STORYTELLING WITH NETWORK DATA VISUALIZATION HASHTAG #PRAYFORTURKEY ON TWITTER

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ABSTRACT. The characteristics of Twitter allow people to create messages of social movements that can distribute throughout the network without having to have friendly relations between Twitter users. In the context of this paper, data visualization uses graph theory and network analysis methods to facilitate the identification and analysis of the distribution of the #PrayForTurkey hashtag message network. This paper tries to analyze the pattern of communication networks and the role of the centrality of actors in hashtags #PrayForTurkey as a disaster mitigation effort in finding the network to reach all actors and identify Key Players in Twitter effectively. This paper provides information on each actor's role in a social network with a social network analysis approach that focuses on the value of the relations between actors. These relations build various #PrayForTurkey network structures. Through network visualization with storytelling technique, the role of key players had identified. At the actor level, the analysis carried out is the centrality of the actors involved connected in the #PrayForTurkey network. Actor centrality analysis to find out the role of key players in distributing the digital solidarity message.

INTRODUCTION

The development of information and communication technology has now entered the fourth phase; according to Rogers (1986), it is called the phase of the interactive communication era. This interactive communication occurs because of the interaction between individuals and groups by using media as an intermediary. The development of this fourth phase of communication, also said Rogers (1986), identifies three main characters marking the presence of the new information and communication technology, namely: (1). Interactivity; is a face-to-face interaction on the Internet. Human interaction and communication are more effective and efficient, utilizing camera technology to see the users interactively. (2). Demassification; is the opposite of the mass media management system that puts forward the centralization of message products. Demassification changes the initial view of information centrally controlled by the media into information disseminated and fully controlled by consumers, who are responsible for providing information in bulk (3). Asynchronous, which is more directed to the user's will in sending and receiving messages from anywhere.

This interactive phase allows someone to obtain and disseminate messages quickly and massively—the message of digital social movements nowadays is becoming a trend among social media users. A digital social movement is a method of delivering opinions throughout the technology of communication networks. Social movements utilizing social media have an essential role and function; similar to delivering opinions through traditional ways, these opinions

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can be collected using the survey method (Tjahyana, 2020). Social movements on social media are a spontaneous response of the public to express their opinions on social media.

Digital social movements nowadays have become more popular due to the growing penetration of internet usage worldwide. From 4.5 billion internet users worldwide, 3.8 billion users have used social media; thus, the rise of social movements on social media is inevitable (wearesocial, 2020). The engagement of digital media with social movements has become a significant power that changes society. At the same time, new social movements in social media such as Facebook and Twitter have provided a new medium to provide a new layer of space for communication and information-based social movements (Lim, 2014).

Social movements in America, for example, after the tragedy of the death of a 17-year-old child, Trayvon Martin, in 2012 emerged the #BlackLivesMatter Movement, which the Black Community initiated to campaign against racism and discrimination against black people (Badaoui, 2020). The hashtag uses in several activities related to the injustices committed by the United States police against African-Americans (Olteanu, Weber, & Perez, 2016). The #BlackLivesMatter social movement re-emerged in 2020 after shooting a white police officer against an African-American. The Black Lives Matter movement received unprecedented support from the international community and united millions in cities worldwide in expressing their anger at police brutality and racism. Public reactions quickly surfaced on Twitter, where millions of tweets, retweets, replies, and likes were generated in no time. Two hashtags were particularly prominent during this period #BlackLivesMatter and #BLM (Badaoui, 2020).

Another movement, which has the support of the international community is the #StopAsianHates Movement. In America, in 2020, crimes against Asian citizens increased, which was followed by a series of mass shootings at massage parlors in major American cities. Six of the eight victims killed were Asian women. Since then, many anti-Asian rallies have been held around the world. Discussions and debates around #StopAsianHate and #StopAAPIHate, which represent social movements that aim to end hate crimes against Asian American and Pacific Islander communities, are heating up on social media platforms such as Twitter (Lyu, Fan, Xiong, Komisarchik, & Luo, 2021).

Whereas in Indonesia, social movements such as #StopAsianHates or #BlackLivesMatter are pretty widespread; the differences are that in Indonesia, social movements like this are more focused on environmental issues. For example, the #MelawanAsap (against the haze) Movement, a fire that always occurs every year in Indonesia, especially Riau Province. This movement is an action or a form of public disappointment with the government through social media Twitter to voice the community's suffering against the haze in Riau. (Mulyana & Muksin, 2017).

