DOI: 10.14421/ijid.2021.2185 IJID (International Journal on Informatics for Development), *e-ISSN: 2549-7448*
Vol. 10, No. 1, 2021, Pp. 1-7

The Social Engagement to Agricultural Issues using Social Network Analysis

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Article History
Received Nov 30th, 2020
Revised Jan 12th, 2021
Accepted Jan 13th, 2021
Published Jan, 2021

***Abstract*— Twitter is one of the micro-blogging social media which emphasizes the speed of communication. In the 4.0 era, the government also promotes the distribution of information through social media to reach the community from various lines. In previous research, Social Network Analysis was used to see the relationship between actors in a work environment, or as a basis for identifying the application of technology adoption in decision making, whereas no one has used SNA to see trends in people's response to agricultural information. This study aims to see the extent to which information about agriculture reaches the community, as well as to see the community's response to take part in agricultural development. This article also shows the actors who took part in disseminating information. Data was taken on November 13 to 20, 2020 from the Drone Emprit Academic, and was taken limited to 3000 nodes. Then, the measurements of the SNA are represented on the values of Degree Centrality, Betweenness Centrality, Closeness Centrality, and Eigenvector Centrality. @AdrianiLaksmi has the highest value in Eigenvector Centrality and Degree Centrality, he has the greatest role in disseminating information and has many followers among other accounts that spread the same information. While the @RamliRizal account ranks the highest in Betweenness Centrality, who has the most frequently referred information, and the highest Closeness Centrality is owned by the @baigmac account because of the fastest to re-tweet the first information.**

***Keywords*—Agriculture; Social Media; Sentiment Analysis; Centrality; Nodes**

1 INTRODUCTION

The use of social media in measuring community response trends is currently increasing. In various lines of fields, social media can be used as data in real-time and efficiently. On social networks, users respond to issues honestly, freely, and can be done at any time, and can show the relationship between one user and another.

Twitter, is considered as a social network that provides broader and more accurate data than others. One of the focuses of Twitter as a social network is the most widely used by people around 140 million active users who make more than 400 million messages every day [1]. One of the advantages of Twitter is its speed and ease of publishing messages that are classified as short (microblogging) with a maximum of 140 characters per message. Users connect with other users through the "follow" feature, so that users who are followed can be seen and followed by other users. Besides, Twitter has a Retweet feature, where users can reply to tweets by including the contents of the source's tweet, this makes it easier to accept the context as a whole and coherently. Not only that, but there is also a symbol "#" which is usually followed by a word without spaces to represent a hashtag, as a context marker of the message (tweet) [2].

The government is currently also incessantly sharing information with the public through social media, which is considered more targeted and quickly conveyed, and free of charge. In the field of agriculture, the ministry of agriculture is also doing the same thing, namely by using social media as a form of communication with the public regarding policies and achievements and listening to the expectations of the community, especially during this pandemic. Therefore, the author wants to analyze how the public responds to this information through social media.

In previous research, Aan [3] discussed the effect of information retrieval systems in social media with the SNA principle. According to him, SNA forms a strong social relationship and represents a relationship or connection, so that the nodes and relationships within it can be observed from a social relationship that occurs. Aan represents SNA in several relationships, namely to internet applications, politics, business, and health, which visualizes the relationship between related stakeholders through SNA. and produce a description that the concept of SNA and its implementation to the needs of society, with the main principle using the centrality of a node and the relationships formed from these nodes. However, Aan suggested that SNA itself is not sufficient to reach a deep understanding so that we need methods and tools that can support the SNA process more perfectly.

Research conducted by Dendy Kurniawan [4], using SNA as a method to see collaboration between workers in an automotive company with a total of 43 workers, in 3 divisions. From the 3 divisions, it was found that the highest interaction pattern that was often contacted was actor 31, who was SPV from one of the divisions, and the most frequently connected was actor 25 who was part of the front desk. And several actors interact not by their divisions so that this research is intended so that companies can evaluate and describe this interaction pattern can provide recommendations for actors who have good interaction patterns so that they can be considered as potential leaders.

In agriculture, Simpson [5] takes a collaborative approach as an effort to unite state and non-state interests to solve environmental problems. An approach derived from the efforts of agricultural organizations to assist local agricultural networks in Ontario, Canada. By combining participant and social network analysis as a mixed-method in his research, it shows that knowledge sharing between stakeholders can occur in the structure of relationships between scales at local and provincial scales.

