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Communication Network Analysis of The Anti-Racism Towards Asian Campaign on Twitter

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ABSTRACT

This study aims to determine the distribution of communication networks of the #StopAsianHate campaign on Twitter. Using the theory of Social Network Analysis and Digital Movement of Opinion Frame, this paper seeks to identify the campaign's networks in system level and actor level. To achieve this, we used a quantitative approach of Communication Network Analysis with the Netlytic and Gephi models, as well as the Content Analysis Method. From the analysis, we found 5 independent clusters in the network. On the level system, we found that information exchange requires only 2 actors to be passed actors retweet or like more than talk, most conversations happened one-sidedly, network dominated by few actors, and network has a clear division between the clusters represented. On the actor level, we identified two accounts that played a dominating role in the campaign, that actors have a close relationship with other actors, no influence in linking the distribution of information related, and found 6 top

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actors with central role. Meanwhile, from the content analysis we found that the focus of the actor's communication campaign is the sharing of opinions, information, and images.

INTRODUCTION

The increasing availability of digital tools, such as social media, has made it easier for the public to conduct campaign of any sort (Tufekci 2017). #StopAsianHate emerged as a response to the increasing racism-based attacks toward members of Asian and Asian-American community in the US (Straus 2022, BBC 2021). The campaign had been rife from mid-2020 until mid-2021.

It is quite difficult to ascertain the number of such crimes and cases of discrimination, as no organization or government agency helps to track such problems in the long term, and reporting standards may vary from region to region. Asian-American advocates say the violence can be linked to rising anti-Asian sentiment in the US.

The "Stop AAPI Hate" coalition, which documents and tackles anti-Asian hate and discrimination amid a pandemic across the US, documented 3,795 cases from March 19, 2020, to September 30, 2021, against people perceived to be 'oriental' (Chinese, Japanese, South Korean as well as from other countries. The cases include verbal harassment (68%), physical assault (11%), well as harassment through cyberspace (6.8%). The report also recorded that 21.1% Asian Americans have experienced a hate incident the past year (Stop AAPI Hate, 2021). The United Nations also released a data report showing "alarming levels" of racially motivated violence and other hate incidents against Asian-Americans (Los Angeles Times, 2021).

It is important to acknowledge that, while the concept of 'Asian' is problematic, the term is still widely used to refer to people from East and Southeast Asian countries, nationality-wise or ancestry-wise. (Zhou 2021, Pillalamarri 2014). In

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the United States, anti-Asian racism and campaign against it is not entirely new. However, social media has helped the concerning public to document, educate, and discuss various incidents. In short, social media has made it easier to scale up and widen the movement.

Tjahyana (2019) states that hashtags can give an emotional feeling to a character based on its location and culture. Racism occurs in many ways, and the easiest way for racist actors is to communicate directly by dropping, insulting, or cursing the victims. Therefore, in addition to support by doing direct action, many things can also be done to stop, or at least reduce the acts of racism that occur, namely by campaigning #StopAsianHate campaign carried out by the community by using Twitter has become a hot topic when the rise of Asian racism that occurred in several parts of the world, especially the US. In fact, the "Stop AAPI Hate" coalition, which documents and tackles anti-Asian hate and discrimination amid a pandemic across the US, released data reporting that there were more than 2,800 first-hand accounts of hate crimes that occurred between late March and late 2020., in 47 states and Washington DC (news.un.org).

A team led by University of Saskatchewan researchers review some 80 million tweets to track how anti-Asian racism escalated during the COVID-19 pandemic. During the pandemic, Asians belonged to the demographic that was more likely to report discrimination or being treated unfairly, and reported increasing frequency race-based harassment, according to Statistics of Canada (cbc.ca). Indonesia, as part of Asia, is indirectly related to this sentiment. The deputy chairman of the MPR, Syarif Hasan discussed in the DPR Building with the MPR Member who is also a Member of Commission I DPR, Christina Aryani regarding anti-Asian racism in the United States to find out how the fate of Indonesian citizens is. that Indonesia needs to learn and be wary of racism related to Asian ethnicity in the United States after several Indonesian citizens have also become victims of bullying in that country.

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The #StopAsianHate movement has indeed been studied by other researchers. Cao et al (2022) revealed 5 themes circulated related to the hashtag, namely: "Asian hate is not new", "Address the harm of racism", "Get involved in #StopAsianHate", "Appreciate the Asian American and Pacific Islander (AAPI) community's culture, history, and contributions" and "Increase the visibility of the AAPI community." While Fan et al (2021) argued that some advocating hashtags n the movement are general slogans and specific functional actions are less common. On the other hand, Lyu et al (2021) documented that while 51 of the Twitter users showed direct support to the campaign, 5.4% displayed negative attitudes.

