes in the frequency of anti-Asian and counter-hate messages on Twitter between January 30, 2020 and April 30, 2021. Anti-Asian content, reflected in the use of keywords such as *#chinavirus/chinavirus* and *#gobacktochina/gobacktochina*, increased steadily throughout the early months of the COVID-19 pandemic before declining, with a pattern best captured by a quadratic growth curve model. Whereas these initial spikes in anti-Asian content followed by a steady decline is consistent with previous studies,[4,16,17] no prior studies used latent growth models to evaluate these trends over time.

In addition to overall trends in anti-Asian activity, our analysis revealed significant individual differences in the frequency and rates of change in the use of anti-Asian keywords among the Twitter users in our sample. Specifically, those who used anti-Asian keywords more frequently at the midpoint of our data collection (September 2020) showed significantly slower rates of deceleration in their use in subsequent months. This variability may reflect differences in exposure to and the perceived acceptability of terms like ''china virus'' within relatively homogenous social networks, thereby creating an echo chamber effect where the exposure to anti-Asian content coincides with an increased likelihood that users adopt similar language in future social media posts.

In contrast, temporal changes in the frequency of counter-hate messages (e.g., *#washthehate/washthehate*) were best captured by a linear growth model, reflecting a linear increase, particularly toward the end of our data collection range. This is consistent with the finding that counter-hate messages, in the context of other online social movements, can help activists disseminate information and encourage online discussion immediately following a catalyzing event.[34–36] We were somewhat surprised by the low frequency of counter-hate keywords throughout much of the period of our data collection, especially before September 2020. This, paired with the significant uptick in counter-hate keywords in February, March, and April 2021—most likely in response to salient violent physical attacks against Asian victims (e.g., the Atlanta-area spa shootings on March 16, 2021[37])—seemed to be a major factor in the linear growth trend.

