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Social roles and structural signatures of top influentials in the #prayforparis Twitter network

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Abstract

Scholars have shown much interest in whether diffusion is inflated through planting a piece of information by influential people (influentials). Although a few attempts have been made to discover structural gaps or gap fillers in the Twitter network, these efforts mainly concentrated on applying topological approaches to detect influentials in online networks. Further, though many studies explored diffusion on the Twitter network, they rarely examined the phenomenon with a theoretical framework. Through the #prayforparis Twitter network, this study attempted (1) to identify top influentials by applying multiple centrality measures and word frequency measures and (2) to examine social roles based on structural signatures of the Twitter network through the lens of the Diffusion of Innovation Theory. To fulfill the objectives of this study, the authors employed an innovative multi-method approach combining Social Network Analysis, word frequency analysis via NodeXL and R, and a qualitative approach to examine behavioral and structural relationships of the #prayforparis Twitter network. Top influentials of the network were pop music celebrities who shared condolences to the victims of the 2015 Paris attacks through their tweets. This study identified "celebrity" and "fan" as social roles based on the structural and qualitative analysis of the network as well as metrical examinations, including indegree and outdegree counts of the social roles of the "celebrities" and "fans." Justin Bieber, the most dominant influential individual in the #prayforparis Twitter network, functioned as a breaking news provider through his tweet about the death of his friend during the Paris attacks. By filling the gap from the past studies, this study utilizes the theoretical improvement in the diffusion research as well as contributes to the methodological approach about influentials and social roles in the Twitter network.

Keywords Twitter · Diffusion of innovation · Social network analysis · Prayforparis · Social roles · Influentials · Structural signatures

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1 Introduction

Launched in 2006, Twitter has obtained 326 million active users and created 500 million tweets every day as of the third quarter of 2018 (Statisca.com, 2018). Twitter has been used to generate and share real-time information including breaking news, personal or public messages, and diverse events and ideas (Tonkin et al. 2012). For example, Twitter was extensively employed for real-time posts about disasters, such as Ebola and Zika virus outbreak during 2015 and 2016, or disseminating awareness about political upheavals, such as the Arab-Spring movement in 2011 and the Candlelight movement in South Korea in 2016 and 2017 (Collins 2017; Liang et al. 2019). How human and societal components influence Twitter has been of interest in academia and practice. Scholars have shown much interest in whether diffusion is inflated through planting a piece of information by influential people (Dong et al. 2018; Eleni et al. 2018). Those influential individuals can play a central role in the diffusion process through their actions and positions on the Twitter network (Bhowmick et al. 2019).

Research studies about identifying influential users in a Twitter network have largely focused on applying topological approaches of the underlying network (Goldenberg et al. 2018; Huang et al. 2014). Although a few attempts have been made to discover structural gaps that link parts in the network and to identify structural gap fillers or gap bridgers as influentials, these efforts mainly concentrated on applying topological structures to detect influentials in online networks (Bhowmick 2019; He et al. 2016 August). This study builds on the topological approach by utilizing multiple methods to examine impacts of influential users (influentials) through various quantifiable measures as well as qualitative analysis (Al-garadi et al. 2017; Huang et al. 2014; Zhang et al. 2014 June). Further, though many studies explored diffusion on the Twitter network, they rarely examined the phenomenon with a theoretical framework (Bhowmick et al. 2019; Romero et al. 2011 March; Stefanone et al. 2015 January). Some studies attempted to employ the Diffusion of Innovation Theory to explain the meme or message diffusion during Boston bombing in 2013 on the Twitter network, but the theory was not fully discussed in those studies (Johann and Bülow 2019; Lee et al. 2015).

A Twitter network driven by influentials, who either intentionally or unintentionally have a great impact on the network, has certain structural relationships in persuading other users. This study argues that these impactful relationships may generate "structural signatures," and social roles can be identified through the behavioral and structural representations of the Twitter network (Welser et al. 2007; Winship 1988). Through examining a case of a disaster Twitter network, the authors of this paper attempted (1) to identify top influentials by applying multiple centrality measures, page rank, and word frequency measures and (2) to examine social roles based on structural signatures of the disaster Twitter network through the lens of the Diffusion of Innovation Theory (Rogers 1962; Rogers 1995; Rogers 2003).

On Twitter networks, information is primarily organized and shared with the hashtag symbol (#). To explain the social aspects of users and the structural relationships of communication on Twitter, this study examined the hashtag network of #prayforparis on Twitter. To fulfill the objectives of this study, the authors employed an innovative multi-method approach combining

(1) Social Network Analysis through centrality metrics and visual implementation;
(2) word frequency analysis via NodeXL and R; and

(3) a qualitative approach to examine behavioral and structural relationships of the Twitter network.

By filling the gap from the past studies, this study utilizes the theoretical improvement in the diffusion research of the Twitter network as well as contributes to the methodological approach of influentials and social roles studies, particularly in the disaster network, such as the Twitter network of #prayforparis.

