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A social network analysis: identifying influencers in the COVID-19 vaccination discussion on twitter

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ABSTRACT

Social media analytics, especially Twitter, has experienced significant growth over the last few years. The data generated by Twitter provides valuable information to many stakeholders. The presence of influencers on social media can invite interaction with other users. An Influencer has the opportunity to create and spread hoax news related to COVID-19 vaccination intentionally or unintentionally that can harm society. This study finds out the influence of influencers and information dissemination channels on Twitter data related to COVID-19 vaccination in Indonesia as one of the hot Twitter discussion trends. This study applies Social Network Analysis (SNA) to show that interactions between users have differences when the analyzed tweets are divided into mention and retweet networks. This study found that the key accounts in disseminating information related to COVID-19 vaccination were dominated by official accounts of government organizations and online news portals. The result of this study can be used as a reference that government policies will be more effective in disseminating information if official government agency accounts carry it out. The official account minimizes incorrect information appearing in the community and can control the flow of information dissemination if the information spread has negative sentiments.

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1. INTRODUCTION

The massive use of social media by the community today makes the dissemination of information very fast. Twitter is one of the most popular social media platforms among internet users today. Based on data from katadata, the active Twitter users in Indonesia are 14.05 million in 2021 [1]. The data generated by social media such as Twitter provides valuable information to many stakeholders regarding users' behavior, preferences, tastes, and characteristics. This information can be used as a reference in policy-making, for example, to develop a marketing strategy for the company.

In certain situations, social media supports users to obtain and share fake news or hoaxes. Hoax news is untrue information that is made as if it is proper to mislead the public. News related to the COVID-19 vaccination in Indonesia is one of the headlines containing many hoaxes. A person or group of people can carry out the spread of hoax news to incite or disturb the public. Accounts that actively share information on social media are usually called influencer accounts. The presence of influencers on social media can invite interaction with other users. An Influencer can create and spread hoax news related to COVID-19 vaccination intentionally or unintentionally, which can negatively impact society.

Twitter users build their network of friends and widely share, discover, and disseminate information. Twitter provides various features for interacting, such as tweeting, following, replying, retweeting, and liking. They can see the dissemination of information on social media by using Social Network Analysis (SNA). SNA is the primary analytical tool that aims to connect existing connections between users to reveal the type and nature of interactions within and between groups and individuals [2]. Twitter users are a social network that forms a graph where each user can be a point and a relationship between other users [3].

Social Network Analysis (SNA) studies patterns of social relationships that comprise social structures, treating these relationships as a network of connections between individuals and groups that enter into it. Specific individuals can form this relationship; social network analysis is not limited to micro-level interactions [4]. Central actors or highly connected people in a social network have more power than people who are less connected [5], [6]. Main actors have early access to information; they can promote any product, spread opinions or movements, predict business outcomes of a network, and so on. Thus, these central actors can play essential roles in finance and business [7], viral marketing [8], the spread of disease [9]–[11], and so on.

Social media data provides the meaning to perform various kinds of analysis. The analysis related to Social Network Analysis (SNA) was used to see social behavior and interactions that occur on social media users, especially Twitter [12]–[14], and to block malicious comments by revealing the main perpetrators [15]. Another study used Social Network Analysis (SNA) was to determine the relationship between influencers and users regarding disseminating information on a cosmetic brand on Twitter [16]. Visiting tourist arrivals [17], it is related to COVID-19 pandemic data to characterize activities and characteristics of online communities [18] and to analyze hashtags [19]. Social Network Analysis (SNA) was used to find criminal actors/behaviors [20]–[22]. In addition, it is also used in the literacy field to help display the relationship between authors from the libraries used [23], [24].

This study aims to create an analytical tool used to see the influence and distribution channels of information related to COVID-19 vaccination in Indonesia on Twitter. The Social Network Analysis (SNA) method was used to know the path of information dissemination on social media to see news sources and users who influence the spread. This study visualized the dissemination of information into a social network and introduce actors who have a high number of interactions in the social network [12]. SNA has the advantage of theoretical concepts, methods, and analytical techniques to reveal the social relationships that individuals and groups have together, the structure of these relationships, and how these relationships and influence by social behavior, attitudes, beliefs, and knowledge [25]. This paper applies SNA as a theoretical and methodological framework to show the interactions between users differ when the entire network is analyzed and divided into mention and retweet networks [26], [27]. There is an apparent gap from the research conducted with previous research, namely that we divide the tweet social network into two networks, namely the mention and retweet network. In addition, we also perform a more in-depth analysis of the two networks. Retweet networks can be a measure of how much attention retweet users are attracted through their posts. The extent to which he provoked a reaction is in the general discussion. The Mention Network points to some users who may be interested or used to prove a point.