We believe that previous studies tend to look public response and did not put enough attention to actors involved in the campaign. Therefore, this paper intends to reveal actors behind the campaign from the perspective of communication network. Specifically, this study aims to: Knowing the level of the system, level of actors, and the focus of the communication campaign on the #StopAsianHate campaign network.

CONCEPTUAL FRAMEWORK

This study pointing that digital media is an inseparable pair of the social movements. Social movement in general characterized by activities with specific objectives. In the need to achieve their goals, social movements have a structure, create an issue, and organization so their goals have a big chance to be achieved. Social movements also have leaders that actively encourage all the participation from members or public to get involved in the movement (Eriyanto, 2019).

Generally, there is link as digital media to a movement initiated by a social movement actor, Digital Movement of Opinion (DMO) as a form of technological development, where is media creates a virtual network of users to another user spontaneously by commenting on an existing problem (Barisione & Ceron in Eriyanto, 2019).

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Barisione & Ceron (2017) have identified that there are 4 main features of the digital opinion movement. First, spontaneous, and disorganized. Thae users of social media spontaneously express their opinions and criticisms when reading news about an issue. In the Digital Movement of Opinion, all the users actively respond the issues by extending their opinions, it can be by posting on social media. Second, in terms of the time, the age of movement is not long. This is a characteristic that a consequence of the first trait. Because the opinions are spontaneous and there is no actor that organize, attention to an issue can change quickly. Third, the opinion is generally homogeneous, i.e., black, and white. The users of social media express their opinions clearly, whether they support or criticize an issue or policy. Fourth, it is cross-sectoral because many groups or sectors are involved.

Communication network analysis (CNA) could be defined as a method to describe and explain social networks and network structures (Eriyanto, 2014: 5). Meanwhile a network is understood as several actors who have certain types of relationships with other actors. The study of communication networks describes the relationship of actors (that includes people, institutions, companies, land, state, and so on) with each other in a certain social structure. CNA is an application of social network analysis (Social Networking Analysis). Rogers and Kincaid (in Eriyanto, 2014:35) described that CNA is a research method aimed at identifying the communication structure in a system. The method also seeks its relational data regarding the flow of communication in it and then analyse it using several types of interpersonal relationships as the unit of analysis.

According to Marin and Wellman (2011:13), there are four characteristics of network research methods, namely: 1. Relationships, Not Attributes. This means that the analysis focus on the relationship between one actor and another, with whom the actors usually interact and get information. 2. Network, Not Group. Network research assumes that each group member could have different networks, and therefore the person is part of a network not a group. 3. Relationships in Certain

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Relational Contexts. In-network research, researchers must understand the context of certain relationships by linking the relationships of the actors. 4. Relations and Structure. Network analysis has a structural nature and is viewed from a structural perspective. The position of the actors could be determined from its constellation towards other actors because in different structures the actor's position could change.

METHODOLOGY

Nicholas Walliman (2012:113) explains that quantitative analysis deals with numerical data and using mathematical operations to investigate the scope of its properties. The quantitative approach was chosen because, in this study, the researchers wanted to map the actor-network pattern and the system of #StopAsianHate hashtag on Twitter as well as analyse the content of the actors' tweets.

This research also uses the quantitative content analysis method, which according to Eriyanto (2011:15), is intended to describe the characteristics of the content, as well as to understand the content by inference. Content analysis is also intended to systematically identify the contents of the communication that emerged where its objectivity, validity, and reliability could be replicated.

For SNA research, Eriyanto describes three steps related to data collection: First, what documents can be analysed. According to Eriyanto (2014:128), CNA requires data related to actors (nodes) and relationships between actors. If the document or archive contains actors (people, state institutions, and so on) and the relationships of the actors, the documents can be analysed using network analysis.

First, Document Type, Eriyanto (2014:134-142) explains that documents or archives can be used if there are actors (nodes) and relationships between actors. The following documents or archives are likely to meet the needs and requirements of SNA research: Biography or autobiography, Daily diary, Court decision, Minutes of

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meeting, Documents of investigation, Prospectus and company report, Media news and electronic materials (e-mail, and social media)

Second, Coding process. This study put together statistical datasets regarding the #StopAsianHate hashtag. After the data was collected, the researchers extracted a dataset within the scope of the #StopAsianHate hashtag with a total of 2500 data. The following is an example of data taken from netlytic regarding the hashtag. In SNA research there are several data analysis techniques. Because in this study the researcher wants to know the actor level and the system level, the techniques that the researcher uses are:

