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Let's Get United and #ClearTheShelters:
The Factors Contributing to Users' Network Centrality in Online Social Networks

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ABSTRACT

This study explores the factors contributing to online users' network centrality in a network on Twitter in the context of a social movement about the "clear the shelters" campaign across the United States. The authors performed a social network analysis on a network including 13,270 Twitter users and 24,354 relationships to reveal users' betweenness, closeness, eigenvector, in-degree, and out-degree centralities before hypothesis testing. They applied a path analysis including users' centrality measures and their user-related features. The path analysis discovered that the factors of the number of people a user follows, the number of followers a user has, and the number of years since a user had his account increased a user's in-degree connections in the network. Together with the user's out-degree connections along with in-degree links, they pushed a user to have a strategic place in the network. They also implemented a multi-group analysis to find whether the impact of these factors showed differences specifically in replies to, mentions, and retweets networks.

KEYWORDS

Network Centrality, Social Media, Social Network Analysis, Social Networks, Twitter

1. INTRODUCTION

Social media includes influential websites and applications for people to share different content, interests, experiences, information, news and many more to participate in social networking. People more and more rely on social media platforms to gain and distribute up-to-date information (Lin et al., 2016). Twitter, one of these social media platforms, is used to share content and is also used to increase public awareness about social events or problems to draw people's attention during emergencies or crises (Pourebrahim et al., 2019). Because Twitter is a real-time social media channel, it is a proper crowdsourcing platform to spread and gather information in any event.

On August 17, 2019, The National Broadcasting Company (NBC) started an animal adoption event across the United States to clear the shelters. This event's initiative was drawing people's attention to find warm and caring homes for an animal in need. Thus, cities, counties, and non-profit organizations came together to support this nationwide event. Many people and organizations preferred to use Twitter and started to share tweets, including the hashtag #ClearTheShelters, to increase everyone's

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awareness. This action fired other Twitter users, and they began to retweet and reply to one another's messages, and they mention various Twitter accounts in their posts.

This chain-movement shows how social media platforms can be a powerful tool to exchange information, reach a wide range of users, and get united (Alp & Öğüdücü, 2018). In this sense, understanding social media data is vital so that organizations, people, and authorities can utilize them (Pourebrahim et al., 2019). They can use these platforms as cost-effective communication tools to reach people's sheer scale (Vu et al., 2019). Therefore, investigating the structures of the online social networks and users' behaviors is essential to accomplish this goal (Pourebrahim et al., 2019).

In this context, this study discovers the flow of information among online users in a social responsibility project known as the "Clear the Shelters" campaign. In general, this study includes two purposes. The first goal is to investigate the factors contributing to an online user's central status, which states a user's strategic location in the network. The second aim is to investigate whether these factors' impacts show differences in various networks, including the "retweets", "mentions", and "replies to" networks. We achieved these goals through social network analysis and path analysis.

We organized the remainder of this paper as follows. Firstly, the literature review part gives information about Twitter network, social network analysis, and related studies focusing on network centralities. Then, it presents the study hypotheses and conceptual model. The methodology part includes the study context and presents data collection and data analysis. The discussion gives implications from the theoretical and practical perspectives, and the conclusion section summarizes the study. Lastly, the section of limitations presents study limitations and includes future study directions.

2. LITERATURE REVIEW

2.1. Twitter Network

Twitter is a social media platform for people to communicate and stay connected by exchanging instant messages and information (New User FAQ, n.d.). In this platform, people post tweets containing text, photos, videos, links, and emoticons. A tweet might also include a hashtag and a mention. A hashtag is a highlighted word or a combination of words, including the symbol "#" in front of it (Riquelme & Gonzales-Cantergiani, 2016). A mention, headed by the character "@," includes another Twitter user's username. Additionally, a user X follows another user Z, then X is called a follower of Z, and Z is called a following of X.

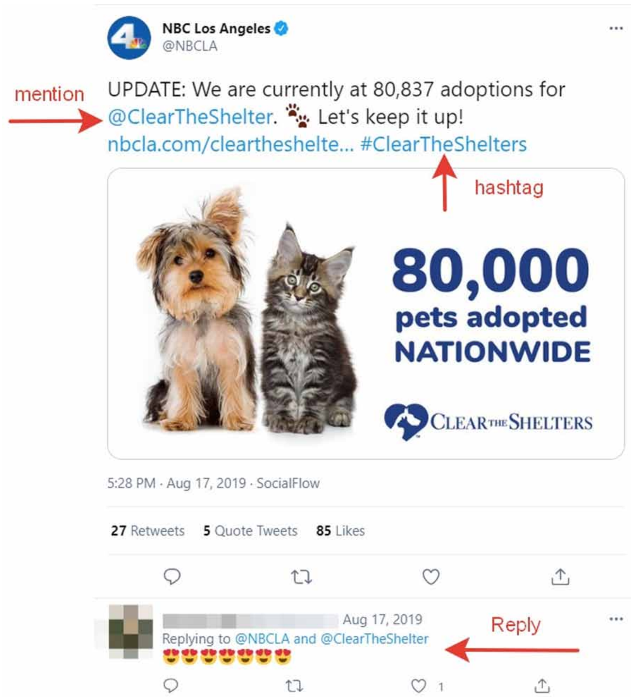
On Twitter, there are different networks such as "retweet", "replies to", and "mentions" networks. A retweet is forwarding a tweet to your followers (New User FAQ, n.d.). When a user retweets another user's tweet, a relationship occurs between these two Twitter users. This network is called the "retweet" network. On the other hand, a reply is giving a response to another user's tweet. When a user replies to another user's tweet, then a link happens between these two users. This network is called the "replies to" network. Lastly, a user mentions another user's username in his/her tweet, and again a relationship occurs between these two users. This network is called the "mentions" network. Figure 1 shows a mention, hashtag, and reply.

2.2. Social Network Analysis

Feicheng and Yating (2014) defined social network analysis as a "quantitative method of analysis developed by sociologists, based on mathematical models and graph theory" (p. 232). A graph includes a set of nodes (vertices) and a set of edges (links or relationships) (Borgatti & Li, 2009; Marin & Wellman, 2011). A graph is represented as G= (V, E) in where V corresponds to a set of vertices, and E corresponds to a set of edges. Vertices can be a person, firm, country, journal article, department, position, webpage, etc., and edges can be friendship, competition, etc.

