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Fake News Conversation Network in Twitter: User Type, Emotional Appeals and Motives in Network Formation

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"Fake news" is nothing new but a type of yellow journalism. Since the 2016 U.S. presidential election, people became more concerned about the spread of fake news on the internet. The hashtag #fakenews has become one of the trending issues among social media conversationalists. The aim of this paper was to conduct a rhetorical investigation on the underlying motives (i.e., affiliation, achievement, power, reward, and risk) and sentiments (i.e., positive and negative) of messages containing #fakenews in Twitter. The paper also examined how the underlying sentiments and motives of such conversations are different from those of other general conversations on Twitter. Using NodeXL 11072 tweets, results analyzed via LIWC software showed all motives and sentiments differed significantly from the LIWC norms for Twitter text. All motives (except risk) were below the LIWC Twitter norms, suggesting that #fakenews conversations were driven by risk-focus, an overarching dimension that referred to dangers, concerns, and things to avoid (Pennebaker, Boyd, Jordan, & Blackburn, 2015), more frequently than other general conversations in Twitter. Insights and results from this study will significantly add value to the current continuing scholarly and practical works on the audience's reactions and concerns regarding the deflation of yellow journalism.

Keywords: fake news, social network analysis, LIWC, sentiment analysis, Twitter

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"Fake news" is conceptualized as "distorted signals uncorrelated with the truth" (Allcott & Gentzkow, 2017, p. 2). Since the wake of the 2016 U.S. presidential election, people have raised serious concerns about the spread of fake news on the internet (Kucharski, 2016; Mele et al., 2017). The virality of forged stories like "pizzagate" regarding hiding a child prostitution sphere under a pizza restaurant concerned both civic and expert society (Kang & Goldman, 2016).

Reasons for such concerns are apparent, as fake news, for example, can deviate people from shared reality (Benkler, Faris, Roberts, & Zuckerman, 2017; Lazer et al., 2018), inject discriminatory and inflammatory ideas in public discourse, normalize prejudices, catalyze and justify violence (Greenhill & Oppenheim, 2017), etc. Pew Research Center revealed that almost two-thirds of U.S. adults are anxious about the impact of fake news on their lives, as forged information and stories create a great deal of confusion about the basic information of current issues and events (Pew Research Center, 2016). It is not surprising that “fake news” or #fakenews has become one of the trending issues among social media conversationalists.

The significance of fake news issues leads us to several research-worthy yet unanswered questions (Dorf & Tarrow, 2017): who are the people talking about fake news? Are elite entities (e.g., CNN, *The New York Times*) more (or less) influential than ordinary people in such conversation? What type of emotions and motives are they expressing? How connected are these people? Are people with similar status and expressing similar motives connected more? The objective of the current study was to investigate these questions in the Twitter platform via a social network analysis perspective. Insights and results from this study will significantly add value to the continuing scholarly and practical works on the audience’s reactions and concerns regarding the deflation of fake news or yellow journalism. Any differences and/or similarities between the structural pattern of people’s behavior will provide the basic groundwork for future researchers in this field (Adamic & Glance, 2005). Further, the study can potentially contribute to the premise of analyzing the diffusion of fake news.

LITERATURE REVIEW

Social media allowed us to generate timely, interactive conversations (Liu, Austin, & Jin, 2011). Both individuals and institutions have increasingly turned to microblog site Twitter, particularly for initiating and engaging in “a real-time information network that connects [users] to the latest stories, ideas, opinions, and news about what [they] find interesting” (Wasike, 2013, p. 8). Analyzing Twitter conversation data on a vibrant national issue like fake news, thus, makes sense (Berkowitz & Schwartz, 2016). First, the study examined what type of emotional appeals and motives were expressed by people while talking about fake news on Twitter. Next, the study analyzed who plays a central role in the conversation. Finally, the structure of the fake news conversation network or topic network on Twitter was analyzed.

Emotional Appeals and Motives

The study first investigated how fake news conversationalists expressed their emotions and motives via tweeted text compared to general Twitter conversations. Conversation in tweets can be considered a statement in which a conversationalist posits a specific view about a topic by using particular emotion and motive (Kim & Hovy, 2004). Emotion is generally referred to as "any mental experience with high intensity and high hedonic content (pleasure/displeasure)" (Cabanac, 2002, p. 69). Based on the level of emotional valence, i.e., intrinsic attractiveness and averseness of an event, object, or situation, emotions can be broadly categorized as positive (e.g., joy) and negative (e.g., anger, fear). However, such a complex state of experience or feeling (either positive or negative) usually results in physical and psychological changes in people influencing their thoughts and behaviors (Myers, 2004). The current study, particularly, examined how emotional appeals, as a rhetorical instrument, were displayed by Twitter users.