Twitter is a social media that is used by the public to disseminate information. Dissemination of information on Twitter can be done quickly and thoroughly through posts by the users themselves. Information provided by Twitter users will be visible to others and can be reposted by users through the retweet feature. (Carnia, Fermadona, Napitupulu, Anggriani, & Supriatna, 2021). Various social movements have occurred on Twitter; this phenomenon occurs because of the asymmetrical and open characteristics of Twitter so that messages of social movements can be distributed throughout the network without having to have friendly relations between Twitter users. The phenomenon of social movements like this has been going on for a long time in Indonesia. Solidarity social movements occur not only in real life but also in virtual spaces such as social media. With the advent of social media, technology has changed the way people communicate online (Rosenbaum & Bouvier, 2020).

Analysing the Twitter social network, we refer to hashtags or labels that group-specific topics on Twitter. Hashtags to collect and group data based on shared interests allow users to participate in conversations about particular topics grouped under the same label (Greenhalgh & Koehler, 2017). Twitter users will find other people similar to their interests based on the tags used (Rosenberg et al., 2016). In the virtual space, the concept of digital social movements or public opinion has shifted the traditional concept of gathering public opinion information through the mediation of an organization. The presence of social media changes the effort to collect information without the need for mediation by an organization; the public can access various opinions or social movements on social media, one of which is specific hashtags (Barisione & Ceron, 2017).

Social movements through digital messages also occurred in a fire that hit southern Turkey on July 28, 2021 (Reuters, 2021). The #PrayForTurkey social movement became Twitter's trending on Twitter from 28-30 July 2021. Various supports and acts of solidarity were given by Twitter users through tweets and retweets decorating the Twitter page during the natural disaster. This social movement emerged due to concern for the community and the environment affected by this natural disaster through internet technology.

The development of massive internet usage provides a wealth of data and information in the digital world related to how information is produced, transmitted, and consumed. According to Rodriguez et al. (2015), the development of information and media creates a new model of media consumption. One of which is a new model of media consumption is narrative visualization. Narrative visualization is a combination of storytelling and interactive data visualization.

Local and international media have widely used narrative visualization, one of which is The New York Times and The Guardian, which use narrative visualization techniques to provide exciting and easily understood information. Data visualization in media coverage is essential because visualization helps someone to see things that are difficult to understand or abstract. According to Card et al. (1999), in the field of human and computer interaction, the capacity of the human brain to understand visual stimuli is to understand external cognition. This social cognition process requires visualization as a medium of information that causes perception research, statistics, graphic design, data mining, and information visualization more effective in delivering messages. (Rodriguez et al., 2015).

According to Watson (2015), people use storytelling to communicate messages through carefully crafted data visualizations. In the context of this research, data visualization uses graph theory and network analysis methods to facilitate the identification and analysis of the distribution of the #PrayForTurkey hashtag message network. Network visualization can identify patterns and network relations to determine messages' effectiveness through digital actors connected through Twitter social media.

Visualization of network data and key players in #PrayForTurkey is told using a storytelling approach. The story is a series of narratives about events in a person's life or the existence of something narrated. At the same time, storytelling is a technique used to present dynamic relations between story points or nodes through the interaction of digital actors (Tong et al., 2018). Social network analysis (SNA) measures node centrality and graphical visualization, which helps us understand the extent and nature of the relations between network nodes (Himelboim, Smith, Rainie, Shneiderman, & Espina, 2017). At the same time, storytelling is a relatively new form of visualization presentation that allows visualization to effectively convey information and knowledge (Gershon & Page, 2001; Wohlfart, 2006). Whereas SNA can help to understand the overall structure of an information network that is structured in social media and concentrate on forming bonds or connections between individual social media users in the process of sharing images, texts, videos, and other digital artifacts (Himelboim et al., 2017; Kurniawan, Iriani, & Manongga, 2020; Majeed, Uzair, Qamar, & Farooq, 2020).

