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Exploring Social Networks of #Election2020results and #BidenTransition on Twitter after the 2020 US Presidential Election

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Using Netlytic, Gephi, and Voyant, this study attempted to provide an in-depth social network analysis of two selected hashtags (#Election2020results and #BidenTransition) after the 2020 US presidential election. The data were collected from November 24 to November 30, 2020, where the tweets of both hashtags increased dramatically. A total of 39,341 tweets of both hashtags were included in this analysis. Results showed that when the mode was considered as a multimode network, five influential nodes were found, with three from the same organization — MyNation based in India. The term, Biden Transition, was consistently repeated (21,571 out of 39,341 tweets) within the network. Moreover, most tweets within the network were retweeted from original tweets, given that #BidenTransition was 20,039 out of 39,341 tweets for both hashtags. Practical implications of tweeters' tendencies among the two selected hashtags: #Election2020results and #BidenTransition were also discussed.

Keywords: social network analysis, Twitter, hashtag, #Election2020results, BidenTransition, presidential election

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The most prominent goal of research in the field of political communication is to influence public knowledge, beliefs, and action on political matters (Bennett & Iyengar, 2008). Social media platforms play an essential role in this field. Twitter, as a key social media platform, is considered as a political tool in several countries (Kreiss & McGregor, 2018). The purpose of Twitter is to serve for public conversation, ensure the participation of most citizens, and assist them to participate in public participation freely and safely. Moreover, Twitter hashtags have become one of the most significant tools that tweeters can connect with others on certain political issues. The characteristic of "hashtag" further allows tweeters to be an important part of interactive communication process under the same unit (Twitter, 2020).

As the most visited website in the US, Twitter is ranked number 7 among other websites and social media platforms, such as Facebook, Google, and Amazon in the Unites States (Hootsuite, 2020). According to Hootsuite, the population of the US reached 330 million in January 2020, and the number of internet users in the US rose swiftly to touch 288 million people by the beginning of 2020 (Hootsuite, 2020).

Throughout its history, the US has never been in the same situation during the 2020 election. Recently, after President-elect Joe Biden won the 2020 election, many implications emerged from President Donald Trump regarding the integrity of the election (Lemire et al., 2020). Former President Donald Trump has relied heavily on Twitter to share his thoughts with Americans and people around the world. However, after questioning the election results, the hashtags #Election2020results and #BidenTransition both appeared on Twitter as global trending topics, and both mocking former President Donald Trump's actions and his denial of the results.

These two selected hashtags directed people's attention toward the results of the #Election2020results in the US. Through the interactivity of tweeters, #BidenTransition emerged a few days after the #Election2020results came to the spotlight. The selections of these two hashtags were based on their emergence and both were globally trending on Twitter during mid-November of 2020.

In social networking, one twitter can be considered a node, and a relationship between tweeters is an edge. By using Netlytic, Gephi, and Voyant analytic tools, this study attempts to offer a social network analysis of the two selected hashtags: #Election2020results and #BidenTransition and provide a further understanding of how tweeters (nodes) engage within the networks. Simply stated, this study may offer some practical insights into the type and mode of the networks, the influential nodes within the networks, and the nature of the tweets within the networks of both hashtags in the post-election period.

LITERATURE REVIEW

Twitter Hashtags

Bastos et al. (2013) stated that Twitter hashtags have always been a key tool for sorting and organizing tweets. When used correctly, hashtags can be extremely powerful in driving traffic and engagement. Bastos et al. used oral history as an approach to understanding how hashtags have been used previously to pass vital information to many tweeters at the same time and concluded that Twitter hashtags are important element when they come to dissemination of important political messages. Bruns and Burgess (2011) discovered that the use of Twitter hashtags can help shape ad hoc publics. They asserted that the use of Twitter, especially in political discussions has increased and the role of Twitter hashtags in coordinating distributed discussions among groups of internet users who did not need to be connected via 'follower' networks. Moreover, Bruns and Burgess concluded that Twitter hashtags, like '#londonriots', '#ausvotes' or '#wikileaks' would not only lead to the formation of public opinion on certain political issues and themes, but also influence the governmental decision makers and other political figures.

Social media platforms play an essential role in developing political discussions in the US and worldwide (Stieglitz & Dang-Xuan, 2013). Researchers have analyzed political microblogging (e.g., Twitter), focusing on social networking structures to figure out how internet users interact with each other within social networks (Ausserhofer & Maireder, 2013; Stieglitz & Dang-Xuan, 2013). According to Tumasjan et al. (2010), politicians widely use Twitter to advance their political aspirations and Twitter is commonly used to influence the dynamics of political communication, given that certain mentions of political parties and figures on Twitter have been identified to influence the election results, which further implies that microblogging messages on Twitter is an influential campaigning tool in dominating the election results.