The remainder of this paper is organized as follows: Sect. 2 provides background information about the 2015 Paris Attack and #prayforparis, explains why Diffusion of Innovation Theory is directly applicable to the adoption of #prayforparis, and then discusses identifying social roles in the network and Social Network Analysis. Section 3 describes data collection and data analysis techniques and findings are provided in Sect. 4. Conclusions and discussion are given in Sect. 5, while Sect. 6 is presenting limitations and future studies.

2 Literature review

2.1 The 2015 Paris attacks and #prayforparis

A series of organized terrorist attacks occurred concurrently in Paris, France, on November 13, 2015. Three suicide bombers crashed near the Stade de France in Saint-Denis during a football match between France and Germany. A few minutes later after this attack, another suicide bombing and several mass shootings took place at restaurants, cafés, and a music theatre in Paris, which resulted in 498 casualties including 130 deaths (The New York Times November 15 2015). This was the deadliest attack in France since the Second World War. The Islamic State of Iraq and Syria (ISIS) claimed responsibility for the attacks, as a retaliation for French airstrikes on ISIS targets in Syria and Iraq (Elgot et al. November 15 2015).

It is not clear when the hashtag #prayforparis was created; however, it is obvious that the hashtag was extensively adopted after the 2015 Paris Attack. In *the Michigan Daily*, Rosenberg (2015) wrote, "Within the 24 h of the terrorist attacks in Paris on Friday, people from all over the world showed an outpouring of support for the French on virtually every social media outlet. Twitter users tweeted their thoughts with the hashtag #PrayForParis; Instagram flooded with the now-circulating symbol of the Eiffel Tower attached to a peace sign…." The instantaneous and innumerable adoptions of the hashtag made #prayforparis the third ranked trending news topics in 2015 on Twitter (twitter.com/top-trends 2015) following #jobs and #Quran. Though other hashtags related to the 2015 Paris Attack were used, such as #parisattacks, #paris, and #prayforpeace, #prayforparis was selected the most by Twitter users.

2.2 Diffusion of innovation

The Diffusion of Innovation Theory (Rogers 1995: Rogers 2003) provides an overarching framework to understand the diffusion phenomenon, including user motivations and their adoption behaviors. Rogers defined *Diffusion* as "the process by which an innovation is communicated through certain channels over time among the members of a social system," and is a unique manner of communication because the innovation is related with new ideas (Rogers 1962).

Drawing from the conceptual model of DoI proposed by Rogers (1995), Chen et al. (2008) described four main components of the DoI adoption process: the innovation, communication channels, time, and the social system (social context) as shown in Fig. 1. According to Rogers (2003), "An *innovation* could be any idea, practice, or object that is perceived as new by an individual or other unit of adoption." The diffusion process normally includes both mass media and interpersonal communication channels (Morris and Ogan 1996). These days, a smart phone demonstrates an excellent example of a diffusion instrument because it integrates features of mass media and interpersonal media through the functionality of the Internet device and a mobile phone.

The time component is engaged in three ways in a diffusion process, which are innovation-decision process, adoption-process, and the rate of adoption (Rogers 1995). The innovation-decision process is an intellectual process in which a person or a community transfers, adopts, or rejects the new knowledge while shaping an attitude toward an innovation (Rogers 1995). Diffusion process involves five steps of the adoption process, which are knowledge, persuasion, decision, implementation, and confirmation. This adoption process occurs over time between the participants of diffusion, and a participant or an organization can reject a new idea at any moment during the adoption process (Rogers 1995). Time is also engaged in the rate of adoption. Rogers defined time as the relative speed at which participants adopt an innovation, and rate is generally determined by the length of time spent for a majority percentage of the members of a social system to adopt an innovation (Roger 1962). Rogers described social system as "a set of interrelated units that are engaged in joint problem-solving to accomplishing a common goal" (Rogers 1995). The participants or units of a social system can be individuals, formal or informal groups or organizations.

Researchers have investigated how the social structure of the system and norms influence diffusion (Rogers 1995). For example, Valente and Davis (1999) proposed the Opinion Leaders model to measure how quickly diffusion occurs when activated by opinion leaders in the level of interpersonal communication networks within a community. Valente and Davis (1999) said, "the credibility and trustworthiness of opinion leaders" can speed up the diffusion process "by allowing the entire community to select opinion leaders" although the opinion leaders are not usually the early adopters in a diffusion process (Valente and Davis 1999). The DoI theory describes how a small number of influential

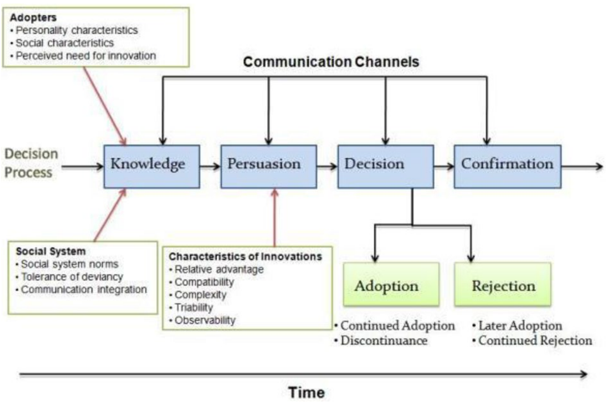

Fig. 1 The four components in the diffusion of innovation adoption (Chen et al. 2008)

people or opinion leaders are the drivers who cause the users to adopt an innovation (Rogers 1962).