Social media provides an opportunity to build bonds and a social network for users by interacting via the Internet. The Internet has become a public space in a virtual context. The Internet facilitates various interactions and communication between its users (Hsu, Yu, & Wu, 2014). Based on these characteristics, the Internet, especially social media, has become a part of everyone's life in the world. According to Lim (2014), social media can encourage mobilization and garner responses quickly. The use of social media Twitter by the public in the event of the fire disaster in Southern Turkey is one of the efforts of the community to mobilize moral assistance for the victims of the fire disaster in Southern Turkey. Any Twitter user can provide moral assistance for the community. One of them is an effort to socialize digital social movements. It can see the role of key players in the community network structure on Twitter with the hashtag #PrayForTurkey. The community network structure on Twitter can be described and visualized using the social network analysis method. All social aspects that exist on the Internet can be analysed using the method of social network analysis.

According to Bakry (2020), social network analysis research can identify and visualize the flow of information in social networks on Twitter. Based on this opinion, all social phenomena in Twitter can be analysed using social network analysis. In a social network, actors can be connected because of the relations built on the same network between the actors involved in interaction and communication. One or more relations can connect a social network. The actors in the network are actors who are connected by relations that have a particular pattern. (Marin & Wellman, 2011). In the context of this research, the network formed is the relations between Twitter users.

The formation of a communication network pattern between network members on Twitter because of several similarities, one of which is interest. Actors in the hashtag network #PrayForTurkey is linked via the same hashtag to support communities affected by natural disasters in Southern Turkey. When the network members want to find information, it will refer to other network members to form a network pattern. SNA (Social Network Analysis) experts are interested in observing the position of actors in social networks. How is the role of one actor with another actor other? The position of the actor is described through the centrality of the network (Eriyanto, 2014)

The roles of individuals in the network system have a solid and interdependent relations that complements each other. The relations between individual roles and network systems identifies each actor who has a significant role in the network society. Therefore, the main goal of social network analysis is to understand the relations between actors in a network and provide an overview of the network formed based on common interests. Prell (2012) analyses a social network through four levels of analysis, namely nodes and nodes, components, and complete network. A graph theory approach can represent the relations between nodes in a network.

Graph theory is used by network analysis researchers to know the relationss and roles between actors in a network and to visualize a social network's relations diagram. According to (Borgatti, Everett, & Johnson, 2013) diagram has two components, points (nodes) and lines (edges) that connect a knot. The relations formed in network analysis is a social relations that consists of knots and ties. The vertices or bonds formed are called edges, links and connections.

With various principles of network theory in social media, Twitter can be used to understand the pattern of effective and fast message distribution to overcome disaster or disaster mitigation in the future. According to Bakry (2020), mitigation efforts through Twitter are possible by identifying communication patterns and digital message distribution channels in the Twitter network using the SNA method. Therefore, the research results conducted by researchers can be used as mitigation efforts in the future to reduce the impact of disasters.

Research conducted by Kim & Hastak (2018) sees social media playing an important role in disaster management by disseminating emergency information to disaster-affected communities by applying social network analysis methods to convert emergency social network data into knowledge. This study found that social networks consist of three entities: individuals, emergency agencies, and organizations. Thus individuals are actively involved in sharing information, communicating with emergency agencies and organizations at the margins of social networks, connecting communities with other communities. Another study used SNA to look at discussions on Twitter social media about COVID-19 and see how the sentiment emerged in those discussions. Hung et al. (2020) found 14,180,603 likes, 863,411 replies, 3,087,812 retweets, and 641,381 mentions in tweets from all discussions COVID-19 during the study period. Sentiment analysis in research by Hung et al. classifies 434,254 tweets as positive, 187,042 as neutral, and 280,842 as having negative COVID sentiments. As well as identifying five dominant themes among COVID-19-related tweets in the United States, namely: Health Care Environment, Emotional Support, Business Economics, Social Change, and Psychological Stress.

Struweg (2020) uses SNA to see the process of exchanging messages on Twitter data through visual mapping of the social network lens and graph theory regarding the announcement of the National Health Insurance Bill (NHI) to the South African parliament. Research by Struweg explored contextual and timely Twitter exchanges of 4,112 tweets from the hashtag "NHI." The findings in this study explain the data dispersion and network structure of the #NHI case. The results identify the influencers – mainly the South African government, certain Twitter users, and gatekeepers in promulgating a highly controversial health care bill that will affect all South African citizens.