Bode et al. (2015) extended the discussion by examining the political alignments and networking on Twitter in the 2010 midterm elections in the US. They investigated 9 million tweets produced by followers who were selected randomly and suggested that tweeters in the election did not follow the right-left division; rather, five unique clusters emerged within Twitter networks. Three of these groups represented the different conservative groupings. In this regard, a specified group engaged in strategic expressions, like retweeting and hashjacking. They further explained that retweeting is referred to the act of sharing another user's tweet with one's followers, while hashjacking is viewed as the act of co-opting the hashtags preferred by political adversaries. Furthermore, they found that the political right's Twitter alignments were more nuanced than those on the political left. This argument was extended by the observations made on the behavior concerning the Tea Party's rise during the 2010 elections.

Another study by Conover et al. (2011) explored how social media platforms shape the political affiliations and orientation of their users as seen from the networked public sphere. They focused on two Twitter networks that are comprised more than 250,000 tweets from six weeks leading up to the 2010 congressional midterm elections. Their findings indicated that the engagements between tweeters exhibited the cross-ideological political discourse. Thus, Twitter creates a communication platform for its users to interact through content injection and mentions, which means that tweeters rarely share information from the cross divide with other members of their community.

Hashtag Engagement

Nason et al. (2015) examined that social media platforms are interactive communication channels that facilitate information dissemination and sharing in web-based networks and virtual communities. By using #ISU14, Nason et al. helped the Irish Society of Urology enhance its social media involvements and used the Symplur healthcare analytics website to evaluate and determine the traffic. They concluded that the use of the hashtag #ISU14 facilitated the interactions among delegates and enabled virtual participation of the users. However, their study failed to look at how to increase tweeters' engagement by using the hashtag #ISU14.

Omena et al. (2020) studied digital methods of hashtag engagement to extensively account for the association between hashtags and their forms of dramatization. They approached hashtags as sociotechnical formations that demonstrated the complexity of online engagement and the entanglement with web platform technicity. Moreover, these digital methods were discussed to introduce the 3L perspective for digital social inquiry and indicate that the number of hashtags activated the engagement of tweets. Since tweets include some suitable number of URLs, pictures, videos and mentions, hashtags would be used to measure users' engagement with others.

As a digital approach to mapping social networks, social network analysis examines social network structures in terms of nodes and edges. Nodes are defined as individual users, people, or things within the network, while edges are viewed as relationships or interactions that connect these nodes (Grandjean, 2016; Khan, 2018). Social networks are often visualized through "sociograms" in which nodes are represented as points and edges are represented as lines, and social network visualizations further provide a means of qualitatively assessing network structures by varying the visual representation of their nodes and edges to reflect attributes of interest (Grunspan et al., 2014). Moreover, the properties of social networks are divided at either node-level or network-level. Node-level properties focus on one node and its position in the network, including degree centrality, betweenness centrality, closeness centrality, and eigenvector centrality, while network-level properties offer insights into the overall structure and health of the network, such as diameter, density, reciprocity, and modularity (Khan, 2018). For node-level properties, degree centrality measures the number of links a node has to other nodes in the network (Hanneman & Riddle, 2005). The nodes with higher degree centrality have more followers. Betweenness centrality is related to the centrality (or position) of a node in the network. The nodes with higher betweenness centrality can control the flow of information between connected nodes due to their central positions in the network (Liu et al., 2005). Closeness centrality measures how close a node is to all other nodes in the network, which is calculated as the average of the shortest path length from a node to every other node in the network (Golbeck, 2013). Eigenvector centrality looks at the importance of a node based on its connections with other vital nodes in the network, which provides an understanding of a node's networking ability relative to that of others (Marsden, 2002).

Regarding network-level properties, the diameter of the network is the largest of all the calculated shortest path between any pair of nodes in the network, which can measure how long it would take for some information/idea/message to pass through the network (Wasserman & Faust, 1994). Density deals with the number of links in the network and can be calculated as the number of links present in the network divided by the number of all possible links between pairs of nodes in the network (Khan, 2018). Similar to clustering coefficient, reciprocity and modularity are to measure the degree to which nodes in the network tend to group or cluster. Specifically, reciprocity refers to the likelihood of vertices in the directed network to be mutually linked (Garlaschelli & Loffredo, 2004), while modularity measures the strengthen of a division of the network into modules. Moreover, networks with high modularity indicate dense connections between nodes within modules, but thin connections between nodes in different modules (Newman, 2006).

Applying social network terminologies to examine network structures of the two hashtags: #Election2020results and #BidenTransition during the post-presidential election in 2020, this study would examine (1) the type/mode of the networks, (2) the influential nodes within the networks, and (3) the nature of the tweets within the networks. Three main research questions are proposed in the following:

RQ1: What is the type/mode of the networks of #Election2020results and #BidenTransition?