Wang [6] analyzed Technology Adoption Efficiency (TAE) in farmers by comparing interactions on social networks and extension applications. referring to the adoption of Water Saving Irrigation Technology (WSIT) from Minqin, China, shows that social networks and extension services can improve farmers' TAE, interactivity and trust perspective, can be seen to have a positive effect on farmer's TAE, while learning and trust show competitive numbers on extension services. In this study, three suggested policy implications are explained, namely; first, the government must pay attention to farmers 'social learning and demonstration effects, as well as to develop farmers' social networks, second; extension services must be improved to meet the various demands of farmers on agricultural technology, third; governments can combine the effects of social networks and extension services and promotion strategies tailored to the conditions of different regions.

In another study, Sreeram Vishnu et al. [7] conducted a study on the delineate and analyze social network configuration of farmers with respect for the acquisition of information on vital livestock technology. By using 3 stages, and interviewing 320 people that involved the participant's locale. This study identifies a district model of social relations and analyzes the social network of farmers. Studies show that veterinarians are highly trusted actors for information. This study does not involve the mass media as a database.

The emergence of the idea to raise this agricultural theme is the author's experience when managing public information about the development of the Ministry of Agriculture's program of activities, especially the export of agricultural products to the public through social media, which is contrary to information and interests from other government's information, so the news from the ministry of agriculture become invisible and covered by other news. This underlies the author to analyze the extent to which agricultural news is received in the community, and what people want to know from Indonesian agriculture.

The needs of an informative and real community, as well as the partisanship of the government in decision making that involves the community as actors in development, make people feel the need to participate in monitoring the presentation of data and news through social media. This is what makes the author want to open up insights about what the community needs, especially in the field of agriculture, and whether what the government is doing is appropriate for the community, all of which can be seen from the public response through social media that is more open, honest and real-time.

Previous research, Social Network Analysis was used in case studies of relationships between one person and another, both in the field of work, in social, not only that, SNA can also map a person in a company, so that it becomes one of the bases for finding a potential worker. In agriculture, SNA is a collaborative approach by the government to share knowledge on regional and provincial relations. Not only that, some researchers have also used SNA as a benchmark in decision making for technology adoption that has been implemented in other areas, so that the public response from the results of the implementation can be seen from the visualization of SNA to see network connectivity and social learning from the area. In addition, SNA is also useful for analyzing the response of vital livestock technology, by looking at how the social networks of farmers share information.

Thus, the authors see that there is no research that analyzes the response to agricultural issues in Indonesia through social networks, using social network analysis.

2 METHOD

The authors using open data from Drone Emprit Academic by entering some keywords related, such as “pertanian”, “polbangtan”, “petani milenial”, “petani”, “kementan” into the project, then DEA make some reports like sentiment, engagement, and media analysis.

Drone Emprit Academic (DEA) is a big data platform initiated by Ismail Fahmi in 2018 which is aimed at capturing and analyzing conversations on social media, especially Twitter. DEA was developed by PT Media Kernels Indonesia in collaboration with the Islamic University of Indonesia for the provision of its services. DEA uses Twitter's API (Applications Programming Interface) service to capture conversations in semi-real time via the streaming method. [8]

By using those data .csv then the authors import the file to Gephi 9.2 to analyze the centrality measurement and visualize it. It can be shown in Fig. 1.

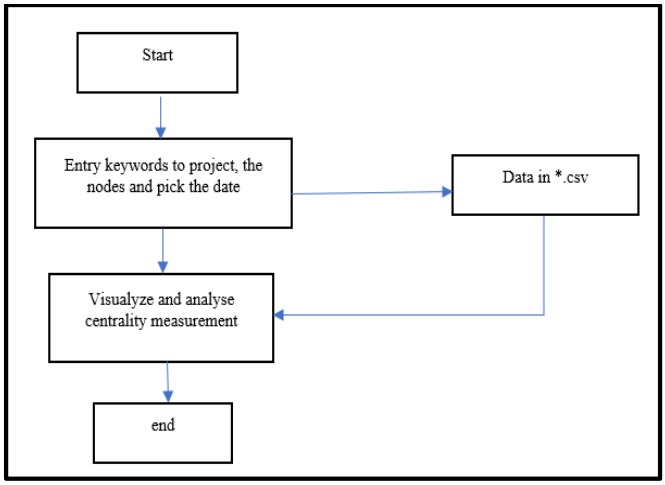

Figure 1. Research flow

3 RESULT AND DISCUSSION

Table 1. Twitter Summary

Twitter Summary	
Mentions	3.940 (28.25%)
Reply	2.747 (19.69%)
Retweet	7.262 (52.06%)
Total	13.949
Interaction Rate	2.54

The inputted data to DEA is for 3000 nodes from November, 13 to 20, 2020. The result as at Table 1 shows that it has 13.949 interactions.[9]

The result has shown that most people (52.06%) retweet the information tweet from one to another. So that some people act as opening information which is then shared via tweet, then retweeted or shared again by other related people and some people can add certain hashtags to the initial retweet post.