In-degree, out-degree, betweenness centrality, closeness centrality, and eigenvector centrality are fundamental social network analysis metrics. Whereas in-degree includes incoming relationships to

Figure 1. Twitter Network



a user, out-degree contains outgoing connections from a user (Haythornthwaite, 1996). For example, when user A retweets, mentions, or replies to B's tweet, there will be a relationship between them. User A creates one out-degree link, and user B acquires one in-degree link. Also, it is not necessary to retweet, mention, or reply to user A's tweets for user B, so the relationship between users has a direction. If a network is a directed network, then every edge (i, j) ϵ E links vertex i to node j. Furthermore, edge weights represent the intensity of a relationship or frequency of the communication between two vertices (Haythornthwaite, 1996). If user A mentions or replies to user B's same tweet more than once, then the frequency will be aggregated and denoted as edge weights.

Betweenness centrality is another metric that explores how vital a user is at bridging the gap between other users in the network (Wasserman & Faust, 1994). Moreover, closeness centrality finds how close a user is to all the other network users (Catanese et al., 2012). Eigenvector centrality states that a user's centrality depends not only on the number of its adjacent users but also on the values of these nearby users' centrality (Abbasi, Altmann, & Hossain, 2011).

2.3. Network Centrality

This study adopted the two-step flow theory that Katz and Lazarsfeld developed in 1955. Katz and Lazarsfeld (1955) stated that information was spread from mass media to opinion leaders, and then these opinion leaders transmitted the information further to the less active population. According to this theory, opinion leaders were considered influential users in social networks like Twitter (Riquelme et al., 2019). These users can motivate other users and encourage community movements by retweeting and replying to other users' tweets and mentioning other users in their posts. In social networks, centrality was widely used to determine the most influential users (Amati et al., 2019). Each centrality, including degree, betweenness, closeness, eigenvector, PageRank, and others, helps to identify users' specific social network properties.

Many studies focused on centrality measures to identify the most influential Twitter users (Riquelme & Gonzales-Cantergiani, 2016). For example, Amati et al. (2019) explored those users and their evolution over time by considering degree, closeness, betweenness, and PageRank centralities. In another study, Baviera (2018) investigated a political conversation on Twitter during a general election in Spain. He analyzed the network of mentions and retweets to find loudspeaker users and users with the most authority by calculating users' degree and eigenvector centralities. Johansson and Nozewski (2018) investigated a journalist-politician network to find gatekeepers on Twitter. They examined the influential positions of users by measuring their closeness and betweenness centralities.

In addition to these studies, Yan et al. (2018) searched tweets consisting of the Champions League hashtag in the context of the 2017 UEFA Champions League Final. They analyzed betweenness and eigenvector centralities of users to provide explanations for networks as relational sources of power. Vu et al. (2019) also studied betweenness and eigenvector centralities along with in-degree, out-degree, and closeness centralities to investigate users who lead the conversation on climate change on Twitter. Moreover, Lemay et al. (2019) researched the American Educational Research Association 2017 Annual Conference. Their study presented closeness, degree, and betweenness centrality measures of users in a graph of the top 100 users based on the number of tweets. Boulet and Lebraty (2018) also focused on degree and betweenness centralities to find the most influential people in a network of Twitter by considering tweets about Uber versus taxi conflict.

Additionally, they proposed a new assessment based on the strong correlation between these centralities. Dewi, Yudhoatmojo, and Budi (2017) collected data from Twitter to observe a rumor about the flood at the Republic of Indonesia palace. They determined the opinion leaders on that rumor spreading using social network analysis.

Some studies also developed a new centrality metric or modified the existing ones. For instance, Juzar and Akbar (2018) utilized and modified eigenvector centrality to detect Twitter influencers. They modified eigenvector centrality by considering interaction within users, level of activeness users, influence level of users. They stated that this modified centrality measure was better than betweenness and closeness centralities, but it took more computational time than calculating degree and eigenvector centralities. In their study, Riquelme et al. (2019) defined a metric called MilestonesRank to identify opinion leaders and tested it in a Twitter network.

Although most network centrality studies have been mostly restricted to the extraction of users' structural positions in a network, the existing research failed to analyze how these structural positions are affected (Amati et al., 2019; Baviera, 2018; Boulet and Lebraty, 2018; Dewi et al., 2017; Johansson and Nozewski, 2018; Lemay et al., 2019; Riquelme & Gonzales-Cantergiani, 2016; Riquelme et al., 2019; Yan et al., 2018). Besides, no previous study has investigated whether users' central status is impacted differently across different networks. In this sense, this study enriched the two-step flow theory by attempting to analyze the impact of user-related features, which are the number of followers, followings, posts, and membership year, on a user's network centrality. Based on the discussion mentioned above, we introduced the following two research questions:

RQ1: What are the factors that contribute to users' central status on social networks?
RQ2: How do the impacts of factors and users' central status vary in different networks?

2.4. Hypothesis Development

We constructed thirteen hypotheses focusing on the relationships among various essential factors related to a user's central status to provide answers for RQ1 and RQ2. These factors included betweenness, closeness, and eigenvector centralities, the number of people a user follows (followings), the number of followers a user has (followers), the number of tweets a user posts (tweets), the number of years since a user had his account (membership age), in-degree, and out-degree (see Figure 2).

When a user has lots of followers, there is a tendency that these followers will probably retweet the user's tweets when they find something valuable or to mention the user in their tweets to strengthen their connections (Feng, 2016). When a user follows more people on Twitter, it means that the user will receive more information. The user will more likely create valuable tweets to be retweeted and mentioned by other users (Feng, 2016; Suh et al., 2010). Additionally, if a user follows more people on Twitter, the user will receive more information to construct valuable tweets to attract more followers. This implication is consistent with the assumption that a user's tweets will be more interesting because of the diverse opinion and information items if the user follows more sources (Suh et al., 2010). Therefore, we developed the following hypotheses:

H1: The number of followings has an impact on in-degree.
H2: The number of followers has an impact on in-degree.
H3: The number of followings has an impact on the number of followers.