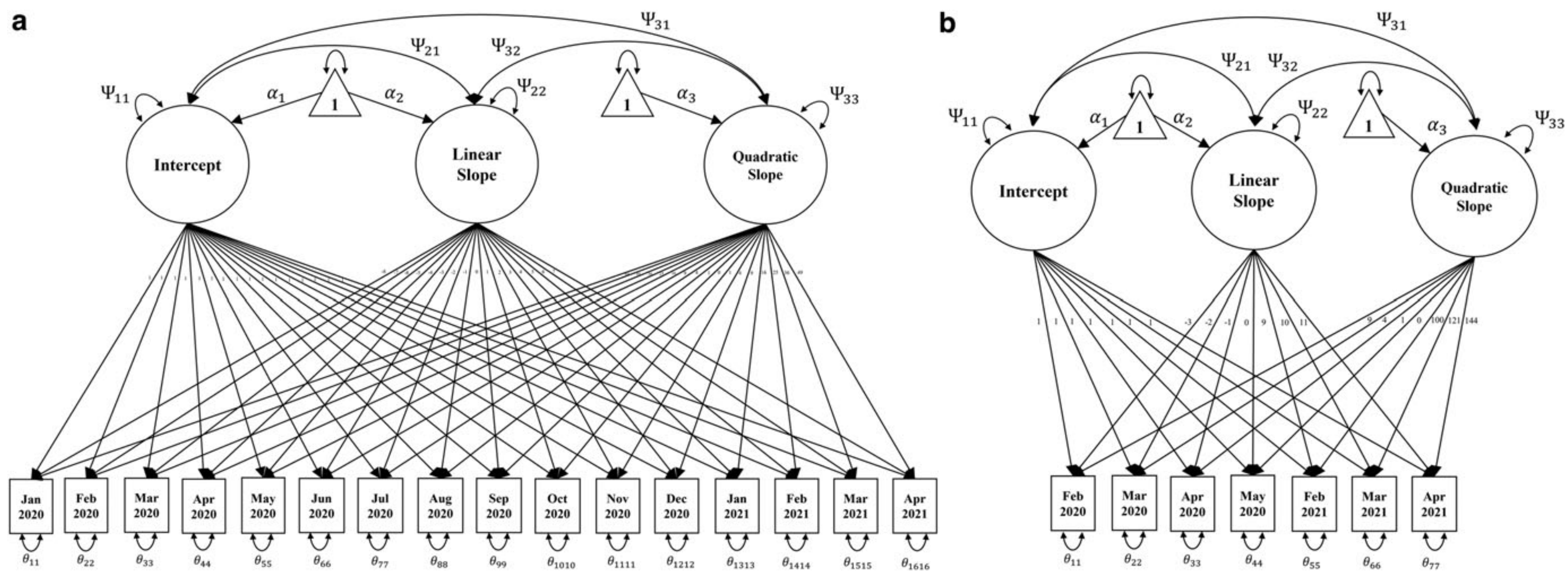

FIG. 4. Path diagram of the quadratic growth curve model for anti-Asian **(a)** and counter-hate **(b)** keyword use. All loadings for the latent intercept were fixed to one, the loadings for the latent linear slope were set to represent 1-month increases, and the loadings for the latent quadratic slope were squared loadings from the latent linear slope. The intercepts for the anti-Asian and counter-hate models were set at September 2020 and May 2020, respectively. Time points in the counter-hate model for months with counts of zero do not appear in the diagram but were accounted for in the statistical model by fixing the loadings to reflect this gap in time.