Based on previous studies, researchers are trying to find gaps blanks that similar studies have not explored. Therefore, researchers seeks to analyse the pattern of communication networks and the role of the centrality of actors in hashtags #PrayForTurkey as a disaster mitigation effort in finding the wrong network effectively reach all actors in Twitter so that it can spread the message information quickly and identify Key Players in the network with hashtags #PrayForTurkey. The use of the SNA method for disaster mitigation efforts in social media is a novelty of the application of SNA in network analysis. Therefore that become the formulation of the problem in this study, namely how the role of Key Players in distributing digital social movements with the hashtag #PrayForTurkey on Twitter?

METHOD

This study uses a qualitative descriptive approach with the method of Social Network Analysis (SNA). SNA is a method to determine the relations between actors in a social network. Network data-based research has several differences from other social sciences. Although this research is also widely developed in sociological and psychological research, the development of SNA research has ups and downs. The SNA method has become a trend again in social science along with the development of communication technology. This research focuses on two main aspects: nodes (actors) and edges (relations), while social science focuses on attribution data such as perceptions or attitudes. According to Mbaru & Barnes (2017), SNA research can determine the main structure of social networks by identifying key players in a network. Therefore, the problem in this research is how to storytelling through data visualization of the #PrayForTurkey hashtag network, which is a trending topic on Twitter.

This research focuses on two main aspects: the structure and density of the #PrayForTurkey hashtag network; second, the key players in the digital message distribution of the #PrayForTurkey hashtag network. Several steps are taken to analyse the network: problem limitation, data collection, data processing, and data analysis.

The limitation of the problem in this research is the use of keywords #PrayForTurkey, "Help Turkey," and "Turkiye Yaniyor." The text mining process is carried out within the period 28 - 30 July 2021. Therefore, the data collected is based on activity on Twitter during that time. This problem limitation is used to focus the data collected through the Gephi application.

They were collecting data in this study using the Gephi text mining application with the help of the Plugin Twitter Streaming Importer, using several keywords to obtain accurate research data. The use of text mining applications aims to collect data using the hashtag #PrayForTurkey on Twitter. After the data is collected, the next step is data processing.

Processing data in this study begins with the relevant data filtering stage; the data used has at least one relations with other actors, meaning that actors who do not have relations or relations with other actors are deleted or removed. This step is taken because the main focus of this research is actors and relations. After selecting data relevant to the context of this research based on the hashtag #PrayForTurkey, the next step is data analysis.

The stages of data analysis in this study went through two stages: First, visualizing the type of group network using the Yifan Hu algorithm. The choice of this algorithm is because the data obtained in this study is quite large, around 23075 Nodes and 63550 Edges. This relatively large data is most appropriate when visualized with the Yifan Hu algorithm (Gephi.org, 2011). Second, analyse the key players in the #PrayForTurkey hashtag network. These two stages of data analysis resulted in the network type, density, and actor centrality in the #PrayForTurkey hashtag network. Based on the stages of data analysis above, the following is the analysis design of this research:

Tabel 1. The Design of Network Analysis and Actor hashtag #PrayForTurkey

Level of Analysis	Unit Analysis	Information Output
Network Analysis	Relation Type	Relation type formed in the network

	Relation Pattern	Relation pattern formed in the network
Actor Analysis	Degree	The actor's popularity degree on the network
	Closeness Centrality	The closeness degree of actors with other actors
	Betweenness Centrality	The actors who act as intermediaries in the network
	Eigenvector Centrality	How closely related are the key actors in the network

Source: (Eriyanto, 2014)

The final result of this research is the analysis of system-level (network) and actor-level (actor centrality). Network analysis has two units of analysis: the type of relations and the pattern of relations, while the actor level has four units of analysis: degree, closeness centrality, betweenness centrality, and eigenvector centrality (Zhang & Luo, 2017). The research data is then analyzed using a storytelling approach and graph theory to communicate the information in the network to make it easier for everyone to read and understand.

According to Carnia et al. (2021), there are four formulations of actor centrality in graph theory. First, Degree Centrality is used to find accounts that have the most significant influence on information dissemination on Twitter by looking at the number of direct relationss that an actor has with other actors. The higher the degree of centrality, the more ties or relationss an actor has with other actors. According to Soumokil et al. (2013), there are two types of identification of the presence of actors in a network, namely indegree and outdegree. Indegree is a message that leads into the actor (contacted by another actor), while outdegree is a message that leads to outside the actor (contacting other actors). To calculate the degree centrality value or C_D (v) as follows:

$$C_D(v) = \frac{d(v)}{n-1} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(1)$$

Where d is the number of relations (links), and n is the number of population members (nodes).