The use of 13-20 November 2020 is a sufficient period for data collection, which is 7 days. While the date was chosen is an opinion author who wants to trace the community's response to the role of agriculture after the trending hashtag #PetanikuPahlawanku on the period of Heroes' Day in Indonesia which falls on November 10. Whether the interaction of community responses to agriculture is still high or decreasing

From the results of the replies, mentions, and retweets, it will be known how the response of the person who shared it, so that we get sentiment analysis on several threads or tweets about agriculture.

3.1 Sentiment Analysis

From the information or issues that have been spread on Twitter, the sentiment results are as shown in Fig. 2 and Table 2 [9].

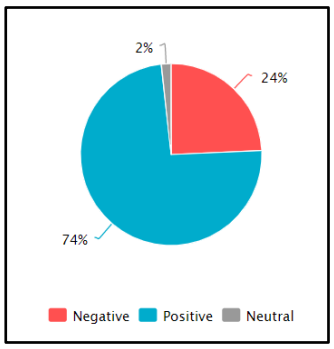

Figure 2. Sentiment result

Table 2. Sentiment Summary

Sentiment Summary	
Negative	3.391
Neutral	243
Positive	10.315
Total	13.949

Most people have positive reactions to information, and it can be parts of emotion like joy, trust, fear, surprise, sadness, disgust, anger, and anticipation. The emotion from users is related to issues that they spread. About 74% of people have a positive reaction, and 24 % have a negative response, and 2 % neutral to the tweet.

24% of netizens' negative reactions to agricultural information show that some people also show a side of distrust, uncertainty, or disagreement with the issues in circulation. while 2% who chose neutral, felt they had no interest in the issue, or were less interested.

Sentiment analysis is obtained based on the words contained in each message (Tweet) related to agriculture through the hashtags "pertanian", "polbangtan", "petani milenial", "petani", "kementan". DEA uses Plutchik's wheel of emotions to dig deeper into the public's emotions in a conversation, from trending emotions on a particular issue. From this analysis, the DEA captures a public tendency towards the issue, what makes the public feel trust, fear, or anger, and how certain emotional trends are related to current events. By using a lexicon-based approach that depends on the existence of words in the sentiment dictionary, it cannot give proper labels to different subjects, so, the sentiment is divided into Joy, Trust, Fear, Surprise, Sadness, Disgust, Anger, and Anticipation.

3.2 Social Network Analysis

The result from open data DEA, show the nodes relations and the edge about 3000nodes.

SNA has a starting point and a goal point to find out the relationship between actors who are interrelated in the network, there are many or few actors and one or more types of relationships between pairs of actors. from this pattern, SNA produces visualization in graph form [10]. A social network describes a pair of actors (nodes) that may have a relationship. So that the perspective generated in social networks is that through social ties, each individual gets access to information, social support, and others [11].

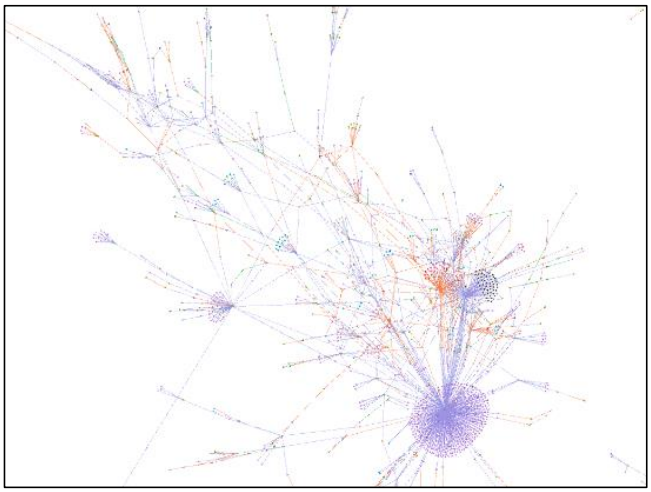

Figure 3. Social Network Analysis from Agricultural Issues on November, 13 to 20 2020

On Fig. 3 shows the graph, the results of the distribution of nodes and edges on the Social Network Analysis of the 5 inserted hashtags, and the data was taken from November 13 to 20, 2020. The graph shows one large point, which is a node that is very influential in news distribution and there are several points that other but not bigger than the lowest point, are actors who are also influential and interrelated in the dissemination of news.