2. RESEARCH METHOD

The analysis process of Social Network Analysis in this research consists of three stages. They are data extraction and preprocessing, building a network model, and measuring centrality value.

2.1. Data Extraction and Preprocessing

This study implements a web scraping technique to extract tweet data related to COVID-19 vaccination from web-based Twitter. Online data extraction refers to the routine extraction of data from expandable web data sources [28]. After the tweet data is collected, the next step is preprocessing. In this step, we filter tweets that are retweets and take the username or actor data mentioned in each tweet data.

2.2. Network Model

The second stage of this research is to build a network model. In the network model, Twitter users are represented as nodes, and their connections are represented as edges. When a user publishes a tweet and mentions another user, a link occurs; or by using the retweet path when a tweet is retweeted or shared by other users. Figure 1 shows a network model representation of this case.

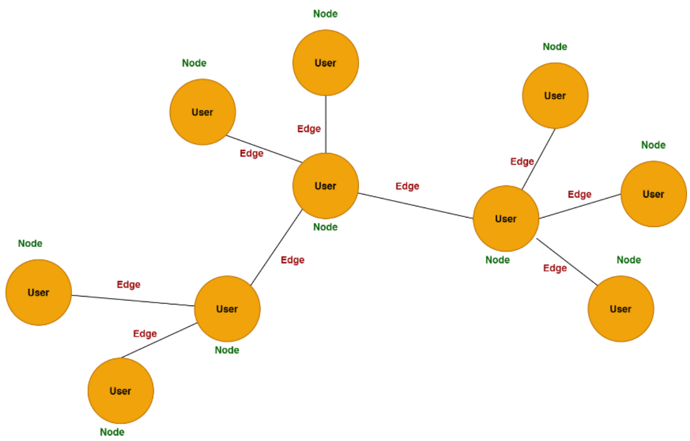

Figure 1. The network model representation

2.3. Centrality Measure

The measure of centrality is one of the most widely used indicators based on network data. They generally reflect the advantages of the unit; in different substantive settings, this may be its structural strength, status, prestige, or visibility. The studies of it often use network-based measures of centrality to explain differences between units in behavior or attitudes [29]. This study uses four centrality measurements, such as degree, betweenness, closeness, and eigenvector centrality, to analyze COVID-19 Vaccination Tweets in Indonesia. We use the four centrality measurements based on the importance of each centrality measurements. Degree centrality and closeness centrality indicate reachability, and this category means whether two actors (nodes) are connected directly or indirectly by any path. Betweenness centrality suggests the shortest route. There are different paths between two nodes in the network. The centrality measure of this category is used to find the fastest way from the source (start point) to the sinking point (endpoint). Eigenvector centrality shows feedback. A node will be necessary if its neighbors are essential. The size of the centrality of a node depends on the size of all nodes [30], [31].

2.3.1. Degree Centrality

Degree Centrality is a simple count of the total number of connections connected to a node. It can be considered a popularity measure but a rough measure that does not recognize the difference between quantity and quality [32]. We used degree centrality to identify the most connected users in a tweet that can be measured using equation (1),

$$C_D(i) = \sum \frac{d_i}{n-1} \tag{1}$$

where user represents as *i* and total nodes (users) in the network represent as *n*.

2.3.2. Betweenness Centrality

Betweenness centrality is to measure the role of a node as a mediator in the network. We use this centrality to show how significant a user is to act as a bridge in the network, which can be measured using equation (2). In this case, the users represent as i, the number of shortest paths from actor j to actor k shown as $g_{j,k}$, and the number of shortest paths from actor j to actor k through actor i shown as $g_{j,k}(i)$.

$$C_B(i) = \sum \frac{g_{j,k}(i)}{g_{j,k}} \tag{2}$$

2.3.3. Closeness Centrality

Closeness centrality measures the distance from one node to another by measuring the average length of other nodes in the network [33]. We use this centrality to show the closeness of the connection between users, which can be measured using equation (3). $C_C(i)$ is the closeness centrality of node *i*, and D_{ij} is the shortest path from node *i* to node *j*.

$$C_C(i) = \frac{n-1}{\sum D_{ij}} \tag{3}$$

2.3.4. Eigenvector Centrality

The eigenvector centrality measures the number of connections of a given node and its relevance in information movement [34]. We used eigenvector centrality to show the importance of users based on their link, which can be measured using equation (4). The users represent as i, constant represents as λ, and $a_{i,j}$ is shown adjacency matrix of the network.

$$C_e(i) = \frac{1}{\lambda}\sum_{j\epsilon G} a_{i,j} \quad (4)$$

3. RESULTS AND ANALYSIS

In this section, we discuss the results of the calculations we have done. For the first time, we performed data profiling from data extraction. After that, we found users who had an essential role in disseminating information regarding the COVID-19 Vaccination on Twitter using SNA.