RQ2: What are the influential nodes within the networks of #Election2020results and #BidenTransition?

RQ3: What is the nature of the tweets within the networks of #Election2020results and #BidenTransition?

METHODS

Social Network Analysis

Social network analysis was developed based upon theoretical and methodological paradigms for the sophisticated examination of complex social structures (Emirbayer & Goodwin 1994). It was reasonable to use social network analysis as a research approach to exploring #Election2020results and #BidenTransition, given that social network analysis was an arithmetical technique analyzing relational patterns of nodes (users) and edges (connections) based on mathematical computations. Moreover, Netlytic, Gephi, and Voyant were three social network analysis tools that can be used to examine the network types, the influential nodes within the networks, and the nature of the tweets within the networks and further provide a better understanding of how tweeters engaged in the networks of both hashtags globally.

Regarding the network structures and metrics, several statistical tests are used to measure the networks of social media platforms, such as diameter, density, reciprocity, and modularity. Golbeck (2013) recognized centrality as the core principle of social network analysis as it measures the ‘central’ node in the network, which is used to estimate the importance of the network and the node's reputation in the network. Moreover, four additional measurements under the centrality, including (A) degree centrality: (B) betweenness centrality: (C) closeness centrality: and (D) eigenvector centrality, were used to look at the network structures and metrics in this study.

Data Collection Procedure

To explore the network structures of the two hashtags: #Election2020results and #BidenTransition. First, Netlytic was used to capture and analyze networks of the hashtags. Netlytic is a cloud-based social network analytic tool that can automatically summarize large volumes of texts and discover online conversations on different social media sites, such as Twitter, YouTube, blogs, online forums, and chats (Netlytic.org, 2020). This tool would gather tweets based on search terms, and two major hashtags in describing the results of the US 2020 election; #Election2020results and #BidenTransition were used to capture the relative discussions on the results of the 2020 presidential election.

After exporting the data from Netlytic into Gephi, social network visualizations were performed in Gephi. Gephi is an open-source software for network visualization and analysis and can be used to intuitively reveal patterns and trends, highlight outliers, and describe stories. Moreover, Gephi applies a 3-dimension render engine to display large graphs in real-time and to speed up the exploration and combine built-in functionalities and flexible architecture to analyze social networks (Gephi, 2020). In addition to calculating metrics of betweenness centrality and modularity, Gephi can also be used to build network structures using a range of layout algorithms. Based on these metrics, network graphs would develop insights into network features visible in size, color, and spatialization of nodes and the linkages between them (Bastian et al., 2009).

Furthermore, the two dataset files of the two hashtags were merged together by Gephi. After that, the directed data were used examine how a tie was given from one actor to another, given that the directed data would be more prosperous than the undirected data and more information was held within the directed data (Bhagat et al., 2009). As a result, a total of 39,341 tweets (13,460 nodes and 31,273 edges) were used for the analysis. For the textual analysis of the tweets, Voyant was used to identify the nature of the tweets within the networks. Voyant, a web-based text reading and analysis environment, is also used to facilitate interpretive practices for scholars in digital humanities (Voyant.org, 2020).