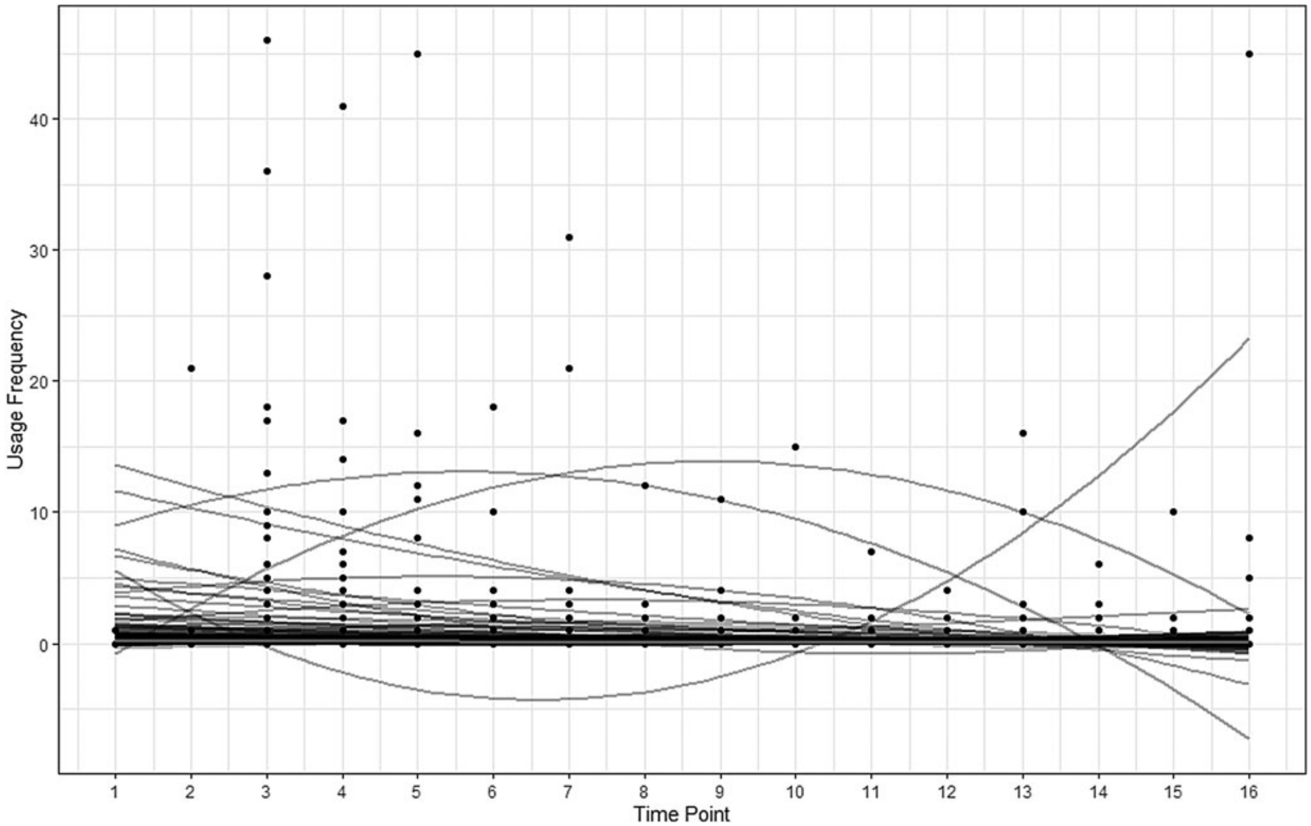

FIG. 5. Individual quadratic growth trends of anti-Asian keyword use. Each line represents the growth trend for one user over the data collection period.

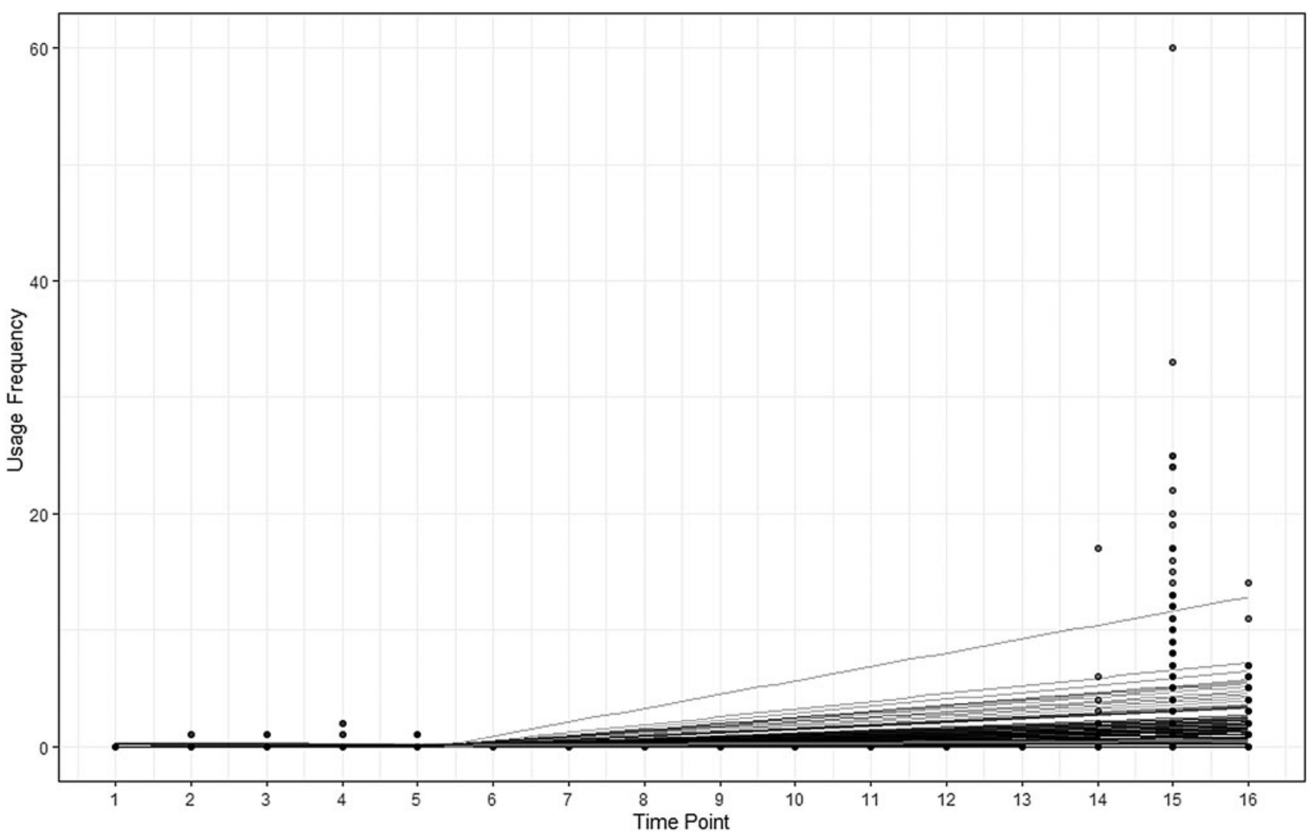

FIG. 6. Individual linear growth trends in counter-hate keyword use. Each line represents the growth trend for one user over the data collection period.