If a user follows more people on Twitter, the user will receive more information, and then the user will start to post more tweets based on incoming information and opinions (Feng, 2016). This implication is parallel with the notion that when users receive attention from many people, they will create tweets more often than users who receive less attention (Huberman et al., 2008). When a user posts more tweets, this user becomes more engaged on Twitter, and he or she will probably be more influential in the network (Feng, 2016). Thus, we proposed the following hypotheses:

H4: The number of followings has an impact on the number of tweets.
H5: The number of tweets has an impact on in-degree.

A user's Twitter experience also plays an important role (Akcura et al., 2018). Experienced users are more likely to have a better idea of what type of information or opinion to post and how to inflame more interest to be more influential. Therefore, we developed the following hypothesis:

H6: The number membership age has an impact on the in-degree.

We predicted that a user with a high level of connectivity in the network would have a more centralized network location (Feng, 2016). We assumed that in-degree and out-degree might contribute to a user's central status in a social network. Thus, we constructed the following hypotheses:

H7-a: A user's in-degree centrality has an impact on the user's betweenness centrality.
H7-b: A user's in-degree centrality has an impact on the user's closeness centrality.
H7-c: A user's in-degree centrality has an impact on the user's eigenvector centrality.
H8-a: A user's out-degree centrality has an impact on the user's betweenness centrality.
H8-b: A user's out-degree centrality has an impact on the user's closeness centrality.
H8-c: A user's out-degree centrality has an impact on the user's eigenvector centrality.

The number of people a user follows, the number of followers a user has, the number of tweets user posts, and the number of years since a user had his account may stimulate to develop of a user's in-degree links, which in turn may reinforce the user's central status in the network (Feng, 2016). Therefore, we suggested the following hypotheses:

H9-a: The number of followings has an impact on the user's betweenness centrality.
H9-b: The number of followings has an impact on the user's closeness centrality.

H9-c: The number of followings has an impact on the user's eigenvector centrality.
H10-a: The number of followers has an impact on the user's betweenness centrality.
H10-b: The number of followers has an impact on the user's closeness centrality.
H10-c: The number of followers has an impact on the user's eigenvector centrality.
H11-a: The number of tweets has an impact on the user's betweenness centrality.
H11-b: The number of tweets has an impact on the user's closeness centrality.
H11-c: The number of tweets has an impact on the user's eigenvector centrality.
H12-a: The membership age has an impact on the user's betweenness centrality.
H12-b: The membership age has an impact on the user's closeness centrality.
H12-c: The membership age has an impact on the user's eigenvector centrality.

Different network types might yield different results. In this regard, we predicted that the network type could have a moderating impact on:

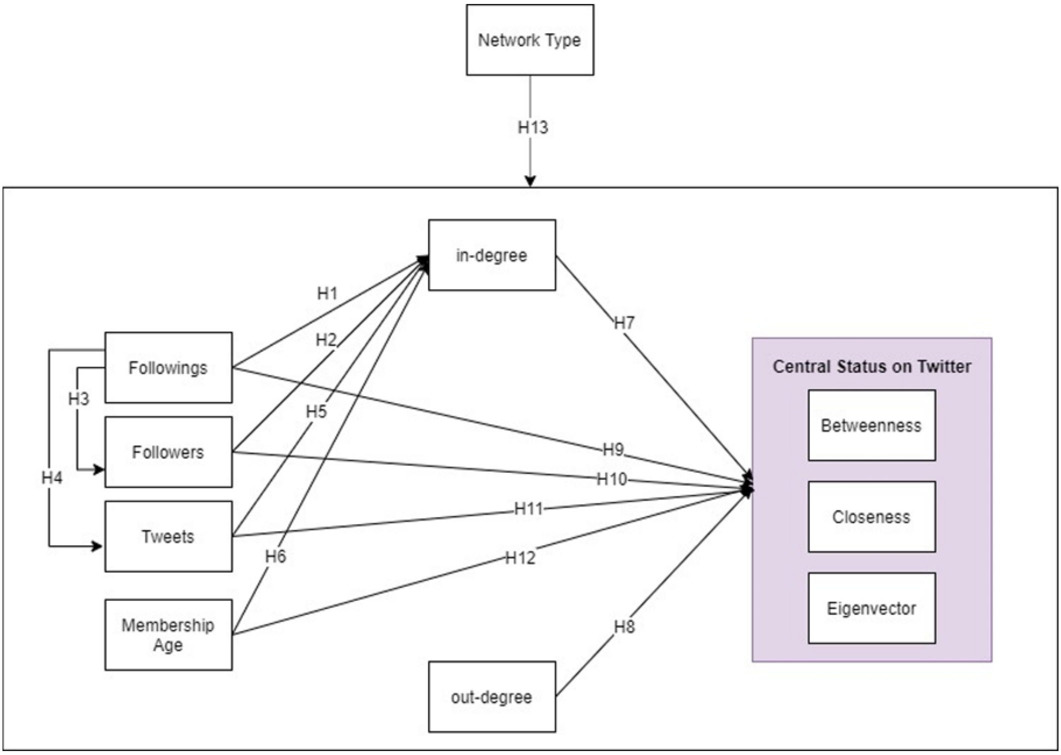
H13-a: The number of followings and in-degree.
H13-b: The number of followers and in-degree.
H13-c: The number of followings and the number of followers.
H13-d: The number of followings and the number of tweets.
H13-e: The number of tweets and in-degree.
H13-f: Membership age and the in-degree.
H13-g: In-degree and the user's betweenness centrality.
H13-h: In-degree and the user's closeness centrality.
H13-i: In-degree and the user's eigenvector centrality.
H13-j: Out-degree and the user's betweenness centrality.
H13-k: Out-degree and the user's closeness centrality.
H13-l: Out-degree and the user's eigenvector centrality.
H13-m: The number of followings and the user's betweenness centrality.
H13-n: The number of followings and the user's closeness centrality.
H13-o: The number of followings and the user's eigenvector centrality.
H13-p: The number of followers and the user's betweenness centrality.
H13-r: The number of followers and the user's closeness centrality.
H13-s: The number of followers and the user's eigenvector centrality.
H13-t: The number of tweets and the user's betweenness centrality.
H13-u: The number of tweets and the user's closeness centrality.
H13-v: The number of tweets and the user's eigenvector centrality.
H13-w: The membership age and the user's betweenness centrality.
H13-x: The membership age and the user's closeness centrality.
H13-y: The membership age and the user's eigenvector centrality.