Users' motives, on the other hand, were the next concept to analyze. The seminal work of McClelland (1975) on need theory suggested that there are mainly three types of motivations that drive people regardless of their gender, age, religion, ethnicity, race, or culture: achievement, affiliation, and power. Achievement motive refers to the extent to which people desire success and challenge and for mastering the skills and standards that are important to them (McClelland, 1975). On the other hand, the affiliation motive focuses on the extent to which people want to create and maintain social relationships (McClelland, 1975). Finally, power motive drives people to enjoy dominance, status, and prestigious position in the social hierarchy (McClelland, 1975). In addition to McClelland's explanation, two more motives were later added by researchers: risk and reward motives (see Pennebaker et al., 2015). Whereas risk is an overarching dimension that referred to dangers, concerns, and things to avoid, the reward is based on positive inducements (Pennebaker et al., 2015). Capturing users' emotions and motives will better understand public concerns regarding fake news (Balmas, 2014). Therefore, the study posed the following research question:

RQ1. What type of emotional appeals and motives will dominate the fake news topic network?

Media Elites vs. Average Public

The study examined how two broad categories of Twitter users (average users and elite users) discussed this topic on Twitter. Rafter (2014) identified the emergence of three types of media elite or pundits based on earlier research. First, "someone of great learning with authority to give opinions" is considered elite due to their credibility and/or authority (Salwen, 2000, p.162). The second type of elite involves the star or celebrity pundits who are defined less by their know-how on a particular topic but by their ability to engage in "provocative, [and] deliberately inflammatory expressions of opinion" (McNair, 2012, p. 65). Finally, journalist experts are considered the third group of media elites or pundits (Rafter, 2014). One way to identify such eliteness in Twitter is via the "verified" status of the account (Grabowicz, Babaei, Kulshrestha, & Weber, 2016). Twitter proactively verifies accounts of public interest and then provides a "badge" in Twitter's interface to show the authentication. Companies, news media outlets (both legacy and online media), opinion leaders, government, politicians, celebrities (actors, sports figures, etc.), and other key interest figures comprise most verified accounts (Gayo-Avello, 2013). Usually, verified accounts have a higher number of followers, and they also follow more people than average users (Gayo-Avello, 2013). They also tweet and retweet more than average users (Gayo-Avello, 2013). Therefore, verified users get much more involved in conversations than any other group of users (Gayo-Avello, 2013).

Regarding the topic of fake news, everyone is talking on Twitter. Are elites (or the average public) playing a central/influential role in the conversation? From a social networking perspective, central or influential actors within a network are well connected to other actors (Kadushin, 2012). An actor's centrality portrays an image of importance, authority, or relevance (Kadushin, 2012). To examine who dominates the fake news conversation network on Twitter, the current study posed the following research question:

RQ2. What type of users will play a central role in the overall fake news topic network?

Social Network Structure

The study looked at the underlying structure of fake new conversation networks. In particular, the question of how elites and average users are engaged in this topic remains unanswered. Connections between actors can be examined via the social network analysis technique. Social network analysis is a sociological approach that considers social network "a finite set or sets of actors and the relation or relations defined on them" (Wasserman & Faust, 1994, p. 20). In the fake news topic network analysis, individual Twitter users are actors (e.g., discrete individual, corporate, or collective social units) or nodes in a network (Wasserman & Faust, 1994). The relational ties between such Twitter actors can be established by many factors, such as who is following whom, who is retweeting/ mentioning whom. To determine the engagement between actors in a topic network, it makes more sense to analyze who is replying to whom (Cha, Haddadi, Benevenuto, & Gummadi, 2010). This aspect can be explored via examining homophylic sub-networks within a network (Lee, Kim, and Piercy, 2019). Homophily provides a basic underlying structure of human relationships. Homophilic attributes (e.g., gender, income, etc.) connects similar entities (McPherson, Smith-Lovin, & Cook, 2001). "Similar others are particularly persuasive in determining adoption of new products, norms, and ideas" (Lee et al., 2019, p. 213). The study examined whether these actors are talking or replying within homophylic groups (or making inter-group connections), whether actors who expressed the same kind of status or motive belong to the same group, how different actors are distributed in the emotion/motive sub-network, how connected and extensive the networks/subnetworks are, etc. In this regard, the following research question was posed:

RQ3. What will be the structure of the fake news topic networks based on (a) user type and (b) motives?