This trend is similar to descriptive patterns found in previous research.[4,38,39] It is worth noting, however, that although a linear trend emerged in this study, it is possible that a quadratic trend might have emerged if data collection continued beyond April 2021. Previous research evaluating social movements online (e.g., #MeToo) has, in fact, found declines in the use of and engagement with relevant hashtags after an initial peak of activity.[40] An exploratory *post hoc* analysis looking only at dates before March 2021 confirmed a significant linear increase in the frequency of counter-hate keywords during this truncated period, however, the extent to which counter-hate messages denouncing anti-Asian prejudice may have mirrored the ebb and flow of other movements involving ''hashtag activism''[40–42] remains to be seen.

Regardless, we believe our findings represent a crucial initial step toward understanding temporal fluctuations in prejudice and hate, on the one hand, and support for those targeted by the hate, on the other, on social media. Understanding these trends is especially important given the profound impact social media can have on its users. For example, repeated exposure to specific media content (e.g., anti-Asian messages) can increase users' adherence to the ideals the content advocates,[43] intolerance of alternative views,[44] and violent intentions.[45] Indeed, future research that speaks more broadly to the complex and potentially bidirectional relations between online and off-line hate and counter-hate can be particularly informative.

A few limitations of this study warrant mention and highlight additional directions for future research. First, our sample was not representative of Twitter users, as a whole. Data were only collected from users who had engaged in some way—through the use of one or more anti-Asian or counter-hate keywords—in a post reflecting or speaking out against anti-Asian prejudice during the COVID-19 pandemic ($N=3{,}298{,}940$). This precluded an investigation of changes in the frequency of nonrelevant keywords for comparison purposes. In other words, one could argue that Twitter use increased or fluctuated, in general, throughout this time period. Evidence against this, however, comes from the finding that Twitter use is reflected in an average of approximately 400 million tweets from 300 million distinct users per day, and that this level of activity remained consistent across the data collection period in our study.[46]

Needless to say, future research that queries a larger and more diverse population of users could offer different and equally beneficial insights. Furthermore, the analyses discussed in this article were performed with a subset of the full data set. Whereas the frequency of the use of anti-Asian and counter-hate keywords among our random sample of 1,000 Twitter users appeared to closely mirror the frequencies for the full data set, future studies would further support the generalizability of our findings. Finally, our data were collected during a select window of time. Given that the pandemic and the global sociopolitical landscape have continued to evolve, our findings should be interpreted within the context of our specific data collection time frame. Nevertheless, we believe much can be gained from analyses that shed light on longitudinal patterns of hate and counter-hate on social media.

Notes

a. Data were accessed using Twitter Academic Research accounts and in compliance with the Twitter Developer Agreement and Policy.

b. A descriptive summary of the frequency of anti-Asian and counter-hate keywords over time is discussed in greater detail in Wheeler et al. (2022).

c. For the anti-Asian linear growth model, the intercept was centered at January 2020. For the counter-hate linear growth model, the intercept was centered at February 2020, as there were no counter-hate keywords used in January 2020.

d. September 2020, the ninth time point, was chosen as the intercept for the anti-Asian quadratic growth model. May 2020 was chosen as the intercept for the counter-hate quadratic growth model, as it marked the midpoint in the data collection time frame when considering only months with at least one counter-hate keyword.

Acknowledgments

The analyses reported in this article were performed on data collected as part of a larger study investigating anti-Asian prejudice and counter-hate on Twitter during the early stages of the COVID-19 pandemic. The data collection process and a range of descriptive analyses are discussed in greater detail in Wheeler et al. (in review, https://ecommons.luc.edu/cs_facpubs/324/). The results discussed in this article have not been published elsewhere.