First, *Degree Centrality*, In Degree Centrality, Eriyanto (2014: 170) explains that the degree in SNA demonstrates actors and their popularity. The degree is the overall link of the actor and to other actors. In a directed network, the degree can be either indegree or the number of links that point to the actor, outdegree, or links that leave the actor. Then in the undirected network, Eriyanto (2014:171) reveals that the total degree can be calculated from the link from actor to another actor, without taking into account which actor acts as the subject (giver) or object (receiver). The calculation or formula in calculating the degree is as follows:

$$C_D = \sum \frac{d_i}{N-1}$$

Cd = *degree centrality*

D = *total link to each actor*

N = *total member or population*

Second, *Closeness Centrality,* the centrality of proximity according to Eriyanto (2014:175) is a description of the proximity of actors (nodes) with other actors in the network. The proximity determines how many steps (path/path) the actor can be contacted or contacted. And measure it from the shortest path. To calculate centrality, the formula is the following:

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$$C_c = \frac{N-1}{\sum D_{ij}}$$

Cc = *closeness centrality*

D = *shorter path from another actor*

N = *total member from population*

Third, *Betweenness Centrality*, the centrality of intermediary according to Eriyanto (2014: 180) is the position of the actor as an intermediary or the betweenness of the actor's relationship with other actors in a network, can directly contact the actor or must go through another actor. In finding betweenness centrality there is also a formula, namely:

$$Cb = \frac{\frac{g_{ij}P_k}{g_{ij}}}{n^2 - 3n + 2}$$

Cb = *betweenness centrality*

$g_{ij}P_k$ = *total shorther path from actor*

g_{ij} = *total path*

n^2-3n+2 = *maximum point*

Fourth, *Eigenvector Centrality*, According to Eriyanto (2014: 182-183), Eigenvector can describe how important the person who has the network is with the actor. The importance is described by the number or how many networks are owned by the person/organisation/institution and their relationship with the actors by Level Analysis.

First, *Size*, Carolan (in Eriyanto, 2014: 196) explains that the size of the network determines its characteristics. A network that has a small size, between actors or nodes will be more cohesive than a network with a large size. Second, *Density*, according to Eriyanto (2014: 197) is a comparison of the existing links in the network with the number of links that may appear. Density displays the intensity

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between members, where a dense network represents that its members interact with each other. In finding this there is a formula as follows:

$$D = \frac{l}{N(N-1)}$$

D = *density*

I = *total link or ties*

N = *total actor*

Third, *Reciprocity*, Monge and Contractor (in Eriyanto, 2014:198) explain that reciprocity is the ratio of two-way links from all links in the network. The ratio will describe the interaction of the actors, coming from two directions or only one direction. Reciprocity can be determined by:

$$R = \frac{(A_{ij}=1) \text{ dan } (A_{ji}=1)}{(A_{ij}=1) \text{ atau } (A_{ji}=1)}$$

R = *reciprocity*

A_{ij} = *link from one actor to another*

Fourth, *Centralization*, Carolan (in Eriyanto, 2014:203) explains that diameter is the furthest distance between two actors in a network. And in two tissues that have the same density, they can have different diameters. While distance is the average step or path required by the actors to interact

$$CD = \frac{\sum(Max(C_{Di}) - C_{Di})}{n^2 - 3n + 2}$$

CD = *centralization*

$\sum(Max(C_{Di})$ = *actor maximum degree*

C_{Di} = *actor degree score*

N = *total actor/network size*

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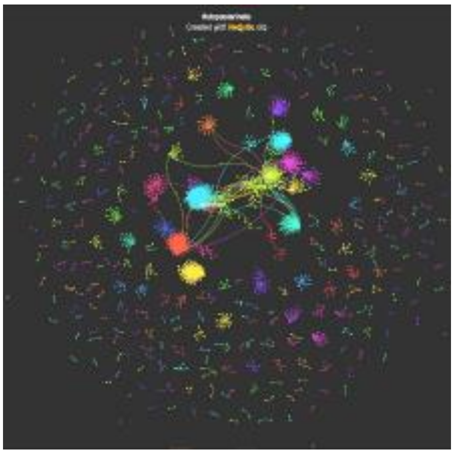
Fifth, *Distance*, Carolan (in Eriyanto, 2014:203) explains that diameter is the furthest distance between two actors in a network. And in two tissues that have the same density, they can have different diameters. While distance is the average step or path required by the actors to interact.