Second, Closeness Centrality is used to find the most influential account by seeing how close the actor is to other actors based on the shortest distance obtained. To calculate the closeness centrality value or CC (v) as follows:

$$C_C(v) = \frac{n-1}{\sum D_{ij}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(2)$$

Where D is the shortest path to another actor, and n is the number of population members (nodes).

Third, Betweenness Centrality is used to find the most influential accounts in disseminating information based on the extent to which they are needed as a liaison in disseminating information on the Twitter social network. To calculate the betweenness centrality value or C_B *(v)* as follows:

$$C_B(v) = \frac{\frac{\delta_{ij} P_k}{\delta_{ij}}}{n^2 - 3n - 2} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots . . (3)$$

Where $\sigma_{ij}\, P_k$ is the number of the shortest stages of the actor, and σ_{ij} is the number of paths in the network, while $n^2 - 3n - 2$ is the maximum value. The value of Betweenness centrality normality is 0-1, where close to 1 is the best.

Fourth, Eigenvector centrality is used to find the most influential accounts by identifying the influence of these accounts throughout the network, not only their effect on directly connected nodes. To calculate the eigenvector centrality value or $C_E\,(v)$ as follows:

$$C_E(v) = X_i \frac{1}{\lambda} \sum_{j=1}^{n} A_{ij} X_j \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots . . (4)$$

Where A_{ij} is the neighboring matrix, n is the number of nodes in the graph is the dominant eigenvector value.

RESULT AND DISCUSSION

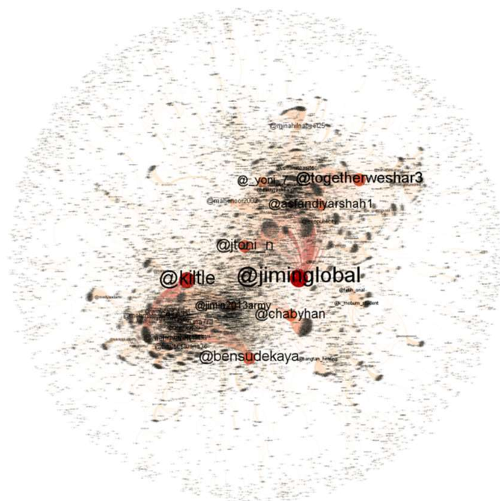
The research data were obtained from digital text mining on Twitter using the Gephi application and the Twitter Streaming Importer plug-in using the keywords #PrayForTurkey, "Help Turkey," and "Turkiye Yaniyor" on 28-30 July 2021, text-mining results were obtained. The number of nodes and edges in the #PrayForTurkey hashtag network is 23075 Nodes or the number of actors using the #PrayForTurkey hashtag, and 63550 edges or relations formed between actors using the #PrayForTurkey hashtag. This research data analysis results at the system level (network type) and actor level (actor centrality) were analyzed using Gephi software with the Yifan Hu algorithm. The selection of the Yifan Hu algorithm is based on the obtained nodes that are notably large, above 10,000 nodes with a directed relations direction (Gephi.org, 2011). Based on the Yifan Hu algorithm analysis, the network type description and actor centrality on the #PrayForTurkey network is obtained.

Storytelling System Data Visualization #PrayForTurkey

Twitter provides an opportunity for its users to establish relations with particular issues. Someone who does not know each other can be connected to the same network through the issue used. When actors communicate in the #PrayForTurkey network, they will need a system that can regulate the flow of information in the network. The system can manage all information that can be understood by the interconnected actors in the same network.

The network is a dynamic system based on the interaction of the actors. The social network formed in this research is due to the common interest of users in distributing digital messages through the hashtag #PrayForTurkey. According to Barisione & Ceron (2017), hashtags are one of the ways to convey public opinion in the era of digital communication freely without the mediation of any party. The hashtag #PrayForTurkey is an attempt by the digital community to express their opinions in interactions on Twitter. Submission of public opinion through social media will connect common interests, thus forming a network pattern that can be analyzed through the SNA approach.