3. METHODOLOGY

3.1 Context of the Study

NBC and Telemundo planned an adoption event to make an animal's dream come true (NBCUniversal Media). For the sixth year, NBC and Telemundo owned stations teamed up with hundreds of shelters across the United States to host the "Clear the Shelters" campaign, a nationwide pet adoption drive. This adoption event was held on Saturday, August 17, 2019, from 9:30 am to 5:00 pm to find loving homes for an animal in need. Cities, counties, and non-profit organizations came together to offer a unified campaign. People and institutions used Twitter and started to post tweets, including hashtag

Figure 2. Research Model (adapted from Feng, 2016)



#ClearTheShelters, to ask for support and spread the campaign. This initiative led to 161,290 pet adoptions from over 1,900 shelters across the United States and showed a united community's power.

3.2 Data Collection

We selected to use NodeXL as a tool. It is a social network application that allows users to visualize networks and calculate various network metrics. This Excel-based tool helps researchers collect and investigate social network data from different sources, including Twitter, Facebook, YouTube, and Flicker. NodeXL also calculates and presents numerous network-related metrics that give insights about each user's connection pattern in the network.

We collected an archive of English tweets with #ClearTheShelters hashtag on August 19, 2019, after the termination of #ClearTheShelters campaign to focus on the online communication patterns among users. We used the NodeXL Twitter Search Network data import feature to retrieve #ClearTheShelters tweets. NodeXL added an edge that described the connection between two Twitter users that was formed when they replied to, retweeted, and mentioned one another. The NodeXL Twitter Search Network data collector generated 29,008 edges and 13,910 Twitter users. NodeXL uses Twitter's public free API, which has limitations. Because of this limitation, The NodeXL Twitter Search Network data collector cannot return more than 18,000 tweets (Social Media Research Foundation, n.d.).

We deleted self-loops, which were not indicating a connection, from the edge list. Then we calculated edge weights by counting the frequencies of the relationships between users. We added them as an edge attribute, representing the frequency of the communication between two Twitter users. As a result, we formed a network including 13,270 vertices and 24,354 edges. Then, we filtered edges based on their relationship type provided by NodeXL. As a result, we created three networks called the "mentions" network, the "replies to" network, and the "retweets" network. The mentions network included 8,672 edges and 4,859 Twitter users/vertices. On the other hand, the replies to network consisted of 948 edges and 1,046 vertices, and the retweet network involved 14,734 edges and 12,372 vertices.

3.3 Metrics

NodeXL generated the following metrics for each user in the data pool: A user's features including the number of people a user follows ("followings"), the number of people following a user ("followers"), the number of tweets a user posts ("tweets"), and the date a user has created his account ("membership date") and a user's network characteristics involving in-degree, out-degree, and betweenness centrality, closeness centrality, and eigenvector centrality scores. We derived a membership age attribute for each Twitter user based on the date the user has created his Twitter account. We calculated this attribute by taking the difference between the data collection date and the account created date. We used Gephi Graph Visualization and Manipulation software with version 0.9.2 to plot the three networks' overall connection patterns.

3.4 Data Analysis

To answer the first research question (RQ1), we derived measures involving users' features and network characteristics by implementing social network analysis through NodeXL to be used in hypothesis testing. To answer the second research question (RQ2), we conducted a multi-group path analysis. We tested all study hypotheses with Partial Least Squares (PLS) by using WarpPLS 6.0. PLS allows researchers to work with non-normal data, minimizes the effect of measurement error, tests, and validates exploratory models (Goodhue, Thompsun, & Lewis, 2013; Moqbel, 2012).

4. RESULTS

4.1 Factors Contributing to Users' Central Status

Table 1 shows that all hypotheses except H5, H9-a, H9-c, H10-b, H10-c, and H11-a were supported. The results indicated that the number of tweets did not significantly impact in-degree and betweenness centralities. Moreover, the number of followers did not affect the user's betweenness and eigenvector centralities. We also could not find the effect of the number of followings on closeness and eigenvector centralities. Additionally, the number of tweets and out-degree impacted closeness centrality and eigenvector centrality negatively, respectively. It implies that when the number of tweets increases, a user's closeness centrality decreases, and while out-degree decreases, a user's eigenvector centrality increases.

Also, the dependent variables including followers, tweets, in-degree, betweenness, closeness, and eigenvector centralities had R^2 of 0.001, 0.124, 0.023, 0.528, 0.040, 0.663, respectively. Although 53% of the betweenness centrality and 66% of the closeness centrality were accounted for, R^2 was very low for other dependent variables.

Table 2 shows the model fit and includes quality indices. The results implied that the research model was robust according to the significance of average path coefficients (APC), average R squared (ARS), and average adjusted R-squared (AARS). Also, the average block variance inflation factor (AVIF) and average full collinearity VIF (AFVIF) were less than 3.3, which was ideal (Kock, 2011). Goodness-of-fit (GOF) shows that the explanatory power of the model. The value of 0.48 implied that the explanatory power of the model was large.

4.2 The Impact of Network Type

We split users into three sub-networks for further analysis to understand how users' central status differs by network type. Figure 3, Figure 4, and Figure 5 depict the mentions network, replies to

Table 1. Hypothesis Testing Results (N=13270)

Hypothesis	β	Result	Hypothesis	β	Result
H1	0.025**	Supported	H9-a	*0.011*	Not Supported
H2	0.14***	Supported	H9-b	0.034***	Supported
H3	0.033***	Supported	H9-c	*0.003*	Not Supported
H4	0.353***	Supported	H10-a	0.034***	Supported
H5	*0.006*	Not Supported	H10-b	*-0.005*	Not Supported
H6	0.036***	Supported	H10-c	*0.006*	Not Supported
H7-a	0.592***	Supported	H11-a	*0.007*	Not Supported
H7-b	0.02**	Supported	H11-b	-0.03***	Supported
H7-c	0.588***	Supported	H11-c	0.016*	Supported
H8-a	0.313***	Supported	H12-a	0.018*	Supported
H8-b	0.486***	Supported	H12-b	0.052***	Supported
H8-c	-0.189***	Supported	H12-c	0.021**	Supported

***$p \leq 0.001$; **$p \leq 0.01$, *$p \leq 0.05$

Table 2. Model Fit

Quality Index	Value	p-Value
APC	0.126	<0.001
ARS	0.23	<0.001
AARS	0.23	<0.001
GOF	0.48	
AVIF	1.084	
AFVIF	1.54	

network, and retweets network, respectively. The vertex size is proportional to the betweenness centrality score, and the edge thickness is equivalent to edge weight.