FINDINGS & DISCUSSION

From conducting the network analysis, the researchers found that the communication network of the #StopAsianHate hashtag has 2593 actors (nodes) and 2309 edges (line/relationship). Of all the actors contained in this network, we could identify several clusters based on the communication patterns and responses of each actor. A cluster is a group of nodes that are densely connected and have a greater possibility to communicate among actors (nodes) than to nodes outside the cluster. The analysis processed by Netlytic divides this network into 5 clusters and each will be represented in the corresponding colours. The results of processing with LGL Layout are as follows:

Figure 1. All Cluster on #StopAsianHate network



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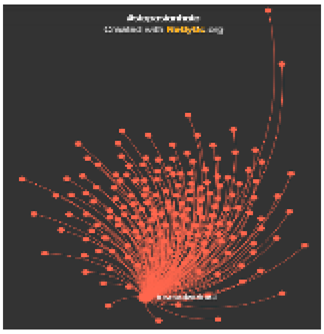
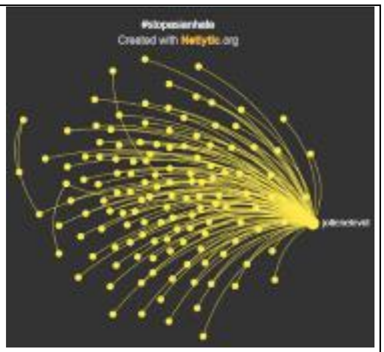
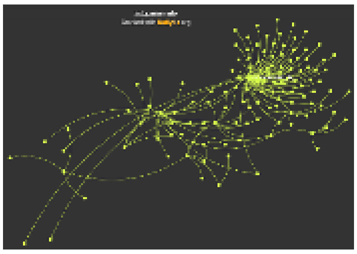
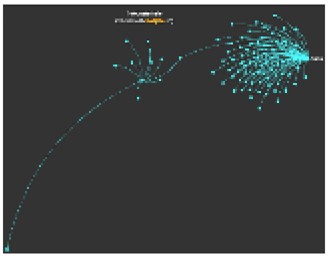
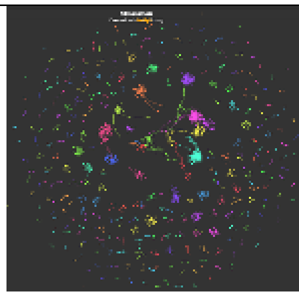
		
Cluster 1	*Cluster* 2	*Cluster* 3
		
Cluster 4	*Cluster* 5	Others

Source: Netlytic.org

Level System

After finding several clusters obtained from Netlytic, this study investigates the network properties that consists of centralisation, density, reciprocity, modularity, and diameter, which described in the following table:

Table 1. Network Properties #StopAsianHate

Diameter	2
Density	0.000385
Reciprocity	0.000000
Centralization	0.087310
Modularity	0.868700

Source: netlytic.org

Diameter calculates the furthest distance between two network participants. The diameter indicates the size of the network, by calculating the number of nodes needed to exchange information with other actors. The #StopAsianHate network has a diameter of 2, meaning the information exchange requires only 2 actors to be passed.

Density is the proportion of bonds present to the total number of possible bonds in a network. Density measurements describe how close the actors are in the network and assess the speed at which information flows. The closer the measurement is to a value of 1, the closer the conversation is, and the actor talks to many other people. Should the value is low or closer to 0, almost no one is connected to anyone else in the network. As in the #StopAsianHate network, the density value is 0.000385. This means that actors retweet or like more than talk, reply and or respond to other actors.

Reciprocity is the proportion of bonds that show bidirectional communication (reciprocity) in the number of bonds present to the total number of bonds in the network (not all possible bonds). In the #StopAsianHate network, the reciprocity value of 0.000000 means that a low reciprocal value indicates a lot of one-sided conversations.

According to Netlytic, centralisation measures the average degree of centrality of all nodes in the network. High-value networks happens when centralisation scores close to 1, meaning only a handful of central participants dominate the flow of information in the network. Meanwhile, low centralisation occurs when it scores close to 0, indicating information flows more freely among many participants. We found that #StopAsianHate centralisation network scores 0.087310, showing this network dominated by central actors/nodes but in low numbers.

To understand the meaning of modularity, we need to understand the concept of clusters in network visualisation. Modularity determines whether the clusters are found to represent different clusters in the network. The modularity value on the

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#StopAsianHate network is 0.868700, meaning that it shows a clear division between clusters represented by clusters in Netlytic.

Actor Level

In SNA research, researchers look for and observe the actors involved in a network. To find out how influential and important these actors are in this network. This could be achieved by looking at degree (including in and out-degree), closeness centrality, betweenness centrality, and eigenvector centrality.

Table 2. *Degree Centrality* #StopAsianHate

Node	*Degree Centrality*
Marktuan	429
jacksonwang852	235
inseoulwetrust	183
Jollenelevid	126
moviesmusic_th_	79
Twitter	77

Source: Gephi 9.2

The degree value is the entirety of the existing relationships of the nodes or actors in the network. We identified that the accounts @marktuan, @jacksonwang852, @inseoulwetrust, @jollenevid, @moviemusic_th_h, and @twitter are the most popular accounts in the #StopAsianHate network with degree values of 429, 235, 183, 126, 79, and 77.