Online opinion leadership depends on the ability to affect information flow (Cha et al. 2010) and has two aspects: to provide information and to impact others through the diffusion of information (Weimann et al. 2007). Due to the nominal cost of online communication, people from diverse socioeconomic status can create a significant amount of information. Competition for attention in the excessive and repetitive online information overflow remains relentless, and thus, the most influential people online are those who not only grab the attention of other users but also compel the redistribution of the information (Xu et al. 2014). The DoI studies impacted other social sciences, which extended to other areas including education, engineering, political science, administration, marketing, and communication studies. Particularly, communication researchers investigated the diffusion of news events, and the idea of diffusion is still resonant through the major news events, such as the September 11 attack, the 2003 space shuttle disaster, the Japan earthquake in 2010, and the 2015 Paris attack (Cvetojevic and Hochmair 2018; Rogers and Seidel 2002).

The concept of "innovation" has been relevant to new goods, services, means, creations, and ideas and can be readily applied to Social Networking Services (SNS), as specifically observed with Twitter. Indeed, Twitter self-defines its service as "a real-time global information network that lets users create and share ideas and information instantly" (Twitter.com). Hashtags are user-created tags that put on another factor to tweets, and sharing hashtags with other users is a community-driven practice that promotes folksonomy at the same time (Chong 2016; Wang et al. 2011 October). Applying a hashtag is a special type of folksonomy because the starting users of the hashtag can be considered innovators, and they cause other groups of users or imitators to use the identical hashtag (Chang 2010).

Rogers defined innovativeness as the level to which a person or unit is comparatively more likely to adopt the new idea earlier than other individuals or units (Rogers 1995). He said that an innovation must reach "critical mass" and be widely accepted to be sustainable (Rogers 1995). Users sharing newly created or trending hashtags can be perceived as innovation adopters since a hashtag itself is a form of innovation proposed by early users and then adopted and disseminated voluntarily through the Twitter network. Not all hashtags are successfully diffused or adopted by Twitter users. If certain hashtags were successfully diffused, the repeated appearance of the topic demarcated by the hashtag and utilized by a variety of Twitter users could demonstrate the adoption of innovation (Chang 2010). However, despite the extensive use of hashtags on Twitter, the hashtag diffusion has not been fully investigated through the DoI theoretical framework.

2.3 Social roles in online networks

The development and quick diffusion of Web 2.0 technologies made a revolutionary leap in the social element of the Internet application, and social media became a great instrument for users to voluntarily generate and spread information through their networks, which consist of friends and other acquaintances (Chong and Chang 2018; Vollmer and Precourt 2008). Social Role analysis of online social media has been one of the popular research areas (Hara and Sanfilippo 2017; Lee et al. 2014; Maia et al. 2008; Newman et al. 2011; Wallach et al. 2009; Welser et al. 2011; Yan et al. 2013). According to Scott (2017), roles can be identified through the social position of each user in social networks. When the users are in the same social positions or share similar typological characteristics in the networks, they share the identical social roles (Liu et al. 2019). Despite lacking consensual definition of social roles, based on the concept of structural equivalence, social roles can be identified by examining "how similar the two nodes when they are connected to the same node" (Bartal and Ravid 2019; Liu et al. 2019, p. 662; Rossi et al. 2013). Network research studies about social roles are premised on the idea that structural characteristics identify a group of analogous actors that conform to social roles (Winship 1988).

Any role could be a synthesis of certain sets of behavioral and structural characteristics, and when individuals present distinctive characteristics in online activities, they are playing a social role (Welser et al. 2007). For example, people who characteristically present recognition or connection can be regarded as playing the social role of a fan. This can be examined within a schema of the definition of a "fan," a schema related to proper mutual relationships and behavioral anticipations (Welser et al. 2007). Data derived from online environments are good sources to investigate social roles, because researchers can collect data and simultaneously visualize network structure and patterns in order to examine the meaning of interactions and identify precise social roles thorough content analysis (Welser et al. 2007).

Developing methods to recognize and define social roles on the web is particularly significant because online data became more available to the public and researchers and frequently contains several aspects that can be used diversely and simultaneously, including marketing, cyber security, and platform management (Liu et al. 2019; Welser et al. 2007). Several significant social roles were discovered in online discussion groups, such as local experts, conversationalists, fans, discussion artists, flame warriors, and trolls (Burkhalter and Smith 2004). Golder (2003) claimed that these roles have mainly been discovered through the study of interaction content in ethnographic research, which improved "visualizations of initiation, reply and thread contribution rates over time to identify distinct patterns of contribution" (Welser et al. 2007, p. 3).

Social roles can be examined in comparison to patterns of behavior and information structures of relationships between people (Nadel 1964). Faust and Skvoretz (2002) coined the term "structural signature" to indicate remarkable characteristics that describe types of networks. The concept of a structural signature can be applied to behavior roles that feature "distinctive positional attributes that distinguish actors as occupants of a social role" (Welser et al. 2007, p. 3). From that perspective and to the extent that a structural signature can be clearly defined, the time and effort necessary to identify specific kinds of contributors can be substantially reduced.