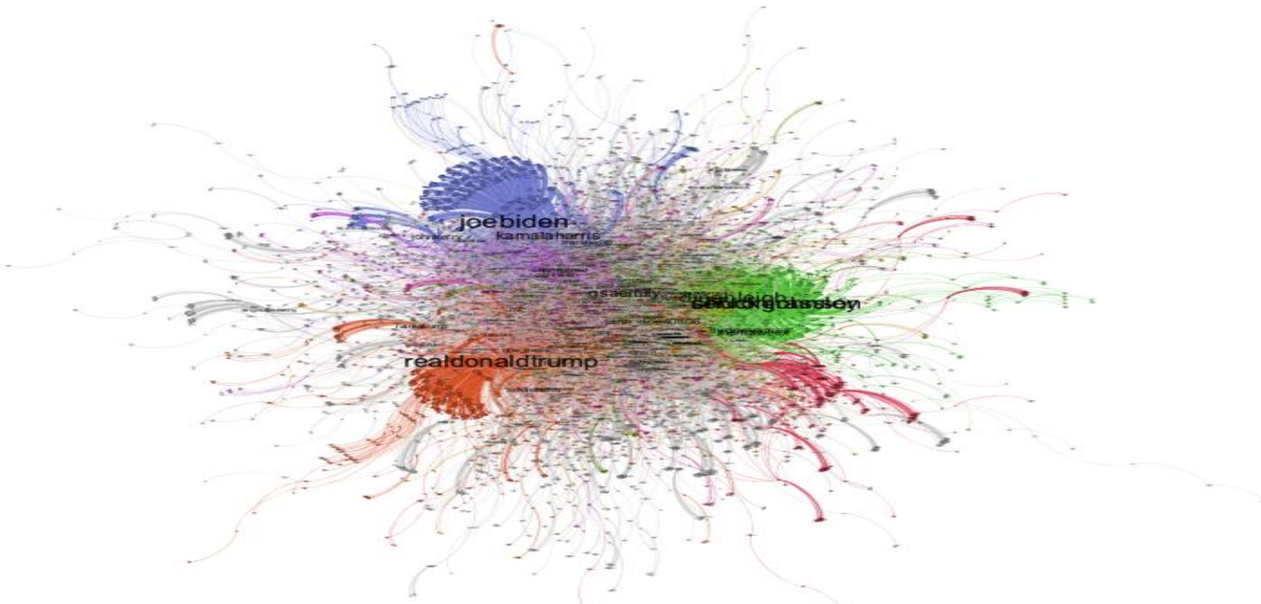
RESULTS

First, this study attempted to figure out the betweenness centrality and the degree of centrality within the networks. Betweenness centrality was used to measure how important a node is to the shortest paths through the network and to capture how important a node is in the flow of information from one part to another in the network (Golbeck, 2013). In this way, Table 1 showed the network properties of both hashtags by using Netlytic. Moreover, the social network data of both hashtags were collected separately by Netlytic for data visualization. In Figure 1, the network graph of both hashtags included 39,341 recorded during November 24 to November 30, 2020 and was summarized into 13,460 nodes and 31,273 directed edges. This graph also showed that there were three major clusters within the network of both hashtags. These clusters were @joebiden, @realdonaldtrump, and @chuckgrassley. Figure 2 indicated the nodes with highest score of betweenness centrality. Betweenness centrality can capture how important a node is in the flow of information within the network. This graph showed three nodes were highly related to the same organization, MyNation, a non-profit organization based in India. Figure 3 demonstrated the nodes with the highest in-degree score within the network of both hashtags. The top five accounts included: @joebiden, @realdonaldtrump, @chuckgrassley, @senronjohnson, and @gsaemily. The higher the degree, the more central the node was. Also, the nodes were the dots that represented tweeters in the online conversation, while edges were the lines that connected nodes and represented some forms of interactive communication, such as retweets or responses.

Table 1. Network Properties of #Election2020results and #BidenTransition

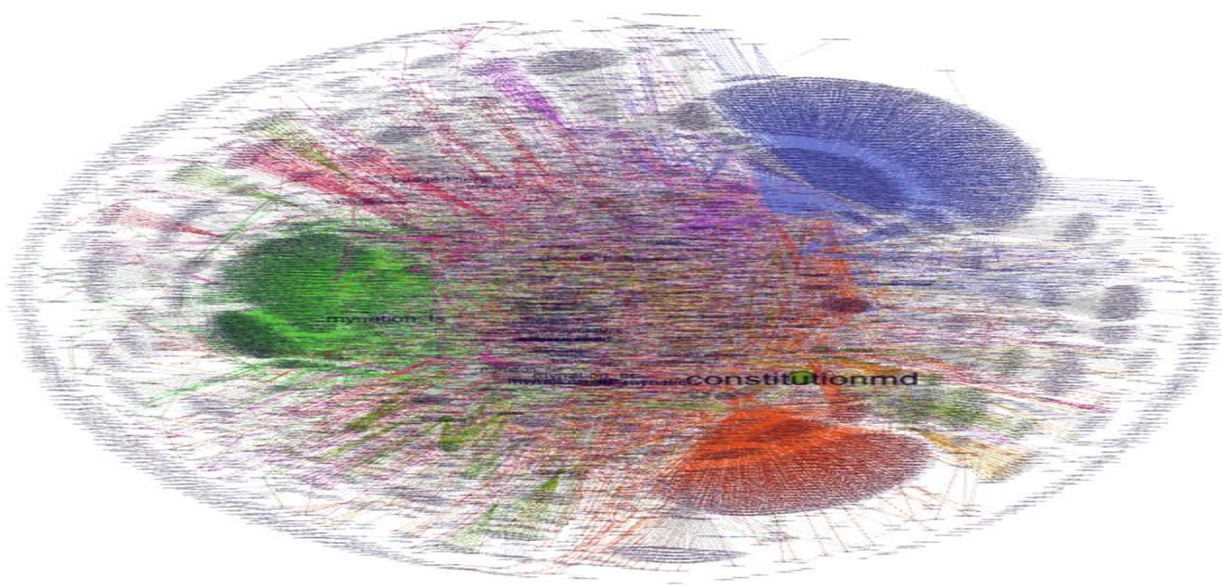
	#Election2020results	#BidenTransition
Diameter	63	32
Density	0.000374	0.000125
Reciprocity	0.002603	0.006616
Centralization	0.119800	0.106300
Modularity	0.768500	0.769700