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Table 3. *In Degree* #StopAsianHate

Node	*In Degree*
Marktuan	429
jacksonwang852	235
inseoulwetrust	183
Jollenelevid	126
moviesmusic_th_	79
Twitter	77

Source: Gephi 9.2

For the In-degree value, the @marktuan account is the account with the largest value, namely 429, then @jacksonwang852, @inseoulwetrust, @jollenevid, @moviemusic_th_h, and @twitter with a value of 235, 183, 126, 79, and 77 which means the In-degree value is the degree is the number of tweets or links linked to the related account in the #StopAsianHate network.

Table 4. *Out Degree* #StopAsianHate

Node	*Outdegree*
Csmeows	17
Tmathux	7
Parkkangtaw	6
fern_sp09	6
mptt33	5
baby_rabbit22	5

Source: Gephi 9.2

Out degree determines accounts with most frequency dissemination of information. In this case, the accounts that share information the most using the hashtag (#) StopAsianHate are @csmeows, @tmathux, @parkkangtaw, @fern_sp09,

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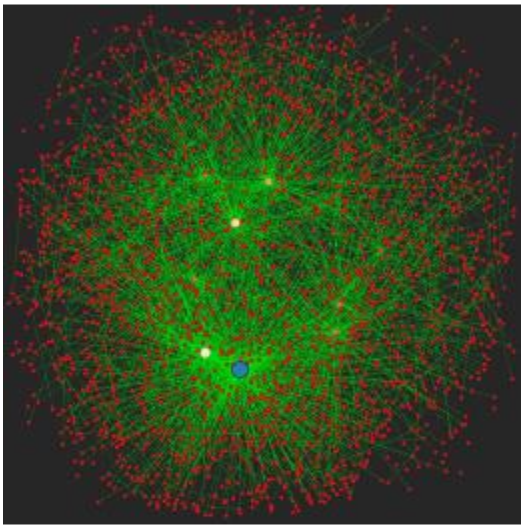
@mptt33, and @baby_rabbit22. These accounts have the largest out-degree values in the #StopAsianHate network with values of 17, 7, 6, 6, 5, and 5.

Figure 2. *Graph degree* #StopAsianHate



Source: gephi 9.2

Table 5. *Closeness Centrality* #StopAsianHate

Total	*Closeness Centrality*
2007	1.0
4	0.666667
580	0.0

Source: Gephi 9.2

The results of the data table on closeness centrality show how close the actor is to other actors in the social network. The results show that 2007 actors have a close relationship with other actors. Therefore, these actors have the freedom to communicate with other actors in the network.

The table shows there are 4 nodes in the closeness centrality. However, their value only reached 0.666667, which indicates they are less popular and do not

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reach a perfect value. It can be concluded alternatively that the 4 are actors whose existence is less popular in distributing information with #StopAsianHate on Twitter media through Communication Network Analysis.

Table 6. *Betweenness Centrality* #StopAsianHate

Betweenness Centrality	0.0

Source: Gephi 9.2

The data in the betweenness table shows the distribution of #StopAsianHate with a value of 0.0 which means that the value is not perfect. The conclusion is that nodes have absolutely no influence in linking the distribution of information related to #StopAsianHate on Twitter media with other nodes.

Table 7. *Eigenvector Centrality* #StopAsianHate

Node (aktor)	*Eigenvector Centrality*
Marktuan	1.0
jacksonwang852	0.5474911177540592
Inseoulwetrust	0.4263441470169908
Jollenelevid	0.2935484290936658
moviesmusic_th_	0.18405020554285395
Twitter	0.1793907066683513

Source: gephi 9.2

The table describes the eigenvector centrality and has the results of 6 (six) top actors or nodes. These accounts are @marktuan with a perfect value of 1.0, meaning that the account is the most important actor in the #StopAsianHate network. The next accounts are @jacksonwang852, @inseoulwetrust, @jollenevid, @moviemusic_th_h, and @twitter which are the next most important actors with

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eigenvector values close to 1. Here is a visualisation of the eigenvector centrality on the #StopAsianHate network.