Authors' Contributions

B.W.: Conceptualization, methodology, software, formal analysis, investigation, writing—original draft preparation, writing—review and editing, visualization, supervision, project administration. S.J.: Methodology, software, formal analysis, investigation. D.L.H.: Methodology, investigation, writing—original draft preparation, writing—review and editing, supervision, project administration. M.P.: Software, formal analysis, investigation, writing—review and editing. Y.S.: Methodology, software, formal analysis, investigation, writing—review and editing, supervision, project administration.

Author Disclosure Statement

No competing financial interests exist.

Funding Information

This research was funded by the National Science Foundation Awards No. 2227488, No. 2036127, and No. 1719722. All data were collected according to Twitter's data collection guidelines and using the proper API access provided to researchers.

References

1. Levin B, Grisham A. FACT SHEET: Anti-Asian Prejudice March 2021. Center for the Study of Hate & Extremism; 2020. Available from: https://www.csusb.edu/sites/default/files/FACT%20SHEET-%20Anti-Asian%20Hate%202020%20rev%203.21.21.pdf [Last accessed: July 1, 2022].
2. Anti-Defamation League. ADL Report: Anti-Asian Hostility Spikes on Twitter After President Trump's COVID Diagnosis. Anti-Defamation League; 2020. Available from: https://www.adl.org/resources/press-release/adl-report-anti-asian-hostility-spikes-twitter-after-president-trumps-covid [Last accessed: July 1, 2022].