In the context of this research, various Twitter users or actors who know each other or do not know each other have a relations line based on the message of the #PrayForTurkey social movement. In SNA's research, the communication phenomenon of relations in Twitter is interesting to visualize. It can find out various information related to the network, one of which is the effectiveness of the #PrayForTurkey distribution message that is spread across the dominant network and the role of key actors in the #PrayForTurkey network. #PrayForTurkey network visualization can be analyzed based on relations type and relations pattern.



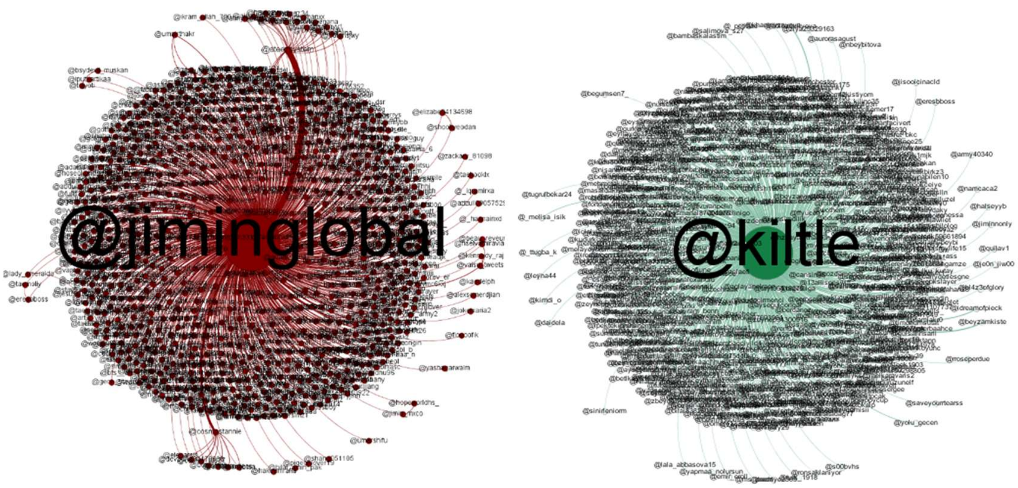
Picture 1. Network visualization #PrayForTurkey
Source : Research Finding, 2021

Based on the #PrayForTurkey network visualization results, the network type formed has an asymmetric network type. According to Kadushin (2012), an asymmetrical relations is a two-way relations where two actors have the same role. If one actor removes, the relations cannot form, while asymmetric is a one-way relations, some actors are active, and some are passive. This study indicates that the type of network relations formed in #PrayForTurkey is an asymmetric or one-way relations. The asymmetric relations type provides opportunities for actors to build relations with other actors even though there is no friendly relations between them, and they can connect to the same network. The asymmetric network relations also can form a network of social movements to other actors in the same media platform. Therefore, media with asymmetrical characteristics like Twitter are often used as a digital message distribution platform to support specific social movements such as #StopAsianHates and #BlackLivesMatter.

The findings of this study differ from the findings of Haythornthwaite (2005), which shows the direction of the asymmetrical relations on the impact of social media use. The differences of the findings could be due to differences in units of analysis, if in Haythornthwaite's research, the focus is on the impact of communication media and the internet on connectivity between people, while in this study, the focus is on the distribution of digital movement messages with the hashtag #PrayForTurkey. The distribution of digital movement can be identified by the pattern of information dissemination, from those who tweet, retweet, mention, like, and comment on this network.

In addition, based on network system analysis, Twitter social media data has two types of relations characteristics. According to Pryke (2012), a two-type network is a network that has actors with different types between individuals and institutions. This research found that the actors like @fatihportakal, @haluklevent, @06melihgokcek, and others as individuals, while the actors, namely @galatasaraysk, @fenerbahce, @bbcturkce, and @hurriyet, are the institutions.

The second analysis is that the network pattern formed in the #PrayForTurkey social movement is a radial personal network. A radial personal network is a communication pattern that centralizes (DeVito, 2016); some actors are providers of information to their respective groups. According to Rogers & Kincaid (in Juditha, 2017), the radial personal network pattern has more advantages in distributing the message efficiently. It can happen because each member of the population has the same opportunity to interact with others (open network). In contrast, interlocking personal networks are much more close to the possibility of new interactions with other users.