Figure 1. Network Graph of Both Hashtags



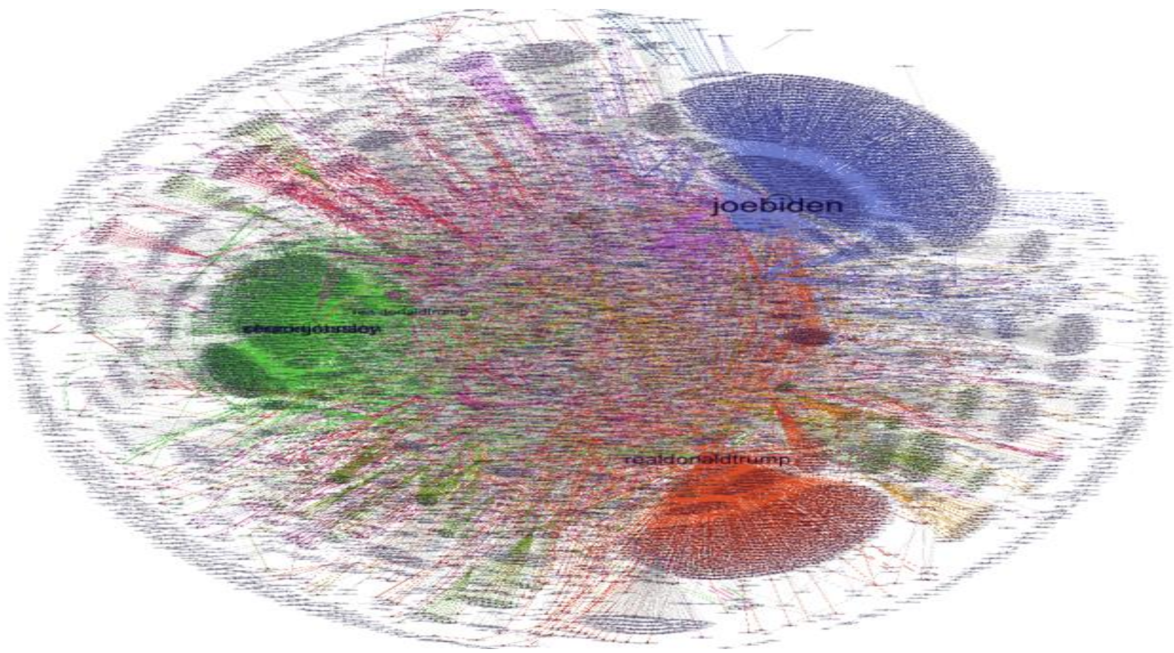
Note. The graph includes 39,341 recorded during November 24th to November 30th, 2020, which was summarized into 13,460 nodes and 31,273 directed edges, indicating three major clusters within the network of both hashtags. These clusters are @joebiden, @realdonaldtrump, and @chuckgrassley.

Figure 2. Fruchterman Reingold Graph for Betweenness Centrality



Note: The nodes with highest score of betweenness centrality that captures how important a node is in the flow of information from one part of the network to another. This graph shows three key nodes are highly related to the same organization— MyNation, a non-profit organization based in India.

Figure 3. Fruchterman Reingold Graph for the Nodes with the Highest In-degree Scores



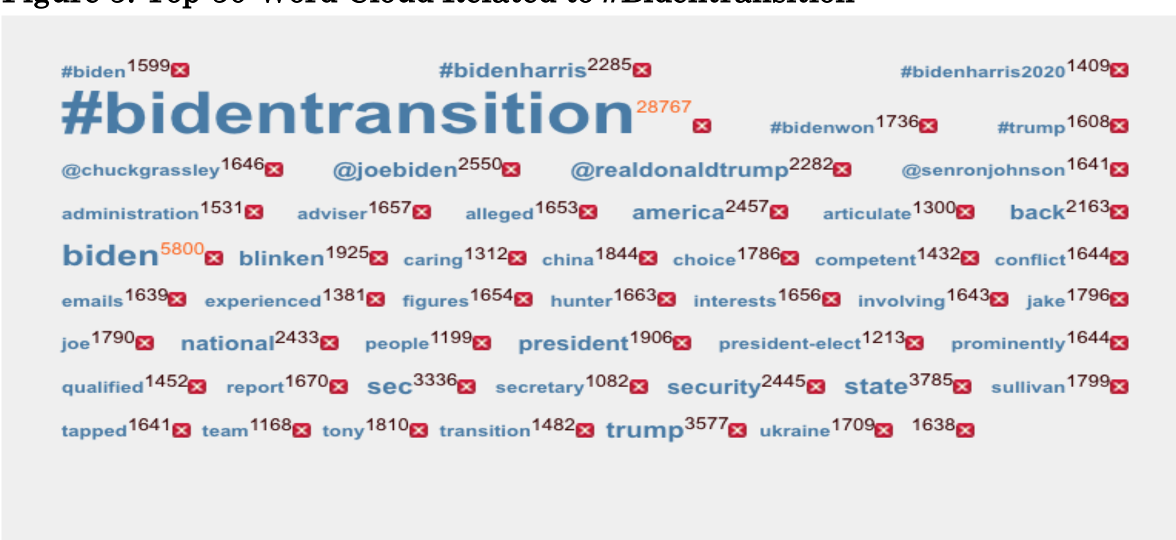
Note. The top five Twitter accounts include: @joebiden, @realdonaldtrump, @chuckgrassley, @senronjohnson, and @gsaemily. The higher the degree, the more central the node is. Also, the nodes are the dots that represent tweeters in the online conversation, while edges are the lines that connect nodes and represent different forms of interactive communication, such as retweets or responses.