2.4 Social network analysis

Social networks have existed since history began, but social media networks, a new aspect of culture in the twenty-first century, have influenced billions of people. Social-networked communication, which creates connections on a global scale between families, friends, and even users who have never met in person, became a necessary part of daily life. These radical social phenomena became new and important research topics of social science and other relevant academic circles.

Social network theory has greatly affected how researchers think and organize concepts about social network structures, including online and social network analysis (SNA) is a strategy for examining social structures rather than an established theory (Otte and Rousseau 2002). Traditional social theory and data analysis describe individual actors as independent choice makers who behave without thinking of others, which disregards the actor within the social context. However, SNA not only prioritizes the relationships among actors within a social environment but also emphasizes individual attributes in order to thoroughly understand social events (Knoke and Kuklinski 1982). Wetherell et al. (1994) explain SNA as follows:Social network analysis

(1) conceptualizes social structure as a network with ties connecting members and channeling resources,
(2) focuses on the characteristics of ties rather than on the characteristics of the individual members, and
(3) views communities as "personal communities," that is, as networks of individual relations that people poster, maintain, and use in the course of their lives. (p. 645)

Two primary structures of SNA are the ego network that focuses on an individual's network and the global network that examines the entire relationships among actors and groups in the whole network (Otte and Rousseau 2002). Several important terms are included in SNA. First of all, vertices, also known as nodes, entities, or items, represent people, agents, or social groups. Edges, also called as links, ties, connections, and relationships, are building elements that connect vertices in networks (Hansen et al. 2011). In SNA, if individuals were represented as nodes and the connections between the nodes were displayed as edges, strength or weakness of the network could be explained in terms of social connections among the individuals. In addition, each node representing the relational state among individuals in the network illustrates whether the individual has adopted the innovation or not (McCullen et al. 2013). Therefore, SNA can be used to examine the adoption of innovations between people linked to each other through a network of peer-to-peer impacts.

As discussed earlier, traditional opinion leadership is related to strong participation and extensive social connectivity. Conventionally, these social involvement and relationships are often investigated via self-report surveys. However, these components and structures can be applied to self-generated social media content in the Web 2.0 environment. Online social network and social connectivity, or relationships, are identified by users' positions (Park and Thelwall 2008). On Twitter, relationships are represented as followings or followers who receive information given by other users. The more followers mean the greater the audience, and by following, the users can expect more information. Tweets in Twitter can be forwarded by followers, and through a forwarded tweet, or retweet (RT), the users of the Twitter account can expand their audience.

Other key concepts in SNA are "density," which indicates interconnectedness of the vertices (nodes) and "centrality," which explains how a certain vertex can be described to be in the "center" of a network. The term "centralization" describes how and how much the networks are centralized. For example, centralized networks own many edges that emerge from a few major vertices (Hansen et al. 2011). In reference to this idea, the study defines user involvement as users' interest and their germaneness to the hashtag adoption of Twitter users. In this regard, the following research questions are proposed:

- *Research Question 1: What type of social structures and sub-clusters does the #prayforparis Twitter network have?*
- *Research Question 2: Who are the top influentials in the #prayforparis Twitter network?*
- *Research Question 3: What types of social roles are identified by examining the top influentials in the #prayforparis Twitter network?*

3 Method

3.1 Data collection

To find answers to the proposed research questions, this study performed SNA by employing NodeXL software. NodeXL, which is an add-in application for Microsoft Excel, allows SNA and social media investigation through importing data from popular social media websites such as Facebook, Twitter, Wikis, and YouTube (Hansen et al. 2011). NodeXL can display social network diagrams by visualizing participants and their connections in the networks and compute the influence of an individual actor on others based on network metrics, including density, centrality, and page rank (Hansen et al. 2011). NodeXL can acquire data on a large scale. Through Twitter application programming interface (API), by applying the hashtag #prayforparis, this study acquired a total of 19,592 tweets (vertices) on November 17, 2015 using the NodeXL Pro application. Theoretically, the NodeXL Pro version allows researchers to gather the last 18,000 tweets on a certain hashtag through the Twitter Search network function. The data collection time for this study was four days after the Paris attacks, and due to the wide attention and seriousness of the event, the retrieved 19,592 tweets created a total of 20,295 edges (relations between tweets). Four different kinds of relationships on Twitter were collected: retweet, replies-to, mention, and tweet. In addition, following and follower relationships among participants in the #prayforparis network were obtained. Twitter.com provides the differences of each term and usage on the Twitter website (About different types of Tweets n.d.).

3.2 Data analysis

The initially retrieved tweet datasets via API are usually disorganized and unstructured, which makes difficulties in construal for the three research questions. To answer the first research question, the dataset was processed into network analysis and visualization of a graph. The unconnected tweets were excluded because the isolated tweets scarcely demonstrate any relationships with other participants in the network. This study applied the group by cluster option resulting in 2772 groups with the Clauset-Newman-Moore method. The whole network was initially separated into 2772 groups and multiple iterations were performed to narrow them down to the top sub-groups (Hansen et al. 2011). A total of 20 groups were discovered that conveys the relationships of tweets and retweets, mentions, and replies-to in the #prayforparis Twitter network.