Picture 2. Radial Personal Network Popular Actors
Source : Research Finding, 2021

Radial Personal Network has a lower connection between actors because each actor only connects to one central actor. The actor @jiminglobal, for example, is one of the communities in the #PrayForTurkey network and is one of the actors who are the center of community relations. This connection occurs because large-scale online communities rely on computer-mediated communication between participants, enabling them to maintain interaction and information exchange among community members (Faraj & Johnson, 2011).

The exchange of #PrayForTurkey messages in the network is one of the efforts to improve relations between actors in the same social network. DeVito (2016) stated that if you can provide other people with helpful information, they are more likely to provide helpful information for you. Therefore, mutually satisfying and productive networks are formed.

Storytelling Actor Centrality #PrayForTurkey

The dataset used in the #PrayForTurkey actor centrality analysis is the obtained data on 28-20 July 2021; therefore, the tweet data obtained is relevant to the issue of national fires in Southern Turkey on 28 July 2021. The actor centrality analysis is analyzed: degree centrality, closeness centrality, betweenness centrality, and eigenvector centrality. This actor centrality analysis is used to determine the role of key players in distributing the #PrayForTurkey digital social movement message.

Table 2. Comparison of the five top key player actors on centrality values of #PrayForTurkey

Username	**Degree Centrality**	**Username**	**Betweenness Centrality**
@jiminglobal	1757	@azearmy	0,00145
@kiltle	1566	@jimin2013army	0,00141
@togetherweshar3	1221	@sopenamjin13	0,00092
@jtoni_n	1186	@felixhoney6	0,00068
@bensudekaya	1181	@kpoptagramtry	0,00065

Username	**Closeness Centrality**	**Username**	**Eigenvector Centrality**
@mehmetpolat444	1,0	@jiminglobal	1,0
@exopublicity	1,0	@kiltle	0,88526
@usmanabbasi56	1,0	@togetherweshar3	0,69738
@k_mobum_student	1,0	@jtoni_n	0,67388
@studywemma	1,0	@bensudekaya	0,67060

From table 2, the @jiminglobal account has the highest degree and eigenvector values. Degree centrality is the most superficial analysis by measuring the number of relationss owned by and to other actors (Borgatti et al., 2013). This research tries to seek the substance relations between the actors with the highest popularity in the network. The @jiminglobal account has high popularity among other accounts as many as 1757 relations. It can be interpreted that the actor contacted (outdegree) and contacted (indegree) 1757 times. The second-degree centrality is @kiltle with a relation of 1566. Degree centrality @togetherweshar3, @jtoni_n, and @bensudekaya have degrees of centrality 1221, 1186, and 1181. Degree centrality relations in the network can be identified based on in-degree and outgoing relations (outdegree). The indegree and outdegree relations in the context of this study are the numbers of relationss that contact the five accounts above in the form of mentions, quotes, likes, and retweets of messages included in indegree. In contrast, outdegree is messages that are mentioned to other actors.

The second analysis is closeness centrality. This analysis finds the substance of the actor's closeness with all other actors in the #PrayForTurkey network. According to Eriyanto (2014) the proximity of an actor can be seen from how many steps an actor can take to contact other actors in a network. In closeness centrality, it measures the shortest path from one actor to another in reaching the actor in the network. Many paths can be passed in this calculation, measured as the shortest path.

Formulated on the closeness centrality table data, five actors have 1.0: @mehmetpolat444, @exopublicity, @usmanabbasi56 @k_mobum_student @studywemma. The five actors mean that these actors want to have relations with other actors only requires an average distance of 1 lane. The value of closeness centrality is between 0 and 1. Borgatti et al.

said that the closer the value to 1, the better (2013). A high value indicates the closeness of the actor's average distance to all other actors in the #PrayForTurkey network.

The third analysis is betweenness centrality. This analysis aims to know the position of an actor as an intermediary for other actors in a network (Borgatti et al., 2013). The existence of this actor is fundamental to unite other actors to stay connected to the network. The existence of this actor is to determine the message flow that can be sent directly or through an intermediary actor. The higher the value betweenness centrality, the more influential the actor's role in the network. Based on table 2, the value of betweenness centrality of the five key players: @azearmy, @jimin2013army, @sopenamjin13, @felixhoney6, and @kpoptagramtry, can be obtained.