3.1. Data Profiling

We have collected 8,279 public tweets from Twitter based on the keywords #VaccinationNational or #vaccinationnasional. Tweet data was taken from March 27 to July 11, 2021, which is about four months. We chose these months because period 2 of the COVID-19 vaccination in Indonesia began in early April 2021 to reach a population of up to 181.5 million people [35]. During this period, there were many public pro and con tweets related to the COVID-19 vaccination program.

3.2. Centrality Measure

The study identified three types of interactions between accounts, namely mention, reply, and retweet. Any tweet that has no mention is considered the original or original message but it does not interact. However, they can be retweeted or replied to. Among the 8279 downloaded tweets, 4795 were retweets, and 3474 were original tweets.

After that, the tweets were classified into two major groups. Mentions and replies are the first groups. We included "reply" in the first group because when a user gives a "reply" to another user, the message is codified by mentioning the account that was given a "reply". The second group is retweets given to messages posted by other users. We included retweets in the second group because retweets are the most effective way to spread the original message to indirect links [36]. Retweets are an essential metric for understanding specific uses of Twitter [37]. The process of distinguishing between mentions and retweets is in line with other authors [38]. But it is rarely used in the literature. This approach allows us to discover hidden interaction patterns that would be difficult to notice in a complete network.

Based on 8,279 tweet data, 1643 nodes were obtained, with 5175 edges for tweets in the mentioned category. As for the retweet category tweets, 1568 nodes were received, with a total of 4772 edges. We will discuss the centrality measure; the calculated centrality measures include degree, betweenness, closeness, and eigenvector centrality. Degree Centrality is a simple measure of centrality that counts how many connections or neighbors a node has. Users who have the highest number of neighbors can be seen in Table 1.

Table 1. Degree Centrality

Mention			Retweet		
No	User	Degree Centrality	No	User	Degree Centrality
1	@KemenkesRI	780	1	@KemenkesRI	769
2	@sikecilmarmut	174	2	@sikecilmarmut	147
3	@Puspen_TNI	84	3	@Puspen_TNI	84
4	@deen_hotfm	81	4	@deen_hotfm	81
5	@TjahjantoHadi	54	5	@SinarOnline	45
6	@SinarOnline	45	6	@zunarkartunis	37
7	@zunarkartunis	37	7	@GajahHardhoni	25
8	@MndJaya	31	8	@RameshRaoAKS	20
9	@Zaindamai	26	9	@pnugroho28	17
10	@GajahHardhoni	25	10	@dink2525	17

Based on Table 1, it is known that ten actors or users are active in disseminating information related to COVID-19 vaccination. These ten users are essential because they have the highest number of connections to other users. The ten users with the highest degree of centrality have differences between mention and retweet groups. We can see that the ten users with the highest Degree centrality value for the mentioned group are @KemenkesRI, @sismallmarmut, @Puspen_TNI, @deen_hotfm, @TjahjantoHadi, @SinarOnline, @zunarkartunis, @MndJaya, @Zainpeace, and @GajahHardhoni. As for the retweet, the group is @KemenkesRI, @sismallmarmut, @Puspen_TNI, @deen_hotfm, @SinarOnline @zunarkartunis, @GajahHardhoni, @RameshRaoAKS, @pnugroho28, and @dink2525.

The following discussion is about Closeness Centrality. Closeness Centrality shows how close the user is to all other users on the network. Closeness Centrality data of users can be seen in Table 2. In the mentioned group, ten users who have the most closeness with all users in the network are @KemenkesRI, @sismallmarmut, @Corona_SSYT, @CaronaUpdates, @CahyoKlaten, @Puspen_TNI, @TjahjantoHadi,

@SinarOnline, @deen_hotfm, and @dink2525. Meanwhile, the retweet group is @KemenkesRI, @sismallmarmut, @Corona_SSYT, @lignummare, @CaronaUpdates, @CahyoKlaten, @Puspen_TNI, @SinarOnline, @deen_hotfm, and @dink2525. These users can be used to get the maximum speed of information flow related to COVID-19 vaccination data.