The relationships between people in the community connect them as a network, then describe the mapping the key individuals in the groups within the network, or associations between the individuals, are the aim of social network analysis. A network is several nodes that are engagement to another node by a link. SNA shows the nodes as people and the links are the connections between them [12].

Social network analysis describes the modeling of the user by symbolizing the points (nodes) and the interactions between the nodes which are denoted by lines (edges). From that description, analysis is needed because it can bring new opportunities to understand individuals or communities in social interaction patterns [13]. Besides, SNA can be used to study organizational network patterns, ideas, and people connected in an environment/network [14].

SNA has network properties to map relationships in creating knowledge management in a network [15]. The network properties referred to are nodes, edges, average degree, diameter, and average path length.

The measurement most commonly used is centrality, which is to determine the actors who play a role in a social network, thus showing the degree of the center of an actor [16]. The author uses four centrality measurements, namely degree centrality, betweenness centrality, closeness centrality, and eigenvector centrality.

SNA is depicted in a graph connected by edges or lines between nodes, in two ways, namely [17]: *Undirected Graph*, graph connected by edges or lines between nodes without using arrows on the line. *Directed Graph*, a graph that can show clearer relationships between nodes because the edges or lines connecting them are drawn using arrows.

The measurement of the SNA method in graph theory is described in terminology as follows:

1. *Degree centrality* describes the number of connections a node has. is the most important individual with the most relationships, it can be calculated by the following Equation 3.1:

$$C'_D(n_i) = \frac{d(n_i)}{g-1} \quad (3.1)[17]$$

$C'_D(n_i)$ = normalized degree centrality node i

$d(n_i)$ = degree from node i

g = total nodes

2. *Closeness Centrality* describes the closeness between individuals who are connected in the network. said to be important if an individual is close to another

individual. can be calculated using the following Equation 3.2:

$$C_c(n_i) = \left[\sum_{j=1}^{g} d(n_i, n_j)\right]^{-1} \quad (3.2)\ [17]$$

$C_c\ (n_i)$ = closeness centrality node *i*

$d(n_i, n_j)$ = node distance

3. *Betweenness Centrality* is used to calculate the number of shortest paths from one node to 2 other nodes so that the following Equation 3.3 can be calculated:

$$C_B(n_i) = \sum_{j<k} \frac{g_{jk}(n_i)}{g_{jk}} \quad (3.3)[17]$$

$C_B(n_i)$ = betweenness centrality node *i*

$g_{jk}(n_i)$ = total path where the node *i* is.

g_{jk} = total path which connecting node *j* to node *k*

4. *Eigenvector Centrality* is a measure of a node connected to another node that has the highest value. To calculate this value, Equation 3.4 can be used:

$$C_i(\beta) = \Sigma(\alpha + \beta c_j)\, A_{ji}$$
$$C(\beta) = \alpha\, (I - \beta A)^{-1} A 1 \quad (3.4)[18]$$

Description [18]:

α = normalization constant (vector scale).

β = symbolizes how much a node has a centrality weight in the node which also has a high centrality value.

A is the adjacency matrix, I is the identity matrix and 1 is the matrix. The amount of β is the radius of power of a node.

Here the SNA shows several strongholds and a fairly large distribution of information as well as relations that are spread out from several points. if one finds a point with the largest node, then it is a node that has a role in the wide and large distribution of information and that makes the first issue.

3.3 *Centrality Measurements*

3.3.1 *Eigenvector Centrality*

Eigenvector centrality shows a node or actor that is most connected to other actors in a network. The eigenvector centrality of a node is the sum proportion of the other nodes connected to it. [19] The @AdrianLaksmi account has the highest value, namely 1.0, and @RamliRizal is ranked below it with a value of 0.315907, which is the account that has the most connections with other connection connectors.