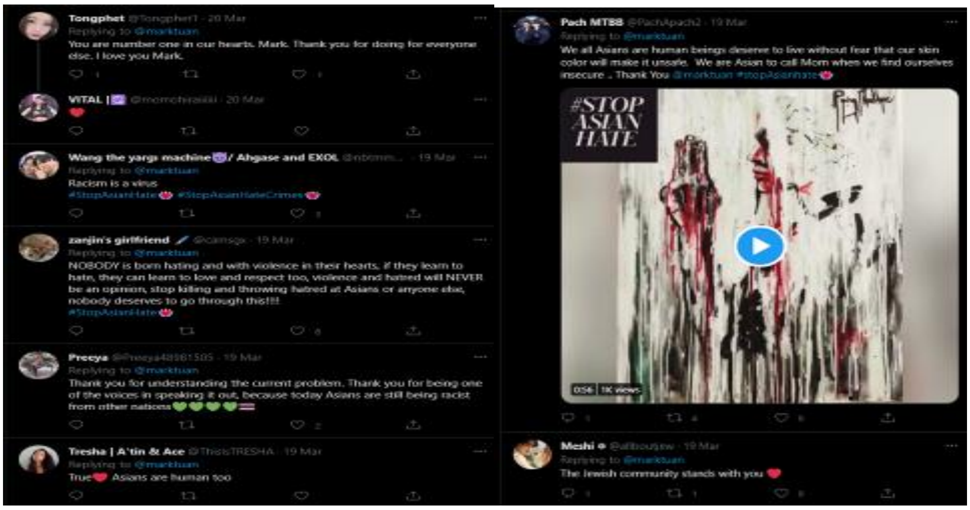
Figure 3. Visual graph Eigenvector #StopAsianHate

Source: gephi 9.2

Tweet and Response (*Degree Point)*

The following are the contents of the tweets communicated by the actors with the highest degree of centrality value. Along with it, the responses given by the community in the #StopAsianHate communication network to the contents of the tweets of these actors.

Figure 4. Public response



@marktuan

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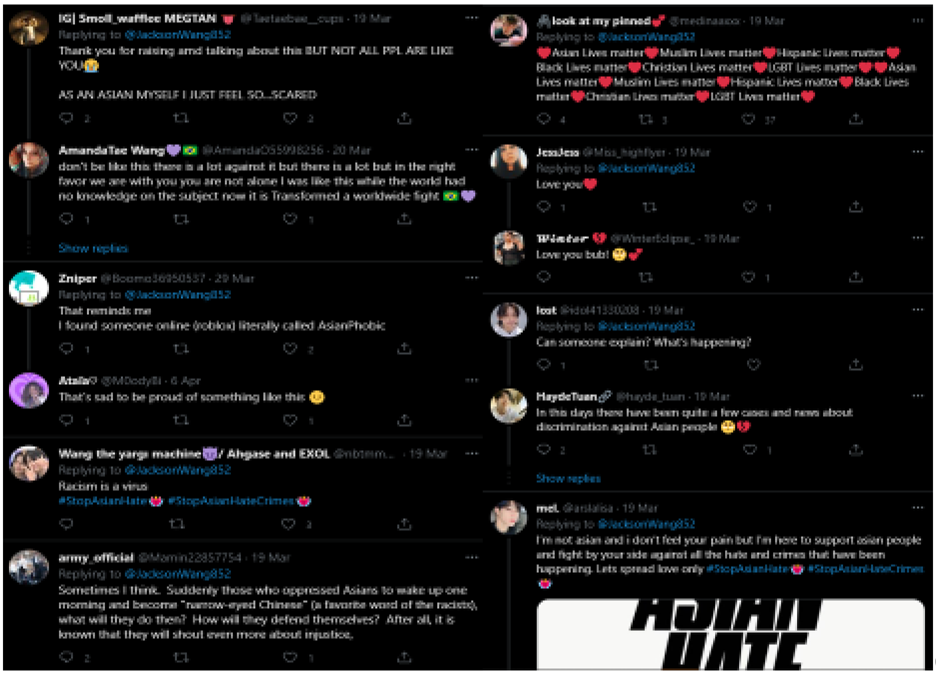