METHODS

Data Collection

Given the paper's interest in understanding the topic network of fake news conversations on Twitter, 20,108 tweets were generated via NodeXL (Smith et al., 2010), an open-source Microsoft Excel-based software to analyze and visualize networks. NodeXL also allows researchers to download attributes about nodes (e.g., number of follower/following, location, pictures, account verification status, etc.) and posts (e.g., the date/time, number the post is "favorited" or "re-tweeted"). Regarding this study, tweets originating during a period of six months before and after the 2016 U.S. election were generated. This time frame was methodologically appropriate, as it attracted the attention of the fake news conversationalists the most on Twitter (Mele et al., 2017). Topic-network of fake news conversation was developed by using "fake news" or "fakenews" (or the combination of both) as keywords to search related messages. In addition, as mentioned earlier, the eliteness of the account was determined by checking whether the accounts were verified by Twitter (Grabowicz et al., 2016). The number of verified account was 841, while the number of average users' account was 14,266.

Analyzing Emotional Appeals and Motives

To address RQ1 concerning the emotional appeals and motives underlying Twitter text, the study used the Linguistic Inquiry and Word Count (LIWC) program, a text analysis program based on a dictionary-based approach (Tausczik & Pennebaker, 2010). LIWC has been developed and frequently authenticated over three decades (Tausczik & Pennebaker, 2010). The in-built dictionary (or customized dictionary) of LIWC labels different functional words in texts into various socio-psychological features. Then, report the word percentage in the texts analyzed corresponding to that category or segment (Tausczik & Pennebaker, 2010). The present study utilized two LIWC features: emotional appeals (positive and negative emotions) and motives (affiliation, achievement, power, reward, and risk motives). Completed LIWC data sets, they were combined to NodeXL file to make further analysis of network structure. Emotion and motive scores were added as vertex (node) attributes in the NodeXL file. However, it should be noted that text analysis was done only on 4,535 unique tweets, removing duplicate tweets or retweets.

Network Variables and Measures

Defining nodes and ties. Each actor taking part in the conversation was treated as a node. There were 14,154 actors or nodes in our topic network. NodeXL, by default, offers several kinds of relationship status for Twitter, e.g., tweet (self-tie), "mentions" other nodes or "replies to" other nodes. To establish a relational structure, this study proposed that a tie in the network would be established only when the action of "replies to" or "mentions" take place between actors, as one can join conversations on Twitter either by replying to others or by mentioning them in one's own tweets (Twitter Help Center, n.d.). These relations indicate the attractiveness of the tweets and actors as well as the activeness and engagement of the actors on Twitter (Wasike, 2013). The number of unique ties in our topic network was 20,827.

Centrality. To address RQ2, a node-level network analysis was needed. NodeXL accessed central positions in the overall topic network to generate three types of centrality scores: degree, betweenness, and eigenvector closeness. The total number of connections that a node has is known as degree (Kadushin, 2012). In a directed network, which is the case in this study, indegree centrality was indicated by the number of "replies" or "mentions" actors get in their posts and outdegree centrality, on the other hand, was presented by the number of "replies" or "mentions" actors make to other's posts. High out-degree indicated actors' activeness to reply (talkback) than other actors in the network. According to Hanneman and Riddle (2005), actors with more in-degree can "be prominent" or to have "high prestige." In the case of this study, high in-degree indicated actors' capability to attract more people to take part in their fake news conversation. Actors with high in-degree may not necessarily be the most likable persons in the network, but their discussions, for some reason, may generate more replies (e.g., in the form of criticism).