Regarding the common themes of both hashtags, the word clouds of Election2020results and #BidenTransition over time were automatically produced in Figure 4 and 5. The automatic representation of word frequency and influential accounts was allowed for early understanding of large data sets. Furthermore, the data of both hashtags collected by Netlytic between November 24 and November 30, 2020 showed that the tweets of both hashtags increased dramatically, indicating a total of 39,341 tweets from both hashtags.

RQ1 looked at the type/mode of the network. Through social network analysis, the results indicated that the type of the network was considered as a polarized crowded network. Smith et al. (2014) stated that polarized networks usually feature two big and dense groups that have little connections between them. The topics being discussed were often highly divisive and heated subjects related to political issues in the election. In this regard, the type of network revealed a slight conversation between these nodes. In specific reference to the findings, tweeters were polarized in the conversation because the issues being discussed were about the two candidates in the presidential election—Donald Trump vs. Joe Biden. Regarding the mode of the network, this study also found that the mode was considered as a multimode network. Tang et al. (2011) stated that a multimode network consisted of heterogeneous types of nodes (users) with various interactions occurring amidst them. The findings showed that the nodes within the network of both hashtags that were more likely to engage came from different places and with different backgrounds, indicating that these hashtags were trending globally not only across the US.

Figure 4. Top-50-Word Cloud for #Election2020results

Figure 5. Top-50-Word Cloud Related to #Bidentransition



The study also identified three major clusters within the networks of both hashtags. As indicated in Figure 1 and Figure 2, these nodes were the dots that represented tweeters in the online conversation. These nodes can also be individual Twitter accounts, organizations, or groups, while the edges were the lines that connected the nodes and represented some form of communication or interaction, such as retweets. Furthermore, @joebiden, the presidential candidate of the election, was the biggest node because he received 2,863 tweets (in-degree) within the network, followed by @realdonaldtrump, 1,785 tweets. In the same regard, @ChuckGrassley, the senator from Iowa, came with 1,639 tweets, and @SenRonJohnson, the senator from Wisconsin, came with 1,636 tweets. Thus, these Twitter accounts within the networks were among the top clusters among the networks of #Election2020results and #BidenTransition.

RQ2 depicted the influential nodes within the networks. A betweenness centrality test was applied by Gephi to capture how important a node was in the flow of information from one part to another in the network. A tweeter with higher betweenness may be followed by others who did not follow the same individuals, indicating that the twitter may have fewer followers, but connect them to many accounts that were otherwise distant or that the twitter was a reader of many people. Based on the social network data, the top 5 nodes (users) had higher scores of betweenness centrality. The first three were shown to have different accounts but belonged to the same organizations—*MyNation.* It was important to mention that MyNation was a non-profit organization in India. As indicated in Table 2, the rank 4 Twitter account was related to FoxNews corporation, while the rank 5 Twitter account belonged to a data analyst and educator.

Moreover, the degree centrality tactic was utilized to explore the nodes who reached the highest degree (in-degree) and lowest degree (out-degree) within the networks. Degree centrality can identify people who can directly reach many other people and show the number of edges and the total of connections (Golbeck, 2013). The higher the number of degrees or edges, the more the central node was. Simply stated, the nodes with higher degrees have higher levels of centrality. Both Table 3 and 4 showed the top five nodes with the highest degree (in-degree) and top five nodes with the lowest degree (out-degree) within the networks. In Table 3, @joebiden received the highest indegree score (2,863), followed by @realdonaldtrump (1,785), @chuckgrassley (1,639), @senronjohnson (1,636), and @gsaemily (576). On the other hand, Table 4 demonstrated that four of the top five accounts—@mynation_ts, @mynation_hr, @mynation_abhi, @mynation_bh—came from the same organization, MyNation, and their out-degree scores ranged from 100 to 125. Both @mynation_abhi and @mynation_bh took the same percentage of 100 out-degree scores, while @mynation_ts received the highest percent of 125 out-degree scores. Moreover, @constitutionmd was ranked the first place with the highest out-degree score.