Table 2. Closeness Centrality

Mention			Retweet		
No	User	Closeness Centrality	No	User	Closeness Centrality
1	@KemenkesRI	0,4789	1	@KemenkesRI	0,4830
2	@sikecilmarmut	0,3460	2	@sikecilmarmut	0,3413
3	@Corona_SSYT	0,3254	3	@Corona_SSYT	0,3250
4	@CaronaUpdates	0,3152	4	@lignummare	0,3199
5	@CahyoKlaten	0,3040	5	@CaronaUpdates	0,3162
6	@Puspen_TNI	0,2442	6	@CahyoKlaten	0,3039
7	@TjahjantoHadi	0,2384	7	@Puspen_TNI	0,2438
8	@SinarOnline	0,2380	8	@SinarOnline	0,2361
9	@deen_hotfm	0,2346	9	@deen_hotfm	0,2347
10	@dink2525	0,2226	10	@dink2525	0,2216

Betweenness Centrality indicates how often other nodes pass through a node to get to a specific node in the network. This value serves to determine the role of the user as a bridge for interaction in the network. User data that has the highest betweenness centrality value can be seen in Table 3. The ten users with the highest betweenness centrality value for the mentioned group are @KemenkesRI, @sismallmarmut, @CaronaUpdates, @deen_hotfm, @Corona_SSYT, @Puspen_TNI, @SinarOnline, @TjahjantoHadi, @CahyoKlaten, and @dink2525. At the same time, the ten users for the retweet group are @KemenkesRI, @sismallmarmut, @CaronaUpdates, @deen_hotfm, @Puspen_TNI, @Corona_SSYT, @SinarOnline, @CahyoKlaten, @dink2525, and @lignummare. These users are located in the communication channel and can control the flow of information regarding COVID-19 Vaccination data on Twitter.

Table 3. Betweenness Centrality

Mention			Retweet		
No	User	Betweenness Centrality	No	User	Betweenness Centrality
1	@KemenkesRI	0,6083	1	@KemenkesRI	0,5986
2	@sikecilmarmut	0,1683	2	@sikecilmarmut	0,1727
3	@CaronaUpdates	0,0766	3	@CaronaUpdates	0,0785
4	@deen_hotfm	0,0762	4	@deen_hotfm	0,0783
5	@Corona_SSYT	0,0567	5	@Puspen_TNI	0,0758
6	@Puspen_TNI	0,0537	6	@Corona_SSYT	0,0499
7	@SinarOnline	0,0521	7	@SinarOnline	0,0450
8	@TjahjantoHadi	0,0212	8	@CahyoKlaten	0,0199
9	@CahyoKlaten	0,0203	9	@dink2525	0,0191
10	@dink2525	0,0195	10	@lignummare	0,0160

Eigenvector Centrality is used to measure the importance of a node by considering the interests of its neighbors. User data with the highest eigenvector centrality can be seen in Table 4. The ten hashtags for mention groups are @KemenkesRI, @sismallmarmut, @Corona_SSYT, @CaronaUpdates, @CahyoKlaten, @Puspen_TNI, @TjahjantoHadi, @SinarOnline, @deen_hotfm, and @dink2525. At the same time, the ten users for the retweet group are @KemenkesRI, @sismallmarmut, @lignummare, @Corona_SSYT, @CaronaUpdates, @CahyoKlaten, @Puspen_TNI, @deen_hotfm, @SinarOnline, and @dink2525.

Table 4. Eigenvector Centrality

Mention			Retweet		
No	User	Eigenvector Centrality	No	User	Eigenvector Centrality
1	@KemenkesRI	0,7060	1	@KemenkesRI	0,7067
2	@sikecilmarmut	0,0392	2	@sikecilmarmut	0,0327
3	@Corona_SSYT	0,0262	3	@lignummare	0,0261
4	@CaronaUpdates	0,0253	4	@Corona_SSYT	0,0260
5	@CahyoKlaten	0,0253	5	@CaronaUpdates	0,0256
6	@Puspen_TNI	0,0130	6	@CahyoKlaten	0,0255
7	@TjahjantoHadi	0,0107	7	@Puspen_TNI	0,0124
8	@SinarOnline	0,0010	8	@deen_hotfm	0,0010
9	@deen_hotfm	0,0010	9	@SinarOnline	0,0010
10	@dink2525	0,0009	10	@dink2525	0,0009