Next, betweenness centrality focuses on how a Twitter user falls on the shortest paths between other ties (Kadushin, 2012). The high betweenness score of actors indicated that the actors' positions in the topic network are likely to generate more conversation. They connect two otherwise distant actors talking about the same issue. Such brokerage roles of the actor with high betweenness scores may significantly contribute to the quality of the conversation. Finally, closeness centrality indicates the distance of Twitter users to all others in the network, considering the distance from each user to all other users (Hanneman & Riddle, 2005). The current study used the eigenvector closeness centrality, which examines the most central actors, who have the smallest farness from others, in the overall structure of the network (Hanneman & Riddle, 2005). In the current study, a high eigenvector score showed how the central actors could connect indirect actors in the same topic network.

Network structure. The study generated clusters based on three types of actor attributes, i.e., actor type, emotion, and motive. In a network, clusters are referred to as subsets of nodes within which the interconnectivity or density is high, whereas connections between these clusters are sparse (Newman, 2004). The topic network structure was examined via NodeXL based on the size, density, geodesic distance, modularity, and subcomponents of the clustered networks, answering RQ3 (Himelboim, Smith, Rainie, Shneiderman, & Espina, 2017). The size of the network is defined by the number of edges or ties in each network (Xu et al., 2016). A more extensive network indicated that the actors were replying to each other's posts more. Density means how many ties can be formed considering the number of all possible ties (Kadushin, 2012). High density in an actor-based cluster, for example, indicated a higher proportion of connectivity among actors.

Next, geodesic distance is the shortest path between two nodes (McPherson et al., 2001). Low geodesic distance shows communication efficiency – the fewer the nodes involved in communicating, the quicker information moves through the network (Miranda, 2019). Modularity is defined as the extent to which the network comprises components within which dense connections take place but across which connections are thin (Newman, 2006). A network within which all nodes within each cluster was connected to every other node. No node related to a node in another cluster will generate a perfect positive modularity score (Miranda, 2019). Negative modularity, on the other hand, presents more cross-cluster ties than within-cluster ties. As a result, negative modularity may not grasp the true nature of the network (Miranda, 2019). High modularity in an emotion-based cluster, for example, indicated that people with positive (or negative) emotions are highly replying to each other's post but ignoring replying to post with a different emotion. Next, the subcomponent analysis of each attribute-specific clustered network revealed subnetworks (Xu et al., 2016). This analysis allowed us to see the number of actors, the number of subcomponents, and the density of the subnetworks (e.g., subnetwork with negative emotion vs. positive emotion) within each clustered network.

To sum up, network structure analysis showed us whether the actors were talking or replying within their own small groups (or making inter-group connections), whether actors who expressed the same kind of motive belonged to the same group, how different actors were distributed in the user/motive sub-networks, how connected and large the network/subnetwork were, etc. Overall, structural features revealed how different actors and motives developed a topic network of fake news conversations.

RESULTS

RQ1: Emotions and Motives

Research question 1 focused on the uses of emotions and motivations in tweets. Regarding these two components, the study compared LIWC norms for tweets (Pennebaker et al., 2015) and the average usage within our sample to examine whether fake news conversationalists used emotions and motives differently. Table 1 presents a summary of the results. Results show that all motives and emotions varied significantly from LIWC norms. All motives, except for risk, were below the LIWC Twitter norms. In addition, fake news conversationalists used positive emotion less frequently, while they expressed negative emotions more frequently than the general public. An overall network graph is presented in figure 1 to show the emotions between users.

Table 1

Summary of Motives and Emotions Used

Motives and sentiments	Sample (n=4535)		LIWC Norms		Difference	
	Mean	SD	Mean	SD	*t*(df)	Sig.
Motives						
Affiliation	0.87	2.30	2.53	1.28	*-48.72*(4534)	.000
Achievement	0.68	1.97	1.45	0.82	*-26.51*(4534)	.000
Power	1.87	3.41	2.17	1.12	*-5.89*(4534)	.000
Reward	0.63	1.91	1.86	0.81	*-43.38*(4534)	.000
Risk	0.49	1.72	0.46	0.41	*1.*20(4534)	.023
Emotions						
Positive	1.84	3.59	5.48	1.63	*-68.30*(4534)	.000
Negative	8.64	6.37	2.14	1.09	*68.72*(4534)	.000