The position of betweenness centrality is essential because it relates to controlling and manipulating messages in the network (Prell, 2012). These actors are essential in connecting several groups in the network. The information must pass through this actor to distribute messages to other groups in the #PrayForTurkey network. According to Zhang & Luo (2017), betweenness centrality measures the role of mediators in the network. If one actor is at the sole, the information must go through a mediator to connect with other actors such as communication, connection, transportation, or transactions.

The fourth analysis is eigenvector centrality; this analysis is used to know the relations with the actor who has the most central contribution in the network. This analysis does not measure "how many people do you know" but "whom you know" (Eriyanto, 2014). Eigenvector centrality shows actors' most important in the network based on the actor's connections (Alhajj & Rokne, 2014). The data above shows that the five actors have higher eigenvector values than other actors.

Actors @jiminglobal, @jimin2013army, and @azearmy are BTS K-Pop fan accounts, and it shows that users who are connected based on the same interest will retweet, like, comment, and mention the account continuously. This research found that the K-Pop fan base appears in various existing dissemination mechanisms; this study also found that K-Pop fans are active and reactive in distributing social messages. As a result, the message spread widely on the Twitter network; another thing that attracted attention was that the K-Pop fanbase beat online news accounts or journalists in spreading social movement messages on Twitter. According to DroneEmprit data (2021), the @cibancaa account, a K-Poppers from NTT, started creating the hashtag #prayforNTT on the Twitter platform. The hashtag became a trending topic, and most K-Poppers accounts retweeted it. Kompas.com and Equatorial mention that the strength of K-Poppers has the power and an urge or influence public issues, one of which is disaster issues through the Twitter platform (Ekuatorial, 2021; Widodo, 2021).

Twitter is one social media with open network characteristics compared to other social media; with open characteristics, social messages can be distributed optimally throughout the existing network. Users do not need confirmation of friendship from other users to give a message. Therefore, Twitter can be used as a medium for the digital social movement of the community. Twitter is often used in various humanitarian and political activities (Gunawibawa & Oktiani, 2020). The presence of Twitter has transformed public discussion spaces at seminars, lectures, or workplaces into online discussion spaces.

The presence of online spaces provides opportunities for the community to interact and discuss without the limitations of space and time. Conversations on Twitter can be seen in the pattern of communication networks online via the SNA method. Key actors in the dissemination of messages and social movements' digital position and role can be known. An issue in Twitter can be seen in development through networks and actors who use the issue.

CONCLUSION

The shift in community discussion and communication spaces to online discussions has changed the role of the community in environmental issues around them. A person can be a key player in distributing information in various parts of the world, all connected through the same network. This study provides information on each actor's role in a social network with a social network analysis approach that focuses on the value of the relations between actors. These relations build various #PrayForTurkey network structures. Through network visualization with storytelling technique, the role of key players can be identified. BTS fandom accounts such as @jiminglobal, @jimin2013army, and @azearmy have played their functions well. This account has contributed to the spread of digital social movements through its fan network. The #PrayForTurkey social movement is increasingly spreading to several communities and other Twitter users. The research has been carried out on the #PrayForTurkey network through mining the text of tweets, retweets, likes, comments, quotes, and mentions of actors, obtained several conclusions. It includes the characteristics of the type of network in this study are two modes, the actors involved are not only individuals but also K-Pop institutions and communities. In addition, the network communication patterns found are the radial personal network that has the characteristics of an open network and high cohesiveness low when compared to interlocking personal networks. The direction of deep network relations

This research is directed and asymmetric. The direction of this one-way relationship can be seen in each actor's role, and some are to contact (outdegree) and be contacted (in degrees). At the actor level, the analysis carried out is the centrality of the actors involved connected in the #PrayForTurkey network. Actor centrality analysis to find out the role of key players in distributing the digital solidarity message. Based on the results analysis, fifteen actors have the highest centrality metric, namely @jiminglobal, @kiltle, @togetherweshar3, @jtoni_n, @bensudekaya, each of which has the highest degree of centrality and eigenvector centrality among other actors. In contrast, actors @mehmetpolat444, @exopublicity, @usmanabbasi56, @k_mobum_student, @studywemma have the highest closeness centrality values. Whereas actors @azearmy, @jimin2013army, @sopenamjin13, @felixhoney6, and @kpoptagramtry have the highest value betweenness centrality.

LIMITATION AND STUDY FORWARD

This section should discuss research limitations and recommendations for future research.

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