Table 2. Top Five Nodes with the Highest Scores of the Betweenness Centrality

Rank	User	Followers	Bio	Betweenness Centrality
1	@varadha1978	240	Proud Member of MyNation	2655.759.449
2	@prem_mynation	308	Member of Mynation	2444.259.449
3	@mynation_net	4519	MyNation Hope Foundation is a Registered NGO and Support Group for the Victims of Legal Terrorism, DV, Dowry Law [IPC 498A], and Other Gender biased Laws	2382.333.333
4	@seanhannity	650	TV Host Fox News Channel 9	1334.642.857
5	@silvercan1982	3	Data analyst and educator	1275.333.333

RQ3 looked at the nature of the tweets within the networks. Voyant was used to answer RQ3 because Voyant provided several tools of textual analytics, including word cloud, total words, word forms, most frequently used terms in the corpus for corpora, vocabulary density, and average words per sentence. As a result of the textual analysis of #Election2020results and #BidenTransition, a total of 802,683 words were found, with 47,224 unique word forms, while the vocabulary density was equal to 0.059. Also, the average words per sentence reached 20.5, and the most frequently used word was Bidentransition (21,571).

Table 3. Top Five Nodes with the Highest Indegree Scores

Rank	User	Followers	Bio	Indegree Score
1	@joebiden	20.8M	President-elect, husband to @DrBiden, proud father & grandfather. Ready to build back better for all Americans.	2863
2	@realdonaldtrump	88.6M	45th President of the United States of America	1785
3	@chuckgrassley	685.2K	U.S. Senator. Family farmer. Lifetime resident of New Hartford, IA. Also follow @GrassleyPress for news and information.	1639
4	@senronjohnson	177.2K	Proud to serve Wisconsin in U.S. Senate. Chair of Homeland Security and Governmental Affairs Committee & Subcommittee on Europe & Regional Security Cooperation.	1636
5	@gsaemily	38.1K	Administrator of @USGSA. Delivering the best value in real estate, acquisition and technology services to government and the American people.	576

Table 4. Top Five Nodes with the Highest Outdegree Scores

Rank	User	Followers	Bio	Outdegree Score
1	@constitutionmd	6407	#StopTheSteal #MAGA	220
2	@mynation_ts	314	My Nation - Telangana Official	125
3	@mynation_hr	588	We are group of fighters who are fighting the biased law system create by government of India	102
4	@mynation_abhi	603	Member of MyNation	100
5	@mynation_bh	1042	My Nation - Bihar Official	100

Additionally, there were approximately 50% of tweets (15,032 out of 39,341 tweets) posted with other links, indicating that tweeters within the networks offered their political insights with additional sources, such as videos, articles, pictures. Several significant keywords in the contexts were appeared from the textual analyses. Table 5 showed that these words included: America (2,575); Back (2,144), and Choice (1,782) and reflected that these tweets in both hashtags focused on the facts about the election results. For example, *"America is back to normal! a lot of work to fix the mess Donald trump left us" Also, "There will finally be adults back in the house".*

Table 5. Most Frequently Used Keywords in the Contexts

America (2,575)		
The reality of his administration.	**America**	Has Made A Great Decision
Said a little while ago,	**America**	is back #BidenTransition #BidenHarris 2020 https
Their sick hatred of all	**America**	-loving #Patriots. #Election 202results RT @producerilene
You're getting out. That's' all	**America**	Cares about. #BidenTransition #TrumpisPathetic RT
Intellect, experience, commitment to all	**America**	, plans and FACTS are things
Back (2,144)		
There will FINALLY be adults	**back**	in da HOUSE…integrity, dignity
Patriots, science and frankly adults	**back**	into government @TheDemCoalition
Still, we have the adults	**back**	and moving into power to
Happy to see the adults	**back**	in the room #BidenTransition RT
Lovely to welcome the adults	**back**	into the room #BidenTransition @tedlieu
Choice (1,782)		
A coup. You made your	**choice**	; party over country/Trump over
Can prove… Dude, it's your	**choice**	, but Mr. Biden can arrange
Or leave it. It's your	**choice**	#Reparations #BidenTransition @martin…
DiaperDonald #BidenTransition https:/…	**choice**	for news? TheMandalorian #TrumpPat…
It didn't align with your	**choice**	. But it is what it