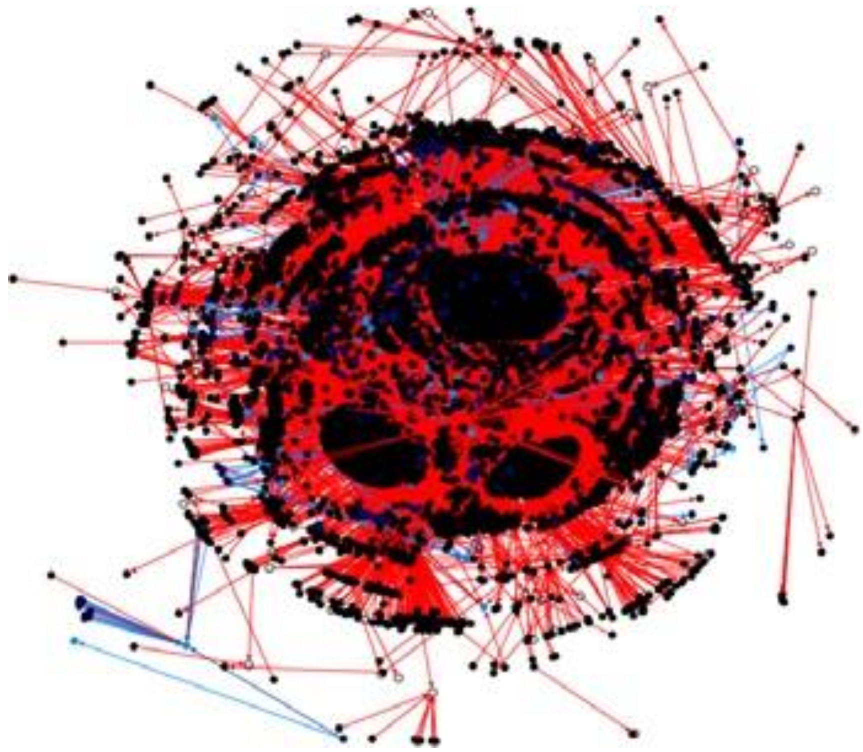

Figure 1. Fake News Topic Network (Blue and red lines indicated positive and negative emotions respectively in the ties. Here circle and disk shapes of nodes indicated unverified and verified accounts)

RQ 2: Influential Users

For RQ2, four different centrality scores (in-degree, out-degree, betweenness, and eigenvector) were calculated. Except for out-degree scores, the remaining three centralities indicate that verified or elite users dominated the conversation. Tables 2a and 2b present the summary of the top ten centrality scores. In the case of in-degree, elite or verified users dominated the conversation; they got more replies and/or mentions in other's post. Elite users also had a higher betweenness score, indicating that they more frequently connected two otherwise disconnected users in this conversation. In addition, elite users had the smallest farness from others. It should be noted that Donald J. Trump scored the highest score in all centrality scores. Three legacy news organizations, *Washington Post*, *The New York Times*, and CNN, also appeared as dominating actors in the conversation. On the other hand, average users dominated the conversation as they made replies or mentioned others more than the elite or verified users.

Table 2a

Top Ten Users by Degree Centrality

Twitter account	Type	In-degree	Twitter account	Type	Out-degree
Donald J. Trump	Verified	2443	Hariom Singh Rawat	Not Verified	24
Brian J. Karem	Not Verified	1765	s.a.prajapati	Not Verified	24
Caroline O.	Not Verified	1256	MIAMI/FLORIDA/TRUMP	Not Verified	20
Washington Post	Verified	1126	Hindu Defence Union	Not Verified	19
The New York Times	Verified	1040	Wendy DuBrow	Not Verified	17
CNN	Verified	547	Corryn us	Not Verified	16
George Takei	Verified	542	BlackCovfefe	Not Verified	16
Jim Acosta	Verified	392	ira	Not Verified	15
Mike Cernovich	Verified	385	Lyin'LibPressSlam	Not Verified	15
The Columbia Bugle	Not Verified	364	DeplorableKatwood	Not Verified	15

Table 2b

Top Ten Users by Betweenness and Eigenvector Centrality

Twitter account	Type	Betweenness	Twitter account	Type	Eigenvector
Donald J. Trump	Verified	59135993.008	Donald J. Trump	Verified	0.014
Brian J. Karem	Not Verified	41945660.327	Washington Post	Verified	0.009
Caroline O.	Not Verified	30245746.480	The New York Times	Verified	0.008
CNN	Verified	14381132.631	CNN	Verified	0.001
George Takei	Verified	11337748.104	Corryn ᴜᴜᴜᴜ	Not Verified	0.001
Washington Post	Verified	9538386.710	Mike Cernovich	Verified	0.001
The Columbia Bugle	Not Verified	8749076.278	TwitlerTweets	Not Verified	0.001
Jim Acosta	Verified	7492036.079	cx	Verified	0.001
Mike Cernovich	Verified	6810131.750	Jim Acosta	Verified	0.001
Wendy DuBrow	Not Verified	5885193.278	Jim	Not Verified	0.001