Based on the values of degree centrality, closeness centrality, betweenness centrality, and eigenvector centrality, we manually check their profiles and classify them for more information on user accounts with high scores. It was found that the accounts were primarily official accounts of government organization, online news portals, personal accounts, and some were unverified accounts because their contents were only retweeted with specific hashtags. Accounts that are official government accounts that are active in disseminating vaccination information are the @KemenkesRI and @Puspen_TNI accounts, and the @KemenkesRI account is the official Twitter account from the Ministry of Health of the Republic of Indonesia, while the @Puspen_TNI account is the official Twitter account from the TNI Infomation Center. Accounts which are online news portal accounts are @SinarOnline, @ Corona_SSYT, @CaronaUpdates. The official Twitter account of government organizations turned out to have an essential role in disseminating information related to COVID-19 vaccination, namely the official account of the Ministry of Health and the TNI Information Center.

The mentioned network is built by observing when a user mentions another user. The link direction goes to the mentioned user. They were a directed network, which reveals the in-degree versus out-degree statistics of the network. Mention networks provide clues about who may have more significant influence. The analysis carried out shows that 1643 nodes are participating in the mention network with 5175 edges, which can be seen in Figure 2.

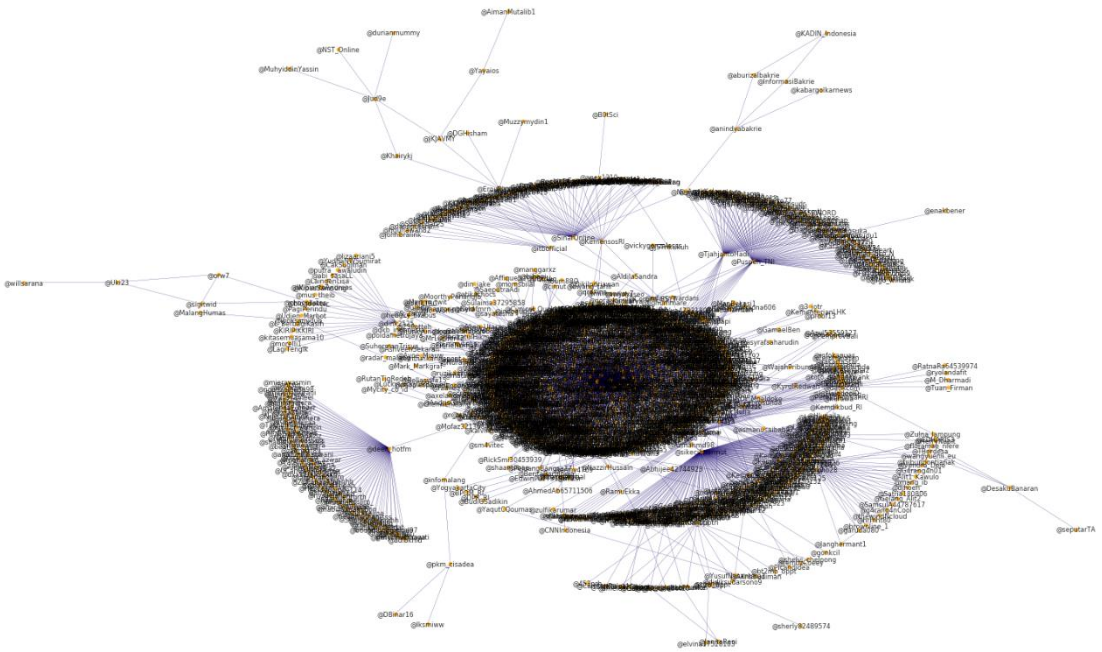

Figure 2. Mention Network

The retweet network is a directional and weighted graph where nodes represent Twitter users, while edges are formed each time a retweet occurs. The direction of the link mirrors the retweet mechanism, with the path pointing to the user being retweeted. Figure 3 illustrates this network. Before building a retweet network, the number of followers is used to determine the importance of nodes. The analysis shows that 1568 nodes are participating in the retweet network with 4772 edges.

The results of our study show that strong and weak bonds are essential to forming a network—the two mix in the network dynamics on Twitter. The first is to expand the web, and the second is to strengthen it. Through weak ties, its users enter new information and content, part of their network, into the leading network. After that, through a strong bond, users increase the flow of information and spread it in the network. Then the data can be picked up by other users and spread to outside networks. Thus, this three-stage process (inserting-streaming-spreading) is related to the importance of retweets because retweets are the most effective way to spread messages [36]. But it should also be emphasized that this information dissemination process can be triggered by mentions or a combination of retweets and mentions.

