Examining a Covid-19 Twitter Hashtag Conversation in Indonesia: A Social Network Analysis Approach

2021 15th International Conference on Ubiquitous Information Management and Communication (IMCOM) | 978-1-6654-2318-2/21/$31.00 ©2021 IEEE | DOI: 10.1109/IMCOM51814.2021.9377382

Stevanus Wisnu Wijaya
Department of Software Engineering
Universitas Prasetiya Mulya
Indonesia
wisnu.wijaya@prasetiyamulya.ac.id
-

Indria Handoko
Department of Management
Universitas Prasetiya Mulya
Indonesia
indria.handoko@prasetiyamulya.ac.id

***Abstract*—Twitter becomes one of the most adopted social media platforms globally, and Indonesia is a country with a rapid growth of Twitter user number in recent years. This paper discusses about the examination of conversation network of Twitter hashtag related to Covid-19 in Indonesia by using a network perspective. During this pandemic situation, Twitter has been increasingly adopted as a medium of conversational interaction amongst people to express their opinion and feeling about the situation, or share information, among others. At the same time, the Indonesian Government has established an official hashtag (#) to coordinate and organize conversations related to a specific topic of Covid-19, namely #BersatuLawanCovid19. In this way, the Government would be able to reach the public interest due to the capability of the hashtag to become a trending topic. This study examines how the Twitter conversations emerged and developed within the Twitter community by using Social Network Analysis approach. We have collected 793 Twitter users and 4441 Twitter chats from the hashtag #BersatuLawanCovid19. We then visualized the relationship network and examined the community using Social Network Analysis metrics with NodeXL. This study found that there is no a mutual engagement amongst the community members in terms of conversational practices. Interestingly, although some members of the community received a high number of engagement efforts from others, they do not actively respond to the initiatives. This suggests that the official account of government who is in-charge of managing the conversation need to enhance their communication strategy to improve the conversation within the community.**

Keywords— Twitter, Social Network Analysis, Hashtag, Covid-19, Indonesia

I. INTRODUCTION.

Twitter is widely adopted as one of social media platforms all over the world. This microblogging service has several unique characteristics compares to other social media platforms such as Facebook and Instagram. Rossi & Magnani[1] found two characteristics that distinguish Twitter with the others. Firstly, the publicly nature of posted message (tweet) equipped with addressivity marker such as mention and reply that allow public conversation to emerge within Twitter. This platform facilitates its users to tweet a message publicly, and then allows anyone to access the message, which can promote a real-time propagation of information widely. Secondly, its capability to organize and coordinate the information through hashtag (#) that also equipped with a trending topic. This enables the conversation to attract public awareness. In this way, a hashtag can serve role as a function for organizing topical conversation for people with similar interest[2]. The combination of the two characteristics makes Twitter as an attractive platform for public conversations.

Furthermore, Twitter users are also able to adopt hashtag to organize and coordinate conversation of a topic. Within a hashtag, a Twitter user can interact with other users through tweet, mention, reply and retweet functions. 'Mention' is a function to address other users within a tweet, whereas '@reply' is similar to 'reply' function in email, and retweet is similar to 'forward' function[3]. In addition, the users are able to explore @reply and retweet networks, so that they can gain an in-depth understanding on the way in which the tweets can attract public awareness. Moreover, the numbers of user involved within a hashtag conversation can drive the conversation to reach a trending topic status nationally and even internationally. In other words, Twitter can help an important message to be shared widely and attract the public awareness in a real-time basis, and be a source of information for mainstream media. Twitter thus is considered as an effective media to distribute messages during an emergency situation such as Covid-19 pandemic.