Table 3 includes hypotheses testing results for each network type. The results suggested that the number of followings had a significant impact on the user's in-degree. The number of followers had a significant effect on the number of followings and tweets in all network types. Also, in-degree significantly impacted betweenness and eigenvector centralities, and out-degree affected betweenness and closeness centralities in all networks. On the other hand, in all networks, we could not find the impact of the number of followers on eigenvector centrality. Additionally, the number of tweets did not have any effect on each centrality in all network types. We could not find the impact of the membership age and out-degree on eigenvector centrality in each network.

In the mentions network, in-degree had a more significant impact than out-degree on betweenness centrality and had the most significant effect on closeness centrality—only in-degree impacted eigenvector centrality in this network. In the replies to network, in-degree had the most significant impact on betweenness. While only out-degree influenced closeness centrality, in-degree and the

Figure 3. Mentions Network (8672 Edges, 4859 Twitter Users/Vertices)

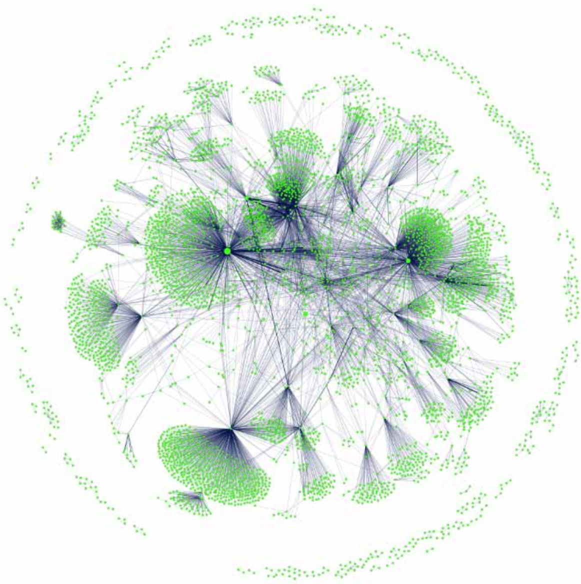
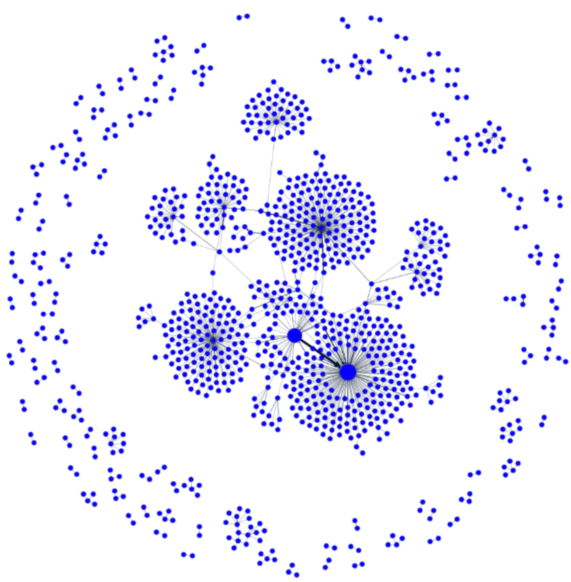


Figure 4. Replies To Network (948 Edges, 1046 Twitter Users/Vertices)



number of followings impacted eigenvector centrality. Like other networks, in the retweets network, in-degree also had the most significant effect on betweenness centrality. Only out-degree impacted closeness centrality that was like the replies to network. Lastly, the only in-degree affected eigenvector centrality in this type of network.

Figure 5. Retweet Network (14734 Edges, 12372 Twitter Users/Vertices)

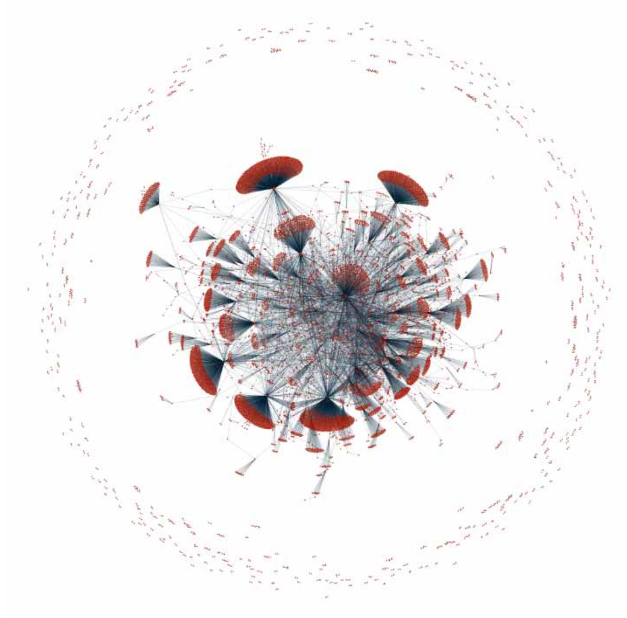


Table 4 also shows that all structural models were fit, and the explanatory power of each model was large (Kock, 2011). Although AFVIF was high, acceptance of at least three fit indices were enough to say that the research model was valid (Hair et al., 2010).

After that, we conducted a multi-group analysis to evaluate the moderating effect of network types whether path coefficients significantly differ across each network type (Kock, 2014). As stated in the literature, "the main goal of this analysis is to compare pairs of path coefficients for identical models but based on different samples" (Kock, 2014, p. 4). WarpPLS 6.0 makes a pair-wise comparison across each type of user. It calculates a critical ratio based on a pooled standard and presents p-values to check the significance of path estimates (Keil et al., 2000). Table 5 includes T-values and their significance levels. The results indicated that only hypotheses H13-a, H13-b, H13-c, H13-f, H13-g, H13-h, H13-j, H13-k, and H13-x were supported.