RQ 3: Network Structure

Table 3 shows a summary of the network structure of user-based and motive-based based clustering. Graph modularity based on user type is -0.125831, suggesting verification or eliteness played a role in the conversation fault lines. But, it also indicated that there were more cross-cluster ties than within-cluster ties, as the score is negative. Graph modularity based on motive was also higher (0.256491) than the user-based clustering, suggesting reason played a role in the conversation clustering. However, the average geodesic distance and graph density scores were similar for both clusters. While lower density indicated less connectedness of users in the subnetworks, the more downward geodesic distance indicated that connections via replies were faster within the sub-networks: figures 2a and 2b present the networks.

The results for the number of ties in each subnetwork of user-based clustering show that unverified users were more likely to induce conversation than the verified users. But both user groups had a low-density score, indicating that only a small number of users in both categories influenced conversation. The results for the number of ties in each subnetwork of motive-based clustering show that users with mixed and power motives were more likely to generate discussion than users with other motives. Based on the size of subgroups, users with power motive, followed by users with affiliation, reward, achieve, and risk motives, respectively, induced conversation. Although users of achievement and risk motive were the smallest subnetworks, they had relatively higher density scores than users with other motives. It should be noted that the most influential elite user of fake news topic network, President Donald J. Trump, belonged to the power-driven subnetwork (Figure 2b).

Table 3
Summary of Fake News Topic Network Clustering

Individual Graph Matric				Overall Graph Metric			
Clustering	Geodesic Distance	Size of subgroups	Density	Average Geodesic Distance	Graph density	Modularity	Average subgroup size
User-based	-	-		4.343624	0.000111146	-0.125831	2359
Unverified	4.626	13329	0.00	-	-	-	
Verified	3.406	825	0.00	-	-	-	
Motive-based	-	-		4.343624	0.000111146	0.256491	7077
Mixed	6.053	6556	0.000	-	-	-	
Power	3.906	3510	0.000	-	-	-	
Affiliation	3.789	3232	0.000	-	-	-	
Reward	1.616	403	0.000	-	-	-	
Achieve	2.543	271	0.002	-	-	-	
Risk	1.179	182	0.001	-	-	-	