To answer the second research question, the dataset was examined via computing with metrics, including indegree, outdegree, betweenness centrality, and page rank within the sample of users. In addition, top word pairs were calculated to discover the frequency of the most used words together in this network. Social connectivity of a user can be calculated by betweenness centrality, which clarifies the number of relationships an individual vertex retains, or degree centrality. Betweenness centrality portrays a network participant's measured position in relation to other participants in the network, it analyses the rate of appearances where a participant is located in the closest connection joining all other participants in the network (Freeman 1978; Hansen et al. 2011). The high degree of centrality is demonstrated by a central network position, which insinuates dominating information flow and therefore, potential to control other users' actions and viewpoints (Burt 1999). Word clouds were created to visualize the diffusion of the hashtag #prayforparis and top influentials' impact on the #prayforparis Twitter network. A word cloud is a type of visual presentation of text data including weighted list of free form text, and the significance of individual word is represented by the size and color of type face Halvey and Keane (2007 May). To create word clouds, this study utilized R software, which is a computer programming language and application for statistics, visualizations, and interdependent spaces of software provisions for data management (The R foundation 2019).

To scrutinize the third research question, the mixed methods were adopted. To identify social roles focusing on the top influentials of the network, this study comprehensively applied previously calculated metrics, such as density and centrality measures, the network visualization examinations, and qualitative approaches to investigate the structural characteristics of the networking relationships and behavioral features of the network participants in the #prayforparis Twitter network.

4 Findings

4.1 RQ1: what type of social structure and sub-clusters does the Twitter network of #prayforparis have?

To categorize the social structure among sub-clusters, the data visualization was laid out using the group-in-a-box method. Then both layout options, the Fruchterman–Reingo and the Harel–Koren Fast Multiscale, were tested to see which one provided greater readability of the data set. Ultimately, the Fruchterman–Reingo layout was chosen, with several iterations conducted to enhance readability of the vertices in each group, especially those in the denser groups (i.e., G1-19). As shown in Fig. 2, G1 was tightly interconnected with large sizes of actors within groups, and it dominantly influenced most of the sub-clusters while primarily bridging across G 3, 4, 5, 6, 10, 12, 16, 17, 18, 20 and G2 (isolates).

Conversational relationships on Twitter generate networks with recognizable curves as users mention and retweet one another in the network. Smith et al. (2014) stated these

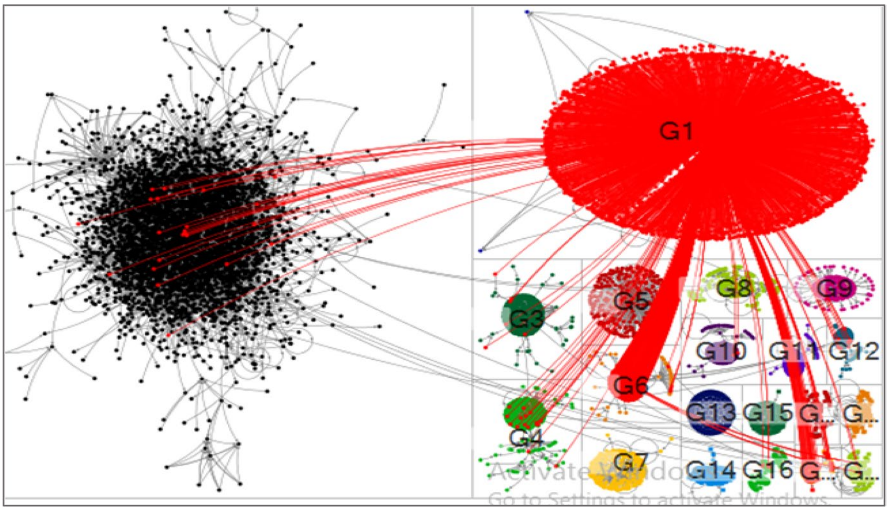

Fig. 2 The top 20 sub-clusters of the #prayforparis Twitter network

Fig. 3 Outward hub and spoke structure (Smith et al. 2014)

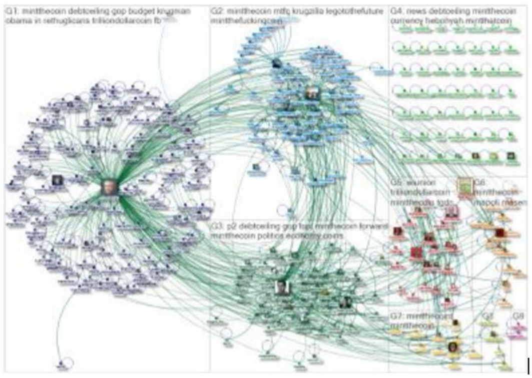

Fig. 4 An example of the broadcast network (Smith et al. 2014)

conversational structures vary based on the topic and users driving the conversation. Smith et al. (2014) observed the contours of the Twitter networks and identified six typological structures: divided, unified, fragmented, clustered, and inward and outward hub and spoke structures. These social structures are generated depending on the network participants' reply patterns to their Twitter messages. After multiple thousands of Twitter network observations, Smith and his colleagues discovered six popular social structures on Twitter (Smith et al. 2014). These structures "tell a story about the nature of the conversation" (Smith et al. 2014, p.1). Drawing from the observations, this study identified the sub-clusters of the #prayforparis Twitter network as a "Broadcast Network" among the six conversational archetypes. The characteristic interactions in the Broadcast Network are a hub (inward)-and-spoke structure with the hub's outreach to others being the central structure as in Fig. 3.