5. DISCUSSION

There was not an agreement on what is meant by influential users (Riquelme & Gonzalez-Cantergiani, 2016). Thus, there are various emerging measures to detect those users. In-degree, out-degree, closeness, betweenness, and eigenvector centralities are some of those intuitive measures (Kim et al., 2017). Various previous studies considered those measures from the structural point of view to determine influential users. They formed different types of networks and only calculated centrality measures to find influencers. However, this study addressed another problem by finding possible factors that could increase or decrease users' central status in the network.

Table 6 shows whether independents impacted dependents or not. The results implied that the number of followings, followers, and a user's membership age were indicators that may increase a user's in-degree connections (Feng, 2016). Although the number of tweets a user post increased a user's central status in a previous study (Feng, 2016), this study could not find a positive impact on it. These results may indicate that a user's level of connectivity and level of personal influence

Table 3. Hypotheses Testing Results across Network Types

Hypothesis	The Mentions Network (N=4859)	The Replies to Network (N=12372)	The Retweets Networks (N=1046)
H1	*0.021*	0.111***	*0.011*
H2	0.105***	0.171***	0.277***
H3	0.037**	0.209***	0.071***
H4	0.329***	0.368***	0.372***
H5	*0.017*	*0.008*	-0.022**
H6	0.062***	0.149***	*0.011*
H7-a	0.8***	0.734***	0.586***
H7-b	-0.136***	*-0.017*	-0.14***
H7-c	0.955***	0.897***	0.991***
H8-a	0.128***	0.572***	0.161***
H8-b	0.113***	0.86***	0.226***
H8-c	*-0.002*	*0.043*	*0.011*
H9-a	*-0.005*	*0.007*	0.03***
H9-b	-0.04**	*-0.036*	-0.044***
H9-c	*0.007*	*0.016*	*0.001*
H10-a	*0.022*	-0.061*	0.034***
H10-b	-0.064***	0.002	-0.032***
H10-c	*0.005*	0.079**	*0.006*
H11-a	*-0.006*	*-0.001*	*0.001*
H11-b	*-0.011*	*-0.019*	*0.009*
H11-c	*0.008*	*0.004*	*-0.002*
H12-a	*-0.005*	*-0.01*	0.018*
H12-b	-0.035**	*-0.038*	-0.115***
H12-c	*0.01*	*-0.013*	*0.004*

***p ≤ 0.001; **p ≤ 0.01, *p ≤ 0.05

Table 4. Model Fit across Network Types

Quality Index	The Mentions Network		The Replies to Network		The Retweets Network	
	Value	p-Value	Value	p-Value	Value	p-Value
APC	0.122	<0.001	0.184	<0.001	0.132	<0.001
ARS	0.3	<0.001	0.462	<0.001	0.284	<0.001
AARS	0.3	<0.001	0.461	<0.001	0.284	<0.001
GOF	0.548		0.68		0.533	
AVIF	1.064		1.121		1.084	
AFVIF	3.333		2.316		12.878	

Table 5. Multigroup Analysis

Hypothesis	Result	Pair-wise Comparisons (T-Values)		
		Mentions/Retweets Networks	Mentions/Replies to Networks	Retweets/Replies to Networks
H13-a	Supported	0.328	-1.792*	-0.938
H13-b	Supported	-5.647***	-1.356	1.027
H13-c	Supported	-0.295	-3.534***	-1.337
H13-d	Not Supported	-1.412	-0.801	0.039
H13-e	Not Supported	1.280	0.179	-0.281
H13-f	Supported	1.674*	-1.732*	-1.294
H13-g	Supported	7.026***	1.401	-1.483
H13-h	Supported	0.131	-2.369**	-1.153
H13-i	Not Supported	-1.182	1.231	0.942
H13-j	Supported	-1.083	-9.427***	-4.119***
H13-k	Supported	-3.710***	-15.861***	-6.355***
H13-l	Not Supported	-0.427	-0.896	-0.300
H13-m	Not Supported	-1.149	-0.239	0.216
H13-n	Not Supported	0.131	-0.080	-0.075
H13-o	Not Supported	0.197	-0.179	-0.141
H13-p	Not Supported	-0.394	1.652	0.891
H13-r	Not Supported	-1.051	-1.314	-0.319
H13-s	Not Supported	-0.033	-1.473	-0.685
H13-t	Not Supported	-0.230	-0.100	0.019
H13-u	Not Supported	-0.657	0.159	0.263
H13-v	Not Supported	0.328	0.080	-0.056
H13-w	Not Supported	-0.755	-0.010	0.263
H13-x	Supported	2.626**	0.060	0.159
H13-y	Not Supported	0.197	0.458	0.159

***$p \leq 0.001$; **$p \leq 0.01$, *$p \leq 0.05$

Table 6. The impacts of independents

	Dependents					
	Betweenness	Closeness	Eigenvector	Followers	Tweets	In-degree
Followings	X	✓	X	✓	✓	✓
Followers	✓	X	X	-	-	✓
Tweets	X	✓	✓	-	-	X
Membership Age	✓	✓	✓	-	-	✓
In-degree	✓	✓	✓	-	-	-
Out-degree	✓	✓	✓	-	-	-

"✓" = impacted; "X" = not impacted

played a crucial role in increasing incoming relationships and a user's access to information (Li, Liao, & Yen, 2013).

Additionally, this study analyzed possible factors influencing betweenness, closeness, and eigenvector centralities. A user who has high betweenness centrality bridges the subgroups in the network and plays the gatekeeper's role (Baek & Kim, 2015; Freemen 1978). For example, if a user seeks information in the network, there is a high probability that this user will firstly look at profiles of users who have higher betweenness centrality (Johansson & Nozewski, 2018). It was expected that the number of followers, the membership age, incoming and outgoing links impacted a user's betweenness centrality.

On the other hand, closeness centrality shows "how particular entities can distribute information through the network" (Johansson & Nozewski, 2018, p. 142). Users with high closeness centrality are in the middle of the network and dominate the shortest paths to communicate with other network users. The results indicated that the number of followings and tweets and the membership age impacted a user's closeness centrality. Those three factors lead a user to reach information faster than the other network users (Li et al., 2013).

In addition to these findings, the results showed that only the number of tweets and the membership age influenced a user's eigenvector centrality. The unexpected result was that a user's number of followings and followers did not play a role in eigenvector centrality. It might imply that even a user has few followers or followings, this user may still be considered central (Juzar & Akbar, 2018). Because these few followers and followings are followed by other users who already has many users.