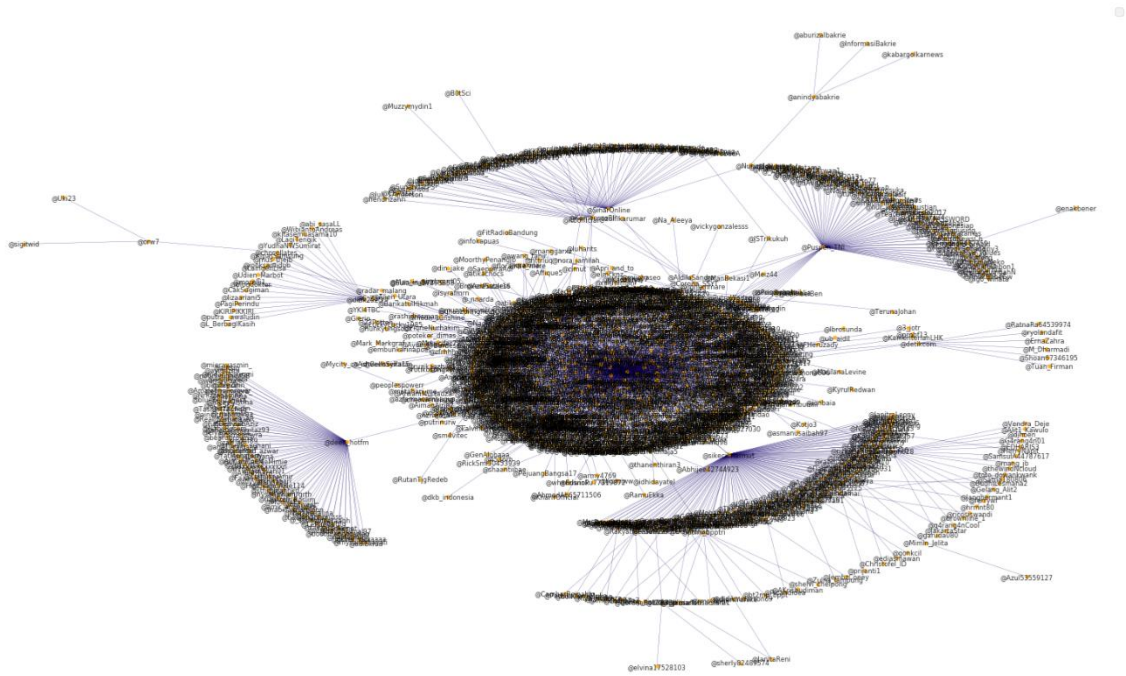

Figure 3. Retweet Network

Social Network Analysis is used to determine the effect of hashtags related to COVID-19 tweet data on social media as in the study [39], but without paying attention on the tweet mentions and tweet retweets. Based on the results of this study, we can see that Social Network Analysis related to COVID-19 data by dividing social networks into mention networks and retweet networks has more in-depth discussion analysis. The use of mention network and retweet network is because the interaction pattern between mentions and retweets has differences in the dissemination of information. In addition, the Social Network Analysis related to the COVID-19 vaccination that has been produced in this study can be used as a reference that government policies will be more effective in disseminating information if official government agency accounts carry it out. The official account minimizes the presence of incorrect information appearing in the community. In addition, the official account can also control the flow of information dissemination if the information spread has negative sentiments.

4. CONCLUSION

This study analyzes a dataset of tweets discussing topics related to COVID-19 vaccination in Indonesia. Our research offers a new perspective to explore users' characteristics and roles in a network on social media Twitter. Using the Social Network Analysis indicator shows that interactions between users differ when the entire network is analyzed and divided into mention and retweet networks. By performing this analysis, hidden interaction patterns are revealed. This viewpoint allows identifying the user functions involved in the network. In addition, this research provides new insights into how the Twitter network is formed and how it can be understood. This research contributes by showing how SNA identifies key actors on Twitter social media with a particular topic. This study found that the key accounts in disseminating information related to Covid-19 vaccination were dominated by official accounts of government organizations and online news portals. The result of this study can be used as a reference that government policies will be more effective in disseminating information if official government agency accounts carry it out. The official account minimizes the presence of incorrect information appearing in the community. In addition, the official account can also control the flow of information dissemination if the information spread has negative sentiments.

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