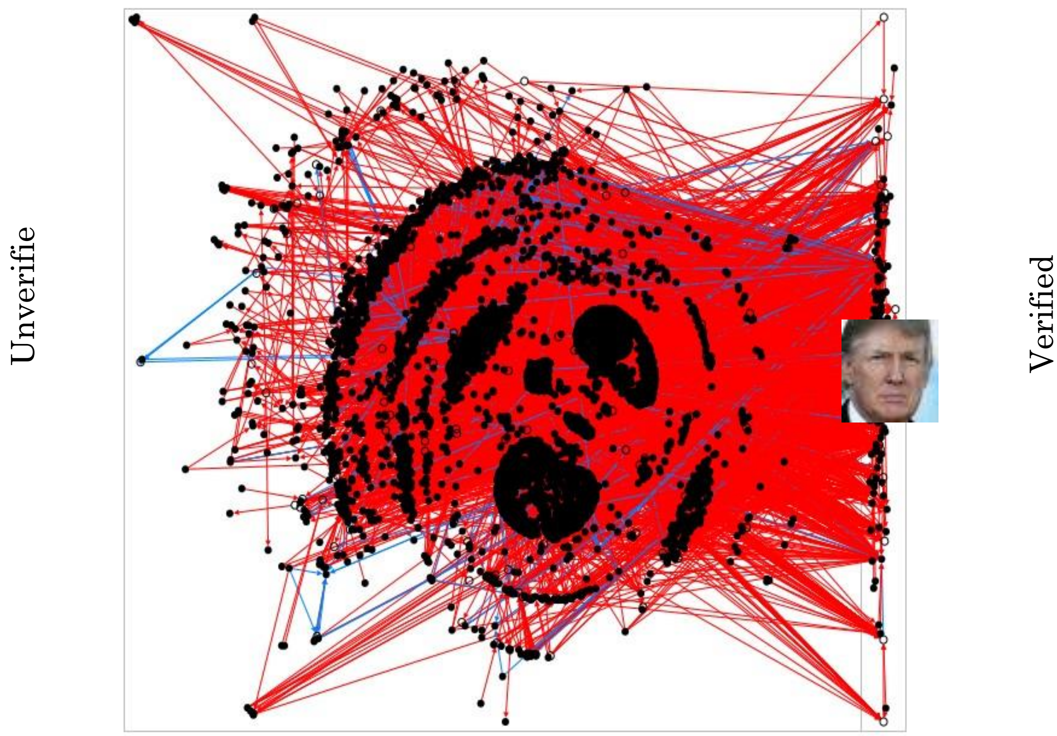

Figure 2a. Fake News Topic Network based on User Type clustering (Blue and red lines indicated positive and negative emotions respectively in the ties. Here circle and disk shapes of nodes indicated unverified and verified accounts)

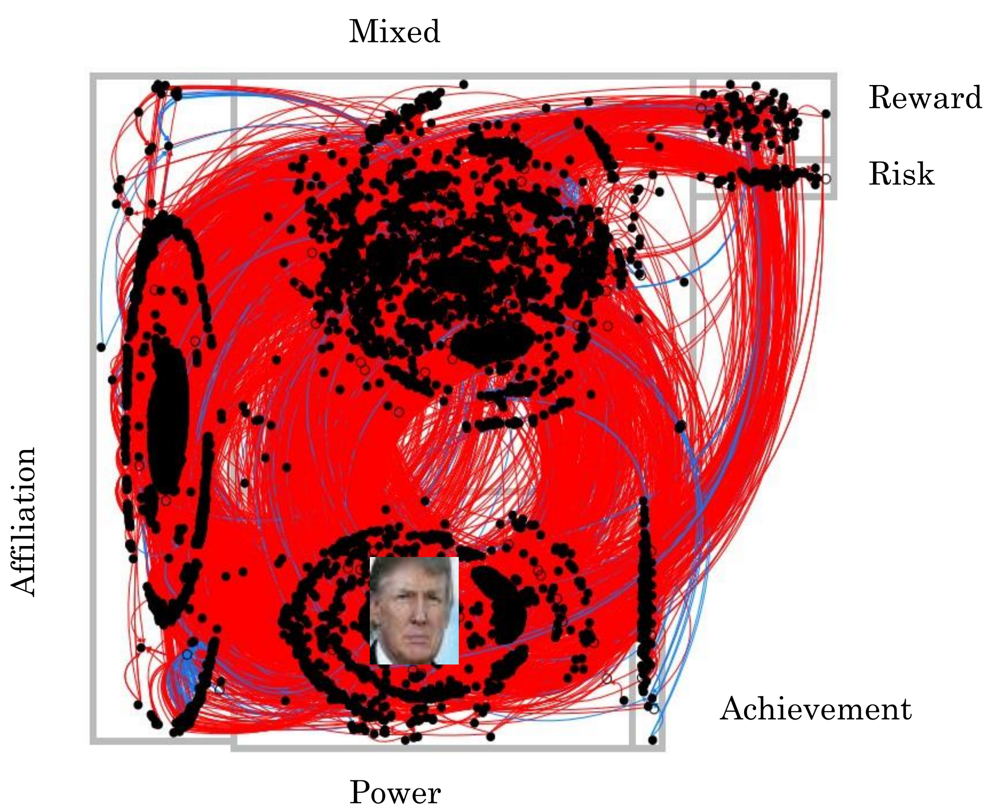

Figure 2b. Fake News Topic Network based on Motive clustering (Blue and red lines indicated positive and negative emotions respectively in the ties. Here circle and disk shapes of nodes indicated unverified and verified accounts)

DISCUSSION

Analysis of conversation on a negative issue like fake news needs special attention. Researchers should focus beyond who is talking and why and how they are talking, and how they talk to each other. A network analysis method thus can add value. This study first reveals the emotional and motivational aspects of tweets related to fake news conversations. Next, the research conducted a node and network-level analysis to find out who are the influential people in this network and how user-based and motive-based subnetworks were formed to understand the structural aspects better.