The understanding of the factors having an impact on users' central status can be useful for various applications such as information propagation, viral marketing, social customer relationship, searching, expertise recommendation, a financial decision, technology or innovation adoption, and criminology (Kim et al., 2017; Riquelme & Gonzalez-Cantergiani, 2016; Riquelme et al., 2019). The results indicated that starting social-media-based communication to connect with the public and take their attention was a viral component to organize a social responsibility campaign (Feng, 2016). It is also essential to determine influencers to reach more audiences and get more social networks to support. Hence, practitioners can identify these influencers by looking at the key indicators, including the number of followings, followers, tweets, and the membership age.

It is known that influencers have a strong social influence on users, and they can change users' thoughts and actions (Li et al., 2012). According to Twitter's Q3 2019 report, there are 145 million monetizable daily active users who see ads on Twitter (Twitter Q3 Report). Instead of randomly disseminating information, practitioners can utilize influencers to increase user satisfaction, take more users' attention, and avoid high advertisement costs. In this sense, practitioners should understand critical social network users (Akar & Dalgic, 2018). These users are gatekeepers, they can reach other users quickly, and they can control the communication in the network.

6. CONCLUSION

In summary, this study investigated the factors contributing to users' central status in social networks based on the two-step flow theory. It unveiled the factors impacting a user's in-degree, betweenness, closeness, and eigenvector centralities by conducting a path analysis. We collected Twitter network data within the context of the "Clear the Shelters" campaign across the United States. We formed a network including 13,270 users and 24,354 relationships. We extracted users' number of followers, followings, tweets, membership age. Besides, we obtained their in-degree, out-degree, betweenness, closeness, and eigenvector centralities. We applied PLS to test all hypotheses. We found significant impacts of the number of followers and the membership age on betweenness centrality. On the other hand, the number of followings, tweets, and the membership age affected closeness centrality. Lastly, the number of tweets and the membership age influenced eigenvector centrality.

In addition to path analysis, we conducted a multi-group analysis to reveal whether the impacts of these factors might vary in the case of a different type of network. In this regard, we tested the mediating effect of network type on each study hypothesis. We split the whole network into three types of network, including the mentions network, the replies to network, and the mentions network. The results indicated that the relationships of in-degree with the number of followings, followers, and the membership age were mediated by network type. Also, the relationships of in-degree and out-degree with betweenness and closeness, the relationship of the number of followings with followers, and the relationship between the membership age and closeness were all mediated by the network type.

7. LIMITATIONS

In this study, we collected tweets, including the hashtag #ClearTheShelters, after the campaign's termination immediately, so that we investigated tweets in two days, and it would not allow trend analysis. Additionally, the exogenous variables accounted for a little variance to explain the number of followers, in-degree, and closeness centralities in the research model. Therefore, future studies can consider the addition of more variables to explain those dependents. Future studies can also view more variables to explore the factors impacting a user's out-degree relationships.

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REFERENCES

Abbasi, A., Altmann, J., & Hossain, L. (2011). Identifying the Effects of Co-Authorship Networks on the Performance of Scholars: A Correlation and Regression Analysis of Performance Measures and Social Network Analysis Measures. *Journal of Informetrics*, *5*(4), 594–607. doi:10.1016/j.joi.2011.05.007

Akar, E., & Dalgic, T. (2018). Understanding online consumers' purchase intentions: A contribution from social network theory. *Behaviour & Information Technology*, *37*(5), 473–487. doi:10.1080/0144929X.2018.1456563

Akcura, T., Altinkemer, K., & Chen, H. (2018). Noninfluentials and information dissemination in the microblogging community. *Information Technology and Management*, *19*(2), 89-106. .10.1007/s10799-017-0274-z

Alp, Z. Z., & Öğüdücü, Ş. G. (2018). Identifying topical influencers on twitter based on user behavior and network topology. *Knowledge-Based Systems*, *141*, 211–221. doi:10.1016/j.knosys.2017.11.021

Amati, G., Angelini, S., Gambosi, G., Rossi, G., & Vocca, P. (2019). Influential users in Twitter: Detection and evolution analysis. *Multimedia Tools and Applications*, *78*(3), 3395–3407. doi:10.1007/s11042-018-6728-4

Baek, S. I., & Kim, Y. M. (2015). Longitudinal Analysis of Online Community Dynamics. *Industrial Management & Data Systems*, *115*(4), 661–677. doi:10.1108/IMDS-09-2014-0266

Baviera, T. (2018). Influence in the political Twitter sphere: Authority and retransmission in the 2015 and 2016 Spanish General Elections. *European Journal of Communication*, *33*(3), 321–337. doi:10.1177/0267323118763910

Borgatti, S. P., & Li, X. (2009). On Social Network Analysis in a Supply Chain Context. *The Journal of Supply Chain Management*, *45*(2), 5–22. doi:10.1111/j.1745-493X.2009.03166.x

Boulet, R., & Lebraty, J. F. (2018). A New Influence Measure Based on Graph Centralities and Social Network Behavior Applied to Twitter Data. *Communications of the Association for Information Systems*, *43*(1), 21. doi:10.17705/1CAIS.04321

Catanese, S., De Meo, P., Ferrara, E., Fiumara, G., & Provetti, A. (2012). Extraction and Analysis of Facebook Friendship Relations. In A. Abraham (Ed.), *Computational Social Networks* (pp. 291–324). Springer. doi:10.1007/978-1-4471-4054-2_12

Dewi, F. K., Yudhoatmojo, S. B., & Budi, I. (2017). Identification of opinion leader on rumor spreading in online social network Twitter using edge weighting and centrality measure weighting. In *Proceedings of 2017 Twelfth International Conference on Digital Information Management (ICDIM)* (pp. 313-318). IEEE.