3. Budhwani H, Sun R. Creating COVID-19 stigma by referencing the novel coronavirus as the ''Chinese virus'' on Twitter: Quantitative analysis of social media data. J Med Internet Res 2020;22(5):e19301; doi: 10.2196/19301
4. He B, Ziems C, Soni S, et al. Racism is a virus: Anti-Asian hate and counterspeech in social media during the COVID-19 crisis. In: ASONAM '21: Proceedings of the 2021 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining. Association for Computing Machinery: New York, NY, USA, 2021; pp. 90–94; doi: 10.1145/3487351.3488324
5. Nanath K, Joy G. Leveraging Twitter data to analyze the virality of Covid-19 tweets: A text mining approach. Behav Inf Technol 2021;18:1–9; doi: 10.1080/0144929X.2021.1941259
6. Nguyen TT, Criss S, Dwivedi P, et al. Exploring US shifts in anti-Asian sentiment with the emergence of COVID-19. Int J Environ Res Public Health 2020;17(19):7032; doi: 10.3390/ijerph17197032
7. Yellow Horse AJ, Jeung R, Matriano R. Stop AAPI Hate National Report 2/19/20-12/31/21. Stop AAPI Hate; 2021. Available from: https://stopaapihate.org/wp-content/uploads/2022/03/22-SAH-NationalReport-3.1.22-v9.pdf [Last accessed: July 1, 2022].
8. United Nations. Impact and Prevention: A Pandemic of Hate. United Nations; 2022. Available from: https://www.un.org/en/hate-speech/impact-and-prevention/a-pandemic-of-hate [Last accessed: July 1, 2022].
9. Paradies Y, Ben J, Denson N, et al. Racism as a determinant of health: A systematic review and meta-analysis. PLoS One 2015;10(9):e0138511; doi: 10.1371/journal.pone.0138511
10. Gee GC, Ro A, Shariff-Marco S, et al. Racial discrimination and health among Asian Americans: Evidence, assessment, and directions for future research. Epidemiol Rev 2009; 31(1):130–151; doi: 10.1093/epirev/mxp009
11. Vines A, Ward J, Cordoba E, et al. Perceived racial/ethnic discrimination and mental health: A review and future directions for social epidemiology. Curr Epidemiol Rep 2017;4(2):156–165; doi: 10.1007/s40471-017-0106-z
12. Lee DL, Ahn S. Racial discrimination and Asian mental health: A meta-analysis. Couns Psychologist 2011;39(3): 463–489; doi: 10.1177/0011000010381791
13. Campbell AF, Ellerbeck, A. Federal Agencies Are Doing Little About the Rise in Anti-Asian Hate. NBC News; 2020. Available from: https://www.nbcnews.com/news/asian-america/federal-agencies-are-doing-little-about-rise-anti-asian-hate-n1184766 [Last accessed: July 1, 2022].
14. Mental Health America. Mental Health and COVID-19: Two Years into the Pandemic, Mental Health Concerns Contribute to Increase. Mental Health America; 2022. Available from: https://mhanational.org/mental-health-and-covid-19-two-years-after-pandemic [Last accessed: July 1, 2022].
15. Yang C, Tsai J, Pan S. Discrimination and well-being among Asians/Asian Americans during COVID-19: The role of social media. Cyberpsychol Behav Soc Netw 2020; 23(12):865–870; doi: 10.1089/cyber.2020.0394
16. Kim JY, Kesari A. Misinformation and hate speech: The case of anti-Asian hate speech during the COVID-19 pandemic. J Online Trust Saf 2021;1(1); doi: 10.54501/jots.v1i1.13
17. Hswen Y, Xu X, Hing A, et al. Association of ''# covid19'' versus ''# chinesevirus'' with anti-Asian sentiments on Twitter: March 9–23, 2020. Am J Public Health 2021; 111(5):956–964.
18. Zhao P, Chen X, Wang X. Classifying COVID-19-related hate Twitter users using deep neural networks with sentiment-based features and geopolitical factors. Int J Soc Syst Sci 2021;13(2):125–139; doi: 10.1504/IJSSS.2021.116373
19. Hohl A, Choi M, Yellow Horse AJ, et al. Spatial distribution of hateful tweets against Asians and Asian Americans during the COVID-19 pandemic, November 2019 to May 2020. Am J Public Health 2022;112(4):646–649; doi: 10.2105/AJPH.2021.306653
20. Kim B, Cooks E, Kim SK. Exploring incivility and moral foundations toward Asians in English-speaking tweets in hate crime-reporting cities during the COVID-19 pandemic. Internet Res 2022;32(1):362–378; doi: 10.1108/INTR-11-2020-0678
21. Curran PJ, Obeidat K, Losardo D. Twelve frequently asked questions about growth curve modeling. J Cognit Dev 2010;11(2):121–136; doi: 10.1080/15248371003699969
22. Arora M, Kim HJ. Stopping the hate: Political condemnations of anti-Asian rhetoric during the COVID-19 crisis. J Asian Am Stud 2020;23(3):387–405.
23. Wheeler B, Jung S, Barioni MCN, et al. WashTheHate: Understanding the prevalence of anti-Asian prejudice on Twitter during the COVID-19 pandemic. In: 2022 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM). IEEE 2022; pp. 484–491; doi: 10.1109/ASONAM55673.2022.10068578
24. Health Communication and Informatics Research Branch. Human subjects considerations for social media research. National Cancer Institute; 2019. Available from: https://cancercontrol.cancer.gov/sites/default/files/2020-06/human-subjects-considerations-for-social-media-research.pdf [Last accessed: May 30, 2023].
25. Cava MD, Lam K. USA Today. Coronavirus Is Spreading and So Is Anti-Chinese Sentiment and Xenophobia. USA Today; 2020; Available from: https://www.usatoday.com/story/news/nation/2020/01/31/coronaviruschinese-xenophobia-racism-misinformation/2860391001/ [Last accessed: July 1, 2022].
26. Chiu A. Trump Has no Qualms About Calling Coronavirus the 'Chinese Virus.' That's a Dangerous Attitude, Experts Say. Washington Post; 2020. Available from: https://www.washingtonpost.com/nation/2020/03/20/coronavirus-trump-chinese-virus/ [Last accessed: July 1, 2022].
27. Shim E. Asian Americans Take Campaign Against'Kung Flu' Slur to the Streets. UPI; 2020. Available from: https://www.upi.com/Top News/US/2020/06/27/Asian-Americans-take-campaign-against-Kung-Flu-slur-to-thestreets/8321593296741/ [Last accessed: July 1, 2022].
28. R Core Team. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria; 2017. Available from: https://www.R-project.org/ [Last accessed: July 1, 2022].
29. Hertzog C, von Oertzen T, Ghisletta P, et al. Evaluating the power of latent growth curve models to detect individual differences in change. Struct Equation Model Multidiscip J 2008;15(4):541–563; doi: 10.1080/10705510802338983
30. Liu H. Growth curve models for zero-inflated count data: An application to smoking behavior. Struct Equation Model Multidiscip J 2007;14(2):247–279; doi: 10.1080/10705510709336746