Figure 4 illustrates an example of the Broadcast Network, which shares similar features with the #prayforparis network in Fig. 2. According to Smith et al. (2014) "Twitter commentary around breaking news stories and the output of well-known media outlets and pundits has a distinctive hub and spoke structure in which many people repeat what prominent news and media organizations tweet" (p. 3). In Fig. 2, the selected vertex in red was identified as @Justinbieber. In this study, Justin Bieber's tweet is considered to be the breaking news source and his Twitter account became the well-known media outlet dominantly influencing the #prayforparis Twitter network. The participants of the Broadcast Network are frequently only linked to the source hub of breaking news while not linking to one another. Sometimes, there are smaller sizes of subgroups regarded as subject groups who are communicating to one another about the news, and they heavily connect network participants. In Fig. 2, G5 is the most active sub-group of G1 while densely connecting the participants of the network and serving the bridge role across G1 and G6.

4.2 RQ 2: who are the top influentials in the #prayforparis Twitter network?

Figure 2 presents group 1, comprising 3811 edges and forming the largest cluster among 20 groups in the entire network. Table 1 demonstrates the detailed metrics, including users with top betweenness centrality. The metrics indicate Justin Bieber has the largest number of indegree at 4196. Indegree means the number of edges toward the vertex in the entire network (Hansen et al. 2011) and illustrates the popularity of the vertex and directly points out the size of audience for the vertex in the network (Cha et al. 2010). The indegree of Justin Bieber (4196) solely occupies more than 20% of the edge relationships (20,295) in the entire network. Justin Bieber also holds highest betweenness centrality with 51,772,745.861 as shown in Fig. 2, which means he is located in the most centralized position and reinforces the social connection within the network of #prayforparis.

Figure 2 represents Justin Bieber's egocentric network highlighted in red, which displays the number (4196) of connections between his tweet and other vertices in the network, but because of the limitation of the graphic visualization, all edges were not distinctly displayed. As shown in Fig. 5, on November 16, 2015, Justin Bieber posted a tweet about the Paris attack and the loss of his friend, Thomas. His tweet was retweeted more than 51,000 times and received 77,000 likes in a few weeks after his posting. By June 14, 2016, the tweet has been retweeted more than 51,000 times and received 81,000 likes. Figure 5 shows Bieber's fan page, Justin Bieber Crew, retweeted Justin Bieber's tweet by adding their own comments. As a matter of fact, careful examination of collected data revealed that more than 19,500 relationships out of the entire 20,295 relationships were consisted of retweets, which comprised more than 96% of the total relationships. This finding implicates that #prayforparis has been dominantly diffused by retweets, which are the most significant content-centered interaction on Twitter (Anger and Kittl 2011 Setpember). Further metrical evidences of Justin Bieber's dominant influence in the network were observed. For example, key words related to Justin Bieber were frequently mentioned through the entire

Table 1 Indegree, outdegree, and betweenness centrality metrics of the #prayforparis Twitter network

Vertex	Indegree	Outdegree	Betweenness centrality
Justin Bieber	4196	0	51,772,745.861
Neutronjh	0	11	7,360,615.576
Allybrookeon	422	0	7,158,689.554
Umairkibatain	73	0	7,136,643.715
Louis_tomlinson	454	0	6,742,289.961
Kassysc	0	5	4,754,168.823
Itele	12	0	4,491,318.935
3ajmee	304	1	4,386,550.000
Nuraunie15	0	4	4,380,334.000
Mathiassurytb	3	5	4,269,911.430

Fig. 5 A retweeted Justin Bieber's tweet by Justin Bieber's fan page, Justin Bieber crew

Table 2 Top word pairs in the #prayforparis Twitter network

Top word pairs in tweet in entire graph	Entire graph count
Thomas, prayforparis	4165
Rt, Justin Bieber	4130
Rip, Thomas	4074
Justin Bieber, rip	4054
Paris, prayforparis	1360
Happened, paris	520

network. As shown in Table 2, top word pairs mentioned in the network include "thomas, prayforparis," "rt, justinebieber," "rip, thomas," and "justinbiber, rip." These word pairs were repeated more than 4000 times in the network and were highly ranked in the statistics of graph metrics. In addition, the page rank of Justin Bieber's tweet was the highest in the network at 1716.563, while the second highest page rank was at 199.964 by Louis Tomlinson's tweet. Page rank is an algorithm used by Google.com to evaluate websites in their search engine result and is a method of calculating the importance of the website pages (Langville and Meyer 2011). Therefore, Justin Bieber is the most influential and dominant user in the Twitter network of #prayforparis, and functions as a super hub by connecting Twitter users in the network.