Feicheng, M., & Yating, L. (2014). Utilising Social Network Analysis to Study the Characteristics and Functions of the Co-Occurrence Network of Online Tags. *Online Information Review*, *38*(2), 232–247. doi:10.1108/OIR-11-2012-0124

Feng, Y. (2016). Are you connected? Evaluating information cascades in online discussion about the #RaceTogether campaign. *Computers in Human Behavior*, *54*, 43–53. doi:10.1016/j.chb.2015.07.052

Freeman, L. C. (1978). Centrality in Social Networks: Conceptual Clarification. *Social Networks*, *1*(3), 215–239. doi:10.1016/0378-8733(78)90021-7

Goodhue, D. L., Thompson, R., & Lewis, W. (2013). Why you shouldn't use PLS: Four reasons to be uneasy about using PLS in analyzing path models. In *Proceedings of System Sciences (HICSS), 2013 46th Hawaii International Conference on System Sciences* (pp. 4739–4748). doi:10.1109/HICSS.2013.612

Hair, J., Black, W., Babin, B., & Anderson, R. (2010). *Multivariate Data Analysis: A Global Perspective* (7th ed.). Pearson Education.

Haythornthwaite, C. (1996). Social Network Analysis: An Approach and Technique for the Study of Information Exchange. *Library & Information Science Research*, *18*(4), 323–342. doi:10.1016/S0740-8188(96)90003-1

Huberman, B. A., Romero, D. M., & Wu, F. (2008). *Social networks that matter: Twitter under the microscope*. arXiv preprint arXiv:0812.1045.

Johansson, E., & Nożewski, J. (2018). Polish and Swedish journalist-politician Twitter networks: Who are the gatekeepers? *Central European Journal of Communication*, *11*(2), 129–150. doi:10.19195/1899-5101.11.2(21).2

Juzar, M. T., & Akbar, S. (2018). Buzzer Detection on Twitter Using Modified Eigenvector Centrality. In *Proceedings of 2018 5th International Conference on Data and Software Engineering (ICoDSE)* (pp. 1-5). IEEE. doi:10.1109/ICODSE.2018.8705788

Katz, E., & Lazarsfeld, P. F. (1955). *Personal Influence: The part played by people in the Flow of Mass communications*. The Free Press.

Keil, M., Tan, B. C., Wei, K. K., Saarinen, T., Tuunainen, V., & Wassenaar, A. (2000). A cross-cultural study on escalation of commitment behavior in software projects. *Management Information Systems Quarterly*, *24*(2), 299–325. doi:10.2307/3250940

Kim, J., Kwon, O., & Lee, D. H. (2017). Social influence of hubs in information cascade processes. *Management Decision*, *55*(4), 730–744. doi:10.1108/MD-10-2016-0681

Kock, N. (2011). *Using WarpPLS in e-collaboration studies: An overview of five main analysis steps. Advancing Collaborative Knowledge Environments: New Trends in E-Collaboration: New Trends in E-Collaboration*. Information Science Reference.

Kock, N. (2014). Advanced mediating effects tests, multi-group analyses, and measurement model assessments in PLS-based SEM. *International Journal of e-Collaboration*, *10*(1), 1–13. doi:10.4018/ijec.2014010101

Lemay, D. J., Basnet, R. B., Doleck, T., & Bazelais, P. (2019). Social network analysis of twitter use during the AERA 2017 annual conference. *Education and Information Technologies*, *24*(1), 459-470. doi: / doi:10.1007/s10639-018-9787-2

Li, E. Y., Liao, C. H., & Yen, H. R. (2013). Co-authorship Networks and Research Impact: A Social Capital Perspective. *Research Policy*, *42*(9), 1515–1530. doi:10.1016/j.respol.2013.06.012

Lin, X., Spence, P. R., Sellnow, T. L., & Lachlan, K. A. (2016). Crisis communication, learning and responding: Best practices in social media. *Computers in Human Behavior*, *65*, 601–605. doi:10.1016/j.chb.2016.05.080

Marin, A., & Wellman, B. (2011). *Social Network Analysis: An Introduction.* In J. Scott & P. J. Carrington (Eds.), *SAGE Handbook of Social Network Analysis* (pp. 11–25). Sage Publications Ltd.

Moqbel, M. (2012). *The effect of the use of social networking sites in the workplace on job performance* (PhD. Dissertation), Texas A&M International University.

NBCUniversal Media. (n.d.). Retrieved from: https://www.cleartheshelters.com/

New UserF. A. Q. (n.d.). Retrieved from: https://help.twitter.com/en/new-user-faq

Pourebrahim, N., Sultana, S., Edwards, J., Gochanour, A., & Mohanty, S. (2019). Understanding communication dynamics on Twitter during natural disasters: A case study of Hurricane Sandy. *International Journal of Disaster Risk Reduction*, *37*, 1–19. doi:10.1016/j.ijdrr.2019.101176

Riquelme, F., & González-Cantergiani, P. (2016). Measuring user influence on Twitter: A survey. *Information Processing & Management*, *52*(5), 949–975. doi:10.1016/j.ipm.2016.04.003

Riquelme, F., Gonzalez-Cantergiani, P., Hans, D., Villarroel, R., & Munoz, R. (2019). Identifying Opinion Leaders on Social Networks Through Milestones Definition. *IEEE Access: Practical Innovations, Open Solutions*, *7*, 75670–75677. doi:10.1109/ACCESS.2019.2922155

Social Media Research Foundation. (n.d.). Retrieved from: https://www.smrfoundation.org/nodexl/faq/

Suh, B., Hong, L., Pirolli, P., & Chi, E. H. (2010). Want to be retweeted? large scale analytics on factors impacting retweet in twitter network. In *Proceedings of 2010 IEEE Second International Conference on Social Computing* (pp. 177-184). IEEE. doi:10.1109/SocialCom.2010.33

Twitter Q3 Report. (n.d.). Retrieved from: https://s22.q4cdn.com/826641620/files/doc_financials/2019/q3/Q3-2019-Shareholder-Letter.pdf

Vu, H. T., Do, H. V., Seo, H., & Liu, Y. (2019). Who Leads the Conversation on Climate Change? A Study of a Global Network of NGOs on Twitter. *Environmental Communication*, 1-15. .10.1080/17524032.2019.1687099

Wasserman, S., & Faust, K. (1994). Social Network Analysis: Methods and Applications. Cambridge University Press. doi:10.1017/CBO9780511815478

Yan, G., Watanabe, N. M., Shapiro, S. L., Naraine, M. L., & Hull, K. (2019). Unfolding the Twitter scene of the 2017 UEFA Champions League Final: Social media networks and power dynamics. *European Sport Management Quarterly*, *19*(4), 419–436. doi:10.1080/16184742.2018.1517272