31. Diallo TM, Morin AJ, Parker PD. Statistical power of latent growth curve models to detect quadratic growth. Behav Res Methods 2014;46:357–371; doi: 10.3758/s13428-013-0395-1
32. Muthen LK, Muthen, BO. Mplus User's Guide (8th ed). Muthen & Muthen: Los Angeles, CA, USA; 1998–2017.
33. Jung T, Wickrama, KAS. An introduction to latent class growth analysis and growth mixture modeling. Soc Personal Psychol Compass 2008;2(1):302–317; doi: 10.1111/j.1751-9004.2007.00054.x
34. Chon MG, Park H. Social media activism in the digital age: Testing an integrative model of activism on contentious issues. Journalism Mass Commun Q 2020;97(1):72–97; doi: 10.1177/1077699019835896
35. Anderson M, Toor S, Olmstead K, et al. Activism in the social media age. Pew Research Center. Available from: https://www.pewresearch.org/internet/2018/07/11/activism-in-the-social-media-age/ [Last accessed: February 7, 2023].
36. Yang G. Narrative agency in hashtag activism: The case of# BlackLivesMatter. Media Commun 2016;4(4):13; doi: 10.17645/mac.v4i4.692
37. Fausset R, Bogel-Burroughs N, Fazio M. 8 Dead in Atlanta Spa Shootings, With Fears of Anti-Asian Bias. The New York Times; 2021. Available from: https://www.nytimes.com/live/2021/03/17/us/shooting-atlanta-acworth [Last accessed: July 1, 2022].
38. Fan L, Yu H, Gilliland AJ. # StopAsianHate: Archiving and analyzing Twitter discourse in the wake of the 2021 Atlanta spa shootings. Proc Assoc Inf Sci Technol 2021;58(1):440–444.
39. Lyu H, Fan Y, Xiong Z, Komisarchik M, et al. Understanding public opinion toward the# StopAsianHate Movement and the relation with racially motivated hate crimes in the US. IEEE Trans Comput Social Syst 2021; 10(1):335–346.
40. Lindgren S. Movement mobilization in the age of hashtag activism: Examining the challenge of noise, hate, and disengagement in the# MeToo campaign. Policy Internet 2019;11(4):418–438; doi: 10.1002/poi3.212
41. Ciszek E. Advocacy and amplification: Nonprofit outreach and empowerment through participatory media. Public Relat J 2013;7(2):187–213.
42. Jenkins H. Fans, Bloggers, and Gamers: Exploring Participatory Culture. NYU Press: New York, NY, USA; 2006.
43. Brugnoli E, Cinelli M, Quattrociocchi W, et al. Recursive patterns in online echo chambers. Sci Rep 2019;9(1):20118.
44. Garrett RK, Weeks BE, Neo RL. Driving a wedge between evidence and beliefs: How online ideological news exposure promotes political misperceptions. J Comput Mediated Communi 2016;21(5):331–348; doi: 10.1111/jcc4.12164
45. Wojcieszak M. 'Don't talk to me': Effects of ideologically homogeneous online groups and politically dissimilar offline ties on extremism. N Media Soc 2010;12(4):637–655; doi: 10.1177/1461444809342775
46. The GDELT Project. Visualizing a Decade of Twitter's Evolution: Jan 2012–Mar 2022. The GDELT Project. Available from: https://blog.gdeltproject.org/visualizing-a-decade-of-twitters-evolution-jan-2012-mar-2022/ [Last accessed: April 6, 2023].

Address correspondence to:
Dr. Deborah L. Hall
School of Social and Behavioral Sciences
Arizona State University
4701 W. Thunderbird Road (MC 3051)
Glendale, AZ 85306
USA

E-mail: d.hall@asu.edu