All motives (except risk) were below the LIWC Twitter norms, suggesting that fake news conversations were driven by risk-focus more frequently than other general conversations on Twitter. Risk-focused motivation is an overarching dimension that referred to dangers, concerns, and things to avoid (Pennebaker et al., 2015). While discussing the topic of fake news, people's risk-focused motivations make sense. Fake news itself is a detrimental issue, and no one wants to be a consumer or victim of fraudulent, which, in a broader sense, can create social chaos via confusion (Allcott & Gentzkow, 2017). Therefore, the topic of fake news might have received more public concern than any general topic on Twitter. In line with this finding, the study also showed that people used more negative emotions while talking about fake news than talking about any other issues on Twitter. Twitter users' concern and negative emotion thus can be indirect signs of social grievance against fake news.

Fake news conversation remained primarily inspired and influenced by the Twitter elites, particularly by politicians and legacy media. They played central roles in attracting others to talk back to their comments and participate in this conversation. As their posts attracted more and more responses, the network grew. Their positions were favorable to exercise influence or power over others, as other actors may depend on their part to make connections to the rest of the network (Hanneman & Riddle, 2005). Unlike elites, ordinary people were more engaged in replying to other's posts. Therefore, elites were influential due to their attractiveness, whereas ordinary people were influential due to their activeness. This overall scenario indeed is a common social media phenomenon, where the "rich get richer." In social media networks, the distribution of ties generally follows a power-law function (also known as a long-tail distribution) due to preferential attachment, which is defined as "individuals' preference for affiliating with those rich in social ties" (Miranda, 2019, p. 94). Some accounts/sites/pages, e.g., Twitter users, gets more attention (e.g., replies and mentions), whereas others get very little (Barabási & Albert, 1999).

Next, the study utilized a network-based approach to understand better the structural or relational aspects of fake news conversation. First, the study could not capture user-based homophily. That means elites and average users did not bypass each other and were well communicated via conversation. This is probably a good thing, as information in conversation was not stuck in a small world. Also, forming a homophilic cluster based on user type is tough, as power-law functions in a social media network. Second, the study found that users with the same motives were flocked together and talked less to people with different motives. Sub-networks of users with mixed and power motives had the largest number of conversational ties. The domination of power-driven users is of no surprise when discussing a negative topic like fake news. People are more likely to dominate others' opinions (Kucharski, 2016) to keep status and prestigious positions on Twitter (McClelland, 1975). Such power-driven users also managed to bypass the conversations that focused on other motives, such as the dangers and concerns of fake news (risk motive) (Pennebaker et al., 2015). Interestingly, the fake news conversation (e.g., replies and mentions) was not equally distributed across individual users in the power-based sub-network. This implies that a small number of users with power motives induced fake news conversations more than users with other motives.

On the other hand, users with risk motives were more connected to each other, although they were small in number. Combining our motive analysis via LIWC with a motive-based network structure, we can generate more meaningful insight. On the one hand, people showed more concern (risk motive) while discussing fake news than any other topic on Twitter. On the contrary, only a small number of people flocked together to talk about it with each other (expressing risk motive). This may minimize the diffusion of quality conversation regarding concerns and the danger of fake news among people.

CONCLUSION, LIMITATION AND FUTURE STUDY

The study utilized a social network approach to analyze users' conversations on fake news. Based on users' emotional appeals and motives, node-level centrality and network-level structure were analyzed. Overall, structural features showed us how and why news media organizations and the general public developed a topic network of fake news conversations. The study will contribute to the current scholarly and practical works on the audience's reactions and concerns regarding the deflation of fake news.

The study had some limitations. It should be noted that NodeXL (Smith et al., 2010) and Twitter do not allow researchers to download data for more than a specific duration (usually 4 to 5 minutes of data time). After this point of time, network data may or may not change in the natural Twitter setting. This imposed a limitation on examining the fake news tweet universe. Besides, the study considered a broad categorization of Twitter users, ignoring the differentiated role of elites (e.g., legacy media vs. online media, journalists vs. politicians, media vs. citizen journalists, etc.). Future research can focus on operationalizing and examining such specific categories and their roles in fake news conversation. Finally, an excellent way to extend the takeaway from this study will be to utilize variables (e.g., centrality, emotion, or motives) to predict tractions (e.g., likes, retweets, favorite, etc.). Such analysis will allow researchers to associate antecedents and outcomes of fake news conversations on Twitter.

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