DISCUSSION

The purpose of this study was to provide a social network analysis of the two selected hashtags: #Election2020results and #BidenTransition. It also aimed to investigate how tweeters used these two hashtags to interact with each other in their social networking activities by using Netlytic, Gephi, and Voyant. Based on the results of this study, tweeters were divided in the content they shared due to the political opposition comprised of the two most popular candidates in the 2020 presidential election: Joe Biden and Donald Trump. Back to what Smith et al. (2014) addressed, the study was in line of the definition that polarized networks usually featured two big and dense groups with very little connections between them. Moreover, during the presidential election, several political issues being discussed were often highly diverged (e.g., COVID-19, Immigration, Climate Change, Racial Justice, and Foreign Policy). The polarized networks offered some clear evidence that Americans' political views were very divided from the network structures. The findings also suggested three major clusters within the networks that mostly focused on Biden, Trump, and other few American senators, but their connections were not observed, indicating that both Biden and Trump supporters were rarely interactive on Twitter and their information flow only existed within their own clusters.

Regarding betweenness centrality, betweenness centrality can capture how important a node was in the flow of information from one part of the network to another, and betweenness centrality was a way of detecting the number of influential nodes over the flow of information in a graph (Golbeck, 2013). The study found that top three nodes related to both #Election2020results and #BidenTransition belonged to the same organization—MyNation. MyNation was a non-profit organization based in India. As discussed previously, tweeters with higher scores of betweenness centrality generated a greater influence on the flow of information. There was no doubt that these three Twitter accounts managed by people in India were more likely to control the flow of information related to #Election2020results and #BidenTransition. Several studies confirmed that the power of Twitter in setting agendas for the publics (Conway et al., 2015), leading public opinion about key issues (Cody et al., 2015) and affecting voting behavior (Karami et al., 2018). In this regard, manipulating Twitter accounts to set political agendas may indirectly lead public opinion in the post-election transition in the US. Thus, it was important to prohibit the network of online participants spreading false or misleading information during elections. Policymakers should attempt to regulate some kinds of interventions that can stop foreign tweeters to get involved in the domestic affairs in order to prevent any political controversies before, during, and after elections.

Furthermore, in-degree centrality was used to explain tweeters with more influences to receive many edges from others in their social networks. The study found that both @joebiden and @realdonaldtrump managed separately by Biden's social media team and Trump's social media team received the highest scores of in-degree centrality, indicating that the supporters of both sides attempted to connect to their presidential candidates and express their supports in the post-election transition when they tagged #Election2020results and #BidenTransition. Specifically, it was clear that tweeters who tied to @joebiden were more active than those who connected to @realdonaldtrump as @joebiden had more ties from its supporters than @realdonaldtrump. In line with social network theory (Hansen et al., 2020), @joebiden can be viewed as the most prominent conversational hub since @joebiden gained most engagements in its tweets and most people frequently mentioned, replied to, or retweeted its posts in the post-election transition.

Regarding out-degree centrality, tweeters with higher scores of out-degree centrality were more likely to exchange with others, or disperse information quickly to many others. Simply stated, those with higher outdegree centrality can be characterized as influential in their social networks (Hansen et al., 2020). The study found that the most influential twitter was Trump's supporter with the bio of #StopTheSteal, while other top four tweeters who were identified as key social network influencers were all from MyNation based in India. Indeed, #StopTheSteal was created by Trump's supporters to overturn the presidential election. However, it can be assumed that some foreign tweeters also attempted to deliver different kinds of information (including both true and false) to others when these top tweeters with higher out-degree centrality were not from the US.

In terms of textual analyses, the study found that the majority of tweeters within the networks of #Election2020results and #BidenTransition mentioned Joe Biden more positively than Donald Trump. The word—Bidentransition was repeated mostly frequently (21,571 out of 39,341 tweets) within the networks and the majority retweeted their ideas to support Joe Biden. There was also evidence that most tweets that included the most-frequently used keywords, including America, Back and Choice, were very positive about the result of presidential election, but relatively negative about the presidency of Donald Trump in the post-election transition.

Some limitations emerged from this study. The collection of the data was conducted on a period from November 24 to November 30, 2020. However, January 20, 2021 was the date that Joe Biden officially took office as the president in the United States. The data from December 1, 2020 to January 19, 2021 was not included in this social network analysis. As multiple political crises related to the presidential election were emerged before Biden's inauguration (e.g., Trump granted clemency to 143 people, Trump denounced violence in his farewell address, and 12 National Guard members were taken off inauguration duty after vetting), tweets related to these political crises may also affect social network structures of #Election2020results and #BidenTransition. Another limitation was that the study only analyzed social networks of #Election2020results and #BidenTransition that may be positively related to Biden's defeat of Trump, but did not examine other hashtags created by Trump's supporters (e.g., #StopTheSteal). Future studies may look at some hashtags created by the supporters of both sides in order to compare how their social networks were manipulated by key tweeters, both domestically and internationally.

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