Id	Eigenvector Centrality
@AdrianiLaksmi	1.0
@RamliRizal	0.315907
@Sahabat_Bangsa	0.227645
@IMF23	0.186106
@RashidYusoff11	0.142683
@Juniaprilia6	0.121373
@JPenerangan	0.106471
@kementan	0.104258
@safirachmany	0.087974
@putAmeliarahman	0.085596

Figure 4. Eigenvector centrality

3.3.2 *Closeness Centrality*

Id	Closeness Centrality
@baigmac	1.0
@OhaSechan	0.866667
@jjsengui	0.857143
@irisxiphium_	0.857143
@Zalfa_Azahra1	0.857143
@Cokolatos40	0.833333
@gemilang06	0.833333
@bbydw_	0.8
@aditya_agaasa	0.8
@Slevin1412	0.8

Figure 5. Closeness centrality

The total geodesic distance that connects the actor with other actors in the network is the value of closeness centrality. This value aims to determine the closeness between actors. the highest value of closeness centrality is the actor with the fastest information or issues in circulation [2]. The @baigmac account has a value of 1.0 which is one of the accounts that got the initial issue.

3.3.3 *Betweenness Centrality*

Betweenness centrality shows an actor that allows being an intermediary in every relationship to actor pairs in the network. so that the value of an actor in betweenness centrality represents the presence of that actor in the shortest path for each pair of actors in the path. this actor is the most frequent intermediary among other actor pairs in the network [2].

The @RamliRizal account has the highest value, namely 1241.5, so the account may have a role as an intermediary for information.

Id	Betweenness Centrality
@RamliRizal	1241.5
@irisxiphium_	534.5
@Natrissh	399.0
@Sahabat_Bangsa	380.0
@zarazettirazr	201.0
@orangdesadamai	179.0
@Panembahan_alit	173.0
@diraezelll	151.5
@vita_AVP	146.0
@L_agentkaymansp	116.5

Figure 6. Betweenness centrality

3.3.4 Degree Centrality

Id	Degree
@AdrianiLaksmi	499
@RamliRizal	136
@IMF23	95
@Sahabat_Bangsa	87
@RashidYusoff11	73
@kementan	51
@Juniaprilia6	45
@JPenerangan	44
@collegemenfess	42
@irisxiphium_	40

Figure 7. Degree centrality

Degree centrality shows the actor who is the center of the network that can influence or be influenced by the surrounding actors. So that indirectly the value of degree centrality represents the number of direct relationships that the actor has [2]. In figure 7, the @AdrianiLaksmi account has the highest value, namely 499.

Twitter is a social media platform that is quite appropriate for data collection because the data in each message can be seen, be it gender, age, and the location where and by whom the message was conveyed. social engagement, which means the relationship between one person and another in every message delivered, and whether these people have a mutual attachment that can be seen from their followers. Connectivity between people in social media is information about where the message was conveyed, by who was tweeted first, and when the tweet was made. Besides, the "love" button is a response from other people to the message. Also, retweets can be said to be a response to sending the message back by including the original message, before giving comments or hashtags in messages by someone who retweeted the previous message. Thus, social engagement in Twitter is openness and relationship between actors in a message that is first triggered by someone which is then responded to by others who follow each other.

4 CONCLUSION

From the results of visualization and analysis that have been applied to social engineering using SNA, namely using open data from the DEA in the period from 13 to 20 November 2020, using 3000 nodes, an assessment of degree centrality, closeness centrality, betweenness centrality, and eigenvector centrality was obtained.

As a result, the @AdrianiLaksmi account has the highest value of 1.0 eigenvector centrality and a value of 499 in-degree centrality, so this account has the greatest role in disseminating information and has the most connections (followers) among other accounts that spread the same information/tweets. While the @RamliRizal account has the highest Betweenness value with a value of 1241.5, which is that the account is the account that is most frequently referred to in information that has been circulating. And the @baigmac account which has the highest closeness value with a value of 1.0, is the fastest person to retweet the first information written.

From the results of this study, it is the number of Twitter users who are concerned about the world of agriculture, the active community in responding to agricultural issues, indicating that the community hopes a lot from the government in activating agriculture as the driving force of the economy in Indonesia through work programs that involve farmers and breeders. live. From there, it can be seen that the role of social media as information delivery is quite effective, even though most of the people who take part in the dissemination of this information are the general public so that the role of official government accounts is expected to be even more aggressive in disseminating information, given the results that can be seen in general. live. In addition to news originators, sometimes official government accounts also answer netizen questions in a fast way, so that people can more easily receive valid information than hoax information. The active role of the government in delivering news is intended so that people will put their trust back in and people feel that the government is indeed on the same side, in economic development and community welfare..

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