While Justin Bieber was identified as the most influential and dominant individual, other influential users were also examined through indegree and betweenness centrality. Ally Brook online, which is a fan website of Ally Brook, and Louis Tomlinson who were ranked 3rd and 5th respectively with the highest betweenness centrality also demonstrated celebrity power in this network. The top ten indegree vertices of the network are Justin Bieber, Louis Tomlinson, Ally Brook fan site, Susan Toney, BTS (Korean idol

Fig. 6 A word cloud of the top seven influentials excluding Justin Bieber's ego network in the #prayforparis Twitter network

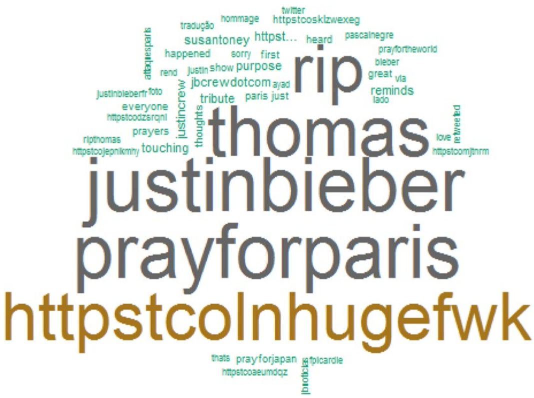

Fig. 7 A word cloud of the Justin Bieber's ego network in the #prayforparis Twitter network

boy group), Justincrew, Justincrewdotcom, Jin_0429, 3ajmee, and YouTube. The seven of them were identified as celebrities or their fan websites except the last three vertices. This accentuates the celebrities' impact in the network. The word cloud in Fig. 6 displays the top seven influentials, excluding the most influential individual, @Justinbieber, which visually confirms the influence of the celebrities in the network.

When manually examined the inter-related activities between the influential celebrities and their fans, the celebrities' fans and their fan sites completely and consistently disseminated the celebrities' posts by, in most cases, including the corresponding hashtags. Figure 6 is the word cloud of @Justinbieber's ego network. In Fig. 7, Rip, Thomas, JustineBieber, and prayforparis are outstanding, which means that they were dominantly shared and repeated in the network.

Comparing the word cloud of the Justin Bieber's ego network (Fig. 7) to a word cloud of the entire #prayforparis, the eminence of Justin Bieber and his tweet was obvious in the network of the #prayforparis (Chong 2016). The central roles of Justin Bieber and top seven influentials' ego networks were conspicuous upon excluding these top influentials from the entire network of #prayforparis (Fig. 8). Therefore, without the celebrities and their fans, the #prayforparis Twitter network would have depicted an entirely different visual representation of diffusion.

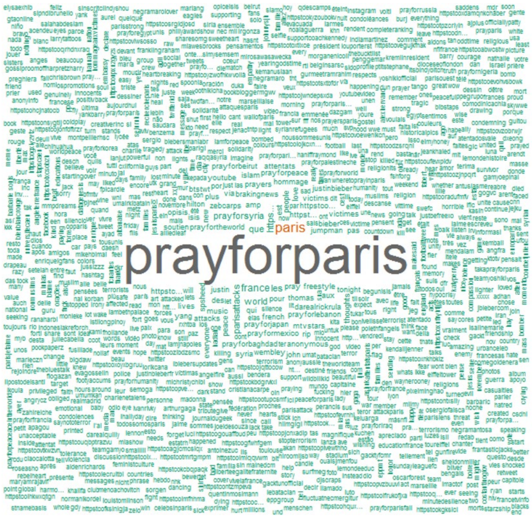

Fig. 8 A word cloud of the #prayforparis network excluding the Justin Bieber and top seven influentials' ego networks

4.3 RQ3: what types of social roles are identified by examining the top influentials in the #prayforparis Twitter network?

Influential users are established through the popularity of their tweets or their locational significance in terms of connectivity in the network. Network research studies about social roles are premised on the idea that structural characteristics identify a group of analogous actors that conform to social roles (Winship 1988). The findings of this study can be used to claim that the top influentials were identified as the social role of the celebrity, not because the identified influential users are celebrities in the real world but because of the structural contour of the #prayforparis network and the behavioral characteristics of the influentials and connected features around them. For example, the network graph was significantly asymmetrical. The network contains mostly directed edges that describe one-way communication between vertices and have clear origin and destination to fans of the celebrities (Hansen et al. 2011). The top ten highest indegree users in the network, including @Justinbieber, Ally Brook online, and Louis Tomlinson, presented the largest number of indegrees but zero number of outdegree. While celebrities, as dominant influential users, are prominent in the #prayforparis network, the social roles of fans were also interchangeably acknowledged, because the fan sites and fans of those identified celebrities reacted immediately by retweeting, mentioning or responding in both ways to almost every single tweet posted by the celebrities.