The present study uses Social Network Analysis metrics to examine the conversational network using a Twitter hashtag #BersatuLawanCovid19 that discusses Covid-19 phenomenon in Indonesia. Social Network Analysis approach was chosen in this research to help us gain a meaningful visualisation. Data was collected using NodeXL Twitter Import tool, and then analysed using NodeXL. Several Social Network Analysis metrics were adopted to examine the conversation network and identify the key individuals. The richness of Twitter data, supported by the metrics, will help us examine the phenomenon that is still rarely studied. The purpose of this study is twofold. First, the study aims to examine how Twitter users based in Indonesia interact with each other within the Covid-19 hashtag community. The second objective is to explore those who participate in the hashtag and the level of user engagement by identifying reciprocities between them. This present study about the specific topic of Covid-19 crisis in Indonesia provides both theoretical and practical contributions. At theoretical level, this study gives a better understanding about the flow of information within a Twitter topical-based conversation community during an emergency situation. At practical level, this study offers an insight about how to enhance users' engagement within a conversation-based community for professionals who want to manage an online community during an emergency situation.

The remainder of the paper is organized as follows. The second section presents the literature review of Twitter and how Social Network Analysis can be implanted in the study of Twitter networks. The third section discusses the research methodology, including data collection and analysis methods. Then, the fourth section presents the findings of this research followed by an in-depth discussion. The last section discusses the conclusion, the limitations of the study, and further research directions..

II. Literature Review

A. Twitter

Twitter is popularly known as a microblogging site that facilitates its users to post messages publicly and to coordinate a topical conversation through a hashtag (#). Twitter allows a topical conversation reaches its wide audiences, not just an individual or a close group of individuals[4]. One Twitter user who initiates a conversation will interact not only with the interlocutors, but also with a wide range of audiences [4]. Hashtag enables a conversation works for public audiences, attracting people with similar interest talking with each other. In this way, the hashtag function can facilitate the emerging of topical online conversation-based community within Twitter platform.

The message posted into Twitter, namely Tweet, is equipped with several tools that are useful to make the message meaningful and promote a conversation[5]. A Tweet can be equipped with a URL, image and video to help make the message become more attractive. Existing literature shows that the three tools of Twitter including @mention, @reply and retweet enable a conversation emerges and develops within a Twitter hashtag.

In 2020, the number of Twitter users based in Indonesia has reached more than 12 million users, according to Statista's Key Market Indicator. With the huge number of users, this microblogging service serves role as an information source and is potentially able to influence the public opinion. In recent years, there is a growing number of Indonesian netizens adopting Twitter platform to voice their aspirations and develop networked conversations through a topical hashtag. Likewise, during the Covid-19 pandemic, where many (if not all) people have been affected, Twitter has been adopted by many netizens in Indonesia to create various topical conversations related to the pandemic. With regard of its high number of users, the conversations via Twitter are able to attract public awareness and mobilize them to voice their aspiration, which then potentially amplify a demand for changes[6].

In a new phenomenon such as the Covid-19 pandemic, where there are still many areas of study to be explored, studying a conversation within Twitter hashtag will be helpful because researchers can access a rich set of data about user digital interactions in a real-time basis, which may lead to map the actual pattern of a digital conversation. Despites its limitation for some people to access, the Twitter API data can provide a meaningful pattern of user interactions. By understanding this pattern, researchers can explore the behaviors of community during the crisis or identify key individuals in the networks, among others. To this purpose, a well-established tool for visualizing network patterns, such as Social Network Analysis, can be used to help researchers gain insights from the conversation networks, specifically to identify the role of a user within a trending topic conversation, and how the user relates to each other[2].

B. Implementing Social Network Analysis In Twitter Network

Social Network Analysis provides a visualization of social structure within a community or society from networks perspective[7]. This method enables us to investigate the relationship amongst actors within a community or society[8]. Actors are represented as nodes and the relationship between actors are represented as ties, edges or links which connect the actors. The relationship amongst actors can provide insights on the social phenomenon arise within the networks[7].

Social Networks Analysis can be implemented to study the social structure of online communities in a social media platform, such as Twitter. The social structure of online communities within social media platform focuses on the relationship between actors by investigating how actors relate to each other. In this study, actors are represented as users in Twitter networks. The relationship between users are represented by the way information flows amongst them or the way of actors relate each other's through follower/ following relationship, like and reply, retweet and mention. Then, the patterns of relationships amongst its users represent the social structure of the online communities based on the way information flow or the way users relate to others. Figure 1 illustrates a @mention networks within a Twitter conversation where user A mentions user B and D within his/her tweet.

Likewise, user C mentions user B and A in his/her tweet. Network type can be grouped based on the vertices and edges point of view. Let us have a look into a network with a focus on its node and type of node. There are two types of network in this categorization. First, an egocentric network or a network that focuses on individual and the network of friends around him/her[9]. For instance, a network visualization that focusses on a Twitter user and his/her followers. This network is an egocentric as it is focused on an individual network and his friends around him. Furthermore, a degree can be assigned on this case to explain how far the network reaches[9]. Degree 1 refers to an ego and his friends. Degree 2 refers to an ego, his friends, and friends of friends. Degree 1,5 means that the network visualizes the ego and his friends and how friends relate to each other's. The second network categorization is based on the type of node or vertices. This categorization consists of unimodal and multimodal network. Unimodal network means a network which consist of one type of node[9]. For instance, the example above connects user to user which means the network having one type of node. Most of networks are a unimodal network where the same type of node connects to each other. Two types of node can be connected to each other, namely multimodal network[9]. For instance, users of Twitter connect to the hashtag page which they belong to. There are two types of node, users and hashtags. In this case, there is no direct relationship between users and between hashtags. To provide meaningful interpretation, a multimodal network is usually converted to a unimodal network.

Moreover, networks can be categorized based on the type of relationship[9]. In this regard, a node can be connected by

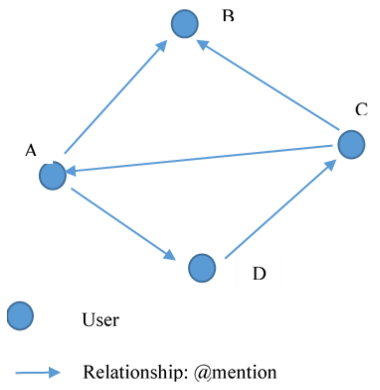

Figure 1. Illustration of @mention networks.

one type of relationship. For instance, Twitter users are connected by @reply relationship. Actually, it is common that Twitter users are connected by various types of relationship, ranging from mention, reply until retweet. This type of network named as multiplex networks. However, in order to reach meaningful interpretation, the multiplex networks commonly are converted to one type of relationship by combining the several network types into one type of relationship[9].

There are two important keys to gain insights from a network. First, network visualization serves roles to visualize how node and link connects each other. Network visualization can help the network analyst to interpret the social structure within the community. There are several algorithms that suit to visualize networks with certain characteristics, such as Fruchterman-Reingold, that is suitable to visualize a large network. Second, network metrics help the network analyst to examine the network patterns overtime, and provide a basis for network comparison [9].

According to Hansen, Shneiderman, and Smith [9], network metrics can be classified into three groups. First is aggregate network metrics. Density and centralization are commonly used for measuring the entire network[10]. Second is vertex specific network metrics. This metric aims to measure the individual position of node within a network. There are several metrics adopted to measure the position of node within a network[9]. The simplest way to measure popularity of a vertex is to count the vertex' connection, namely degree of centrality. Then, betweenness centrality measure the role of vertex to bridge relationship between two or more communities within a network. Closeness centrality refers to how efficient a node can reach others. Eigenvector centrality helps network analyst to identify the most influential people or most important node within a network. Then, based on the visualization and metrics, analyst can determine cluster within a network, and the role of node within a network. For instance, a group of nodes is more connected one another than to other group of nodes. This indicates a cluster within a network. Node within a network also has a specific role-based behaviour, for instance a user within a social media serve role as discussion initiator, a user who like to initiate a discussion within a group. This role describes how the node relate to another through its behavioural contributions to the network.

Hashtag conversation can be seen as a topical conversation-based community in which the member of community is bounded by a similar interest for discussing a topic. Within a community, the role of each node can be identified based on their behavioral contribution to the conversation[9]. Vertex specific metrics also can be implemented to examine the role of each node within the online community. In addition, other metrics can be implemented to examine the entire network such as its density and centralization.

III. Methodology

This section discusses data collection method, analysis and tools employed in this research. This research views a Twitter hashtag as a topical conversation community where individuals interact with each other through their similar interest on a topical conversation. There are three characteristics of topical-based conversation community: who contributes to the conversations, what kind of participant's contribution to the conversation, and the behavioural roles of users. The Social Network Analysis approach was used to reveal the behaviour roles of individuals within the network, and what kind of relationship amongst edges. This approach is able to provide an insightful visualization and metrics which help the network analyst to gain insights from the conversation.

A. Data Collections

Data was collected using NodeXl' Twitter import data tools. This tool helped us to import Twitter data based on keywords related to Covid-19 pandemic in Indonesia directly from Twitter. This tool imports all users' data and tweet. However, there is a Twitter's rate policy that limits the frequency of NodeXl to import such information. This policy restricts the number of users and tweet imported from the platform. Given the limitation, this research focuses only on #BersatuLawanCovid19 as a keyword for the data import process. Using this keyword, we could import all data and tweet which contains the hashtag.

The raw data collected consisted of users with their attributes and their relationships with other users through retweet, reply, mention within retweet and mention. We excluded tweet relationships as we perceived those activities do not result any relationships. In this research, we only need some user attributes as presented at vertices worksheet as follow • Vertex: each row of vertex column presents the name of each Twitter user which is preceding by @ in Twitter. This process resulted 793 vertices

- Followed: presents how many the user following others. The highest number of this column is 119 113 which means this user follows 119113 users, and there are 7 users does not follow any other users.
- Followers: present the number of users' followers. The highest number of followers is 86.944.811, then there are 20 users with no followers.
- Tweet: presents the number of tweets posted by each user. The highest of number of tweets reached 1355588, and the lowest number reached 1 tweet.
- Description: explain the description of user profile posted in Twitter' user profile
- Location: presents the location of user as presented in his Twitter' user profile
- Time zone: user time zone related to his location
- Time zone UTC (offset): user UTC time zone related to his location

- Joined Twitter Date: explain the date of user join Twitter or create his account's

Furthermore, the edge worksheet presents the relationship of each vertex through various type of relationship. The worksheet contains header as follows:

- Vertex 1: define the name of posting user
- Vertex 2: describe the name of targeted user
- Relationship: this column describes the type of relationship which consist of replies to, mention, mention in retweet, retweet and tweet.

B. Data Analysis

The data collected is then analyzed with a purpose to address these research questions:

- How does the network conversation look like? What is the density of the network?
- What type of users participate within the topical based online community?

In order to address Research Question 1, this research employs unimodal network analysis. This unimodal network analysis describes that a user serves as vertex, and relationship between users are described by 'mention', 'retweet', and 'reply to'. This research assumes that all types of relationship have the same weight. The following discussion describes the network metrics related to address the research questions above.

Research Question 1 aims to examine the characteristics of network of conversation as a whole, and thus employs several metrics.

First, this research examined the number of vertices and edges within the network. Vertices represent users and edges represent how users relate with others through retweet, reply and mention. Furthermore, this research also examined the density of the network and reciprocity ration of the network[9]. While density represents the conversation interconnectedness of the online community, reciprocity at network level represents the mutual attachment amongst network' members. [9]

Research Question 2 aims to identify the characteristic of users; therefore, vertices specific network metrics are employed to address this question as follows.

'In-degree centrality': measure the incoming link to the