@jacksonwang852's

@inseoulwetrust's

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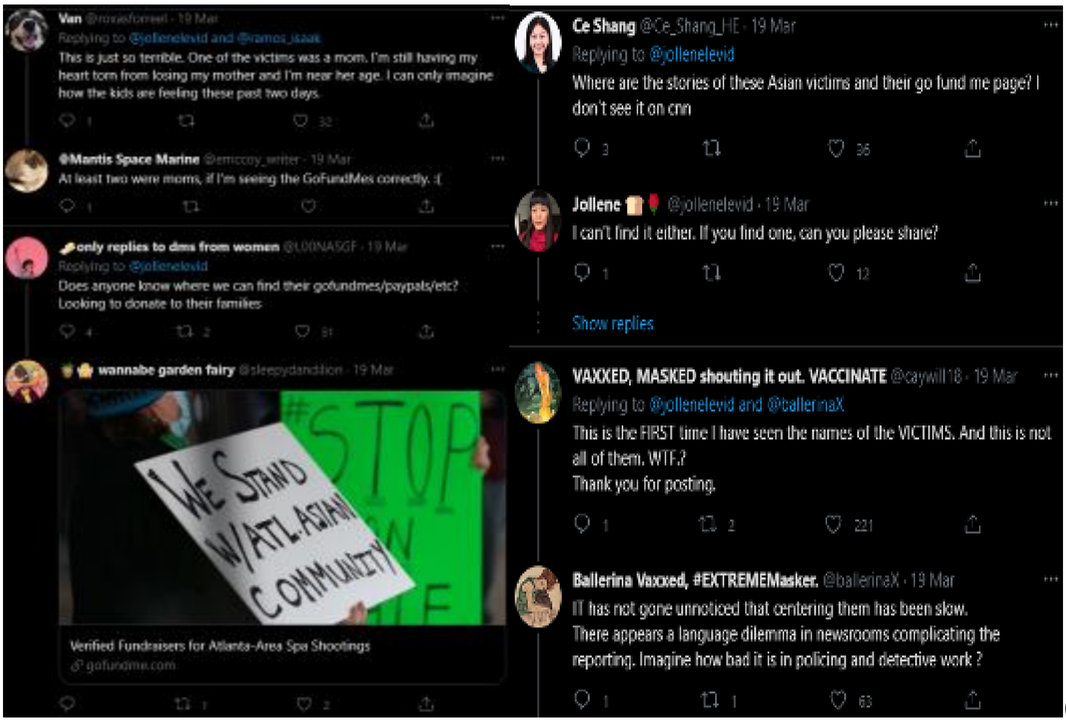
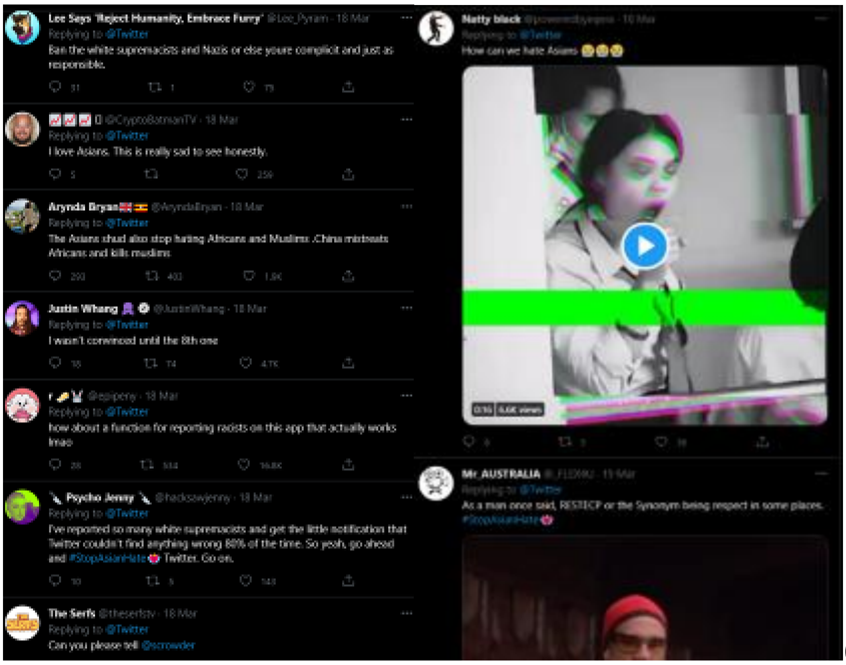


@jollenelevid's



@Twitter's

That the public responded to the @marktuan's tweet by showing agreement and support. Meanwhile, the public's responses to @jaksonwang852's tweet were showing support, expressing thank you, giving information, and giving personal opinions that also support #StopAsianHate. Third, the tweet from @inseoulwetrust was responded by the public with showing agreement, showing support, and giving opinion with the use of the Thai language.

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Furthermore, the response to the tweet from actor @jollenelevid by the community were in the form of asking and providing information, thanking, and giving opinions. In contrary to that, the public responded the @moviemosic_th_'s tweet only by retweets and likes. Finally, the @Twitter's tweet received responses in the form of pictures and videos along with giving opinions and showing support.

Based on the grouping from a total of 2500 tweets in the #StopAsianHate network, we identified 5 categories, namely: supportive, informative, critical, unrelated, and unsupportive. The data in table 4.7 shows that the "supportive" category has 1771 tweets, followed by "informative" with 607 tweets, then "critical" with 115. "Unrelated" and "unsupportive" came as the bottom two with 5 tweets and 2 tweets respectively. The following is an image of an example of a tweet in group 1.

Figure 5. Tweet from Supportive Group

In the "supportive" category, a tweet with informative and appreciative qualities was posted by account @jdschang along with a video. In the tweet, @jdschang said "Made this animation to pay tribute to Xiao Zhen Xie, the brave 76-year-old Asian grandmother from San Francisco that fought off her attacker and put him in a stretcher #StandUpBack #StopAsianHate". Support and appreciation for @jdschang garnered 1.4 thousand likes.

Another example of supportive content was a tweet by RajahMaggay. The account uploaded a video along with a caption saying "There's nothing that

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compares to this feeling of terror. And that's what this was an act of terror against our community #StopAsianHate". The support in the form of the clip got 329 likes.

Information contained in the supportive tweets can be categorised into 2, namely "influence" and "influenced". From accounts or figures who provide information or opinions, 49 actors in the network are influenced. While there are 33 actors with tweets influencing other actors in the #StopAsianHate communication network. Here is an image of a category 2 tweet.

Figure 6. Tweet from Group *influence*

The "influenced" category finds the accounts @NattyPiyanee and @enews as examples. The former uploaded a fundraising poster related to Asian Hate by quoting the contents of another actor's tweet which said, "I truly believe no one is born hating. Those who have hated must have learned to hate. If anyone can learn to hate, then they can learn to love". Furthermore, there is a tweet from the media @enews saying "Let us all join to #StopAsianHate. — Sandra Oh (Instagram)".

Chen Sibo, Wu Cary. (2021) did the research before with #StopAsianHate: Understanding the Global Rise of Anti-Asian Racism from a Transcultural Communication Perspective. It discusses the intersection of global and local factors underlying the rise of anti-Asian racism in Canada, namely first, the historical and ongoing impacts of settler colonialism. Second, the flaws of Canadian

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multiculturalism, and third, the insider or outsider dichotomy adopted by mass media's framing of the pandemic. By explicating these structural factors from a transcultural communication perspective, this article argues that politicized transcultural discussions on white supremacy are urgently needed for initiating constructive conversations over anti-Asian racism worldwide. Secondly, Fajar Rizali Rakhman, et al. (2021) did the research before with the same frame and method on Gerakan Opini Digital #Indonesiaterserah Pada Media Sosial Twitter Di Masa Pandemi Covid-19. The research is to find out the perceptions or opinions that are formed in the community on the hashtag #IndonesiaTerserah during the Covid-19 pandemic.

The research method is mixed methods, quantitative methods, and qualitative methods. To analyse the text using the Digital Movement of Opinion which explains the social network and its network structure. The results showed that #IndonesiaTerserah was able to create mobility of citizens' opinions in a communication network with the help of the roles of @radioelshinta, @cnnindonesia (popular actor), 449 proximity actors, @ridwanhr (intermediary actor), @donadam68, @reiza_patters, @toperendusara1, @bangariza, @kholil78 (important actor). The main disappointment of netizens was shown to people who were not aware of the spread of Covid-19 in Indonesia with an analytical value of 32%, secondly to the government regarding policies that were confusing and did not provide an analytical value of 21%, and lastly to both at 11%. The use of hashtags is interpreted broadly and differently by 36%.

While this research is in line with and continues from previous research, the difference in this research with the first is using the hashtag #StopAsianHate to studied with different method and theory, meanwhile the difference in this research with the second is on the hashtag and theory. The similarity of the first research is on the subject is #StopAsianHate and the concern on it, and the similarity of the second research are using the Digital Movement of Opinion Frame, the theory of Social or Communication Network Analysis. From the first study, it was agreeable for

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further discussion globally because of the never-ending bullying of Asians, from the second study the efficiency of research using the SNA method on a topic to find out and research more deeply.

CONCLUSION

Based on the research, the communication network of #StopAsianHate is found to be not very large nor dense. The network was also characterised with little dominance, where anyone can spread information without being tied by certain actors. One-way communication and perfect cluster representation are other defining descriptions of the network.

We found that the most important actor and the recipient of the most information in this network is @marktuan. While @csmeows provides most information. In this network, actors can directly relate to other. In addition to that, the dissemination of information on this network is quite fast. By analysing the tweets with the highest value of degree centrality, we found that the campaign focuses on sharing opinions, information, and pictures.

LIMITATION AND STUDY FORWARD

Based on the results of the study and the conclusions obtained, the researcher aware of the shortcomings. With the limited number of tweets that can be analysed that is only as much as 2500, the author provides suggestions for further researchers related to Communication Network Analysis or Social Network Analysis can be more maximize research by adding facts from other data based on CNA or SNA research such as picture evidence, data evidence excel, then processed into supporting data.

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