Interestingly, Susan Toney, an American pop singer, appeared as an influential in this network only because she retweeted Justin Bieber's tweet as shown in Fig. 6. A qualitative examination of her tweets confirms that she frequently posts tweets about Justin Bieber by mentioning Justin Bieber and including "@JustinCrew" and "@JustinCrewdotcom" in her tweets. Thus, she was identified in the social role of "celebrity" and "fan" simultaneously in the network. Like Susan Toney, the fan websites can also be categorized in the social role of celebrity as well as fan, because the fan websites have been followed by the fans and also follow the celebrity. These characteristics were identified by structural signature and recognized through graphical and metrical findings of the study, which verified the social role of celebrity and fan in the Twitter network of #prayforparis.

5 Conclusions and discussion

Applying the DoI theory as the overarching framework, this study examined a hashtag diffusion through the #prayforparis Twitter network. This study claimed that a hashtag is a type of innovation, and the diffusion process of the DoI framework is applicable to the diffusion phenomenon on Twitter. The theory also explains how a small number of influential people can be the driving force to adoption of an innovation. In other words, while focusing on the means that innovative information is passed on, the theory claims that influential people can create a strong impact at little cost. This study uncovered the top influentials and social roles of the #prayforparis Twitter network based on structural features of the network and behavioral characteristics of the network participants. Top influentials were mainly pop music celebrities who shared condolences to the victims of the Paris attacks through their tweets. This study identified "celebrity" and "fan" as social roles based on the structural and qualitative analysis of the network and metrical examinations, including indegree and outdegree counts of the celebrities in the network. The distinctive characteristics of fans' idiosyncratic behavior supported the social role of celebrities diffusing new ideas combined with the hashtag throughout the entire network.

The sub-clusters of the #prayforparis Twitter network presented similar characteristics to the Broadcast Network (Smith et al. 2014). Justin Bieber, the most dominant influential user in the network, functioned as a breaking news provider through his tweet that informed the public, including his followers, of the death of Thomas (a friend of his) during the Paris attacks. This tweet became a breaking news in the #prayforparis Twitter network and had a huge impact on the network as shown in Fig. 2. This is more due to Justin Bieber having millions of followers worldwide rather than the content of his tweet as presented in Fig. 5. The top influentials set the directionality of the relationships in the network by affecting information flows of their followers. These dynamics are worth notice because the influentials can be powerful agenda-setters or conversation initiators on any topics due to their structurally built follower relationships with their loyal followers on Twitter.

This study concludes that the identified top influentials contributed to the quick diffusion of the hashtag, which helped the adoption of #paryforparis to reach to the level of critical mass within a short period of time when compared to the diffusion process in real life cases. SNA recognized the strong social and structural relationships between celebrities and their fans through the "structural signature." With the widespread increase of social media use, many celebrities have used social media as a medium for communicating with or sometimes mobilizing their fans. This study discovered the celebrities played key roles as an information hub in a disaster Twitter network of the #prayforparis. This is a significant finding because the structural relationships between the celebrities and their fans or the networks having similar structural signatures with those relationships in the Twitter network could be powerfully adopted to diffuse new information during disaster-related circumstances.

6 Limitations and future studies

This study identified overwhelming influence of several influentials in the #prayforparis Twitter network, which may extend to other areas of study, such as communication, politics, and marketing, and applicable strategies to practice, such as marketing choices and policymaking, by effectively leveraging influential users' impact. However, having a million followers does not necessarily mean the user is a powerful influencer, and indegree alone rarely demonstrates the actual influence of a user (Cha et al. 2010). Thus, more precise and diverse measures, such as semantic analysis, could help further evaluate and clarify the meaning of the popularity of a celebrity's tweets and elucidate the impact of influentials on the Twitter network.

True interactive online networks are characterized by activities, interactivities, and associations among users in the network, and analyzing the social media network features data-driven research. In this study, the #prayforparis Twitter network was characterized by high density and centrality in Justin Bieber's remarkable ego network; therefore, in order to fully understand a highly interactive celebrity and fan Twitter network, researchers need to investigate the structural characteristics of the network resulting from interactive relationships between fans and celebrities as well as fans and other fans within the network.

Identifying social roles in the Twitter network is an ongoing research area. Further theoretical framework and analytical methods must be developed in order to improve the detection of social roles and the structural signature in the Twitter network. As this study observed, an innovative idea incorporated the hashtag #prayforparis, and the adoption of #prayforparis quickly occurred i.e., within 24 h after the creation of the hashtag. When compared to the past cases of DoI studies, the rate of adoption was rapidly increased because the previous DoI studies generally dealt with the adoption of real-world cases. Additionally, the small number of influential people also were the actual people having physical contacts to expedite diffusion process, which made the adoption process occur over a longer period of time through the participants in spreading an innovative idea.

A Twitter network is an information-sharing network. Diffusion of innovation can be described as diffusion of information on a Twitter network. In this study, the five-adoption process of diffusion, which are knowledge, persuasion, decision, implementation, and confirmation, was not fully examined because the adoption of #prayforparis occurred incredibly fast as well as no measures have been established to define the adoption process on a Twitter network. Therefore, inspecting each step of the five-adoption process remains as a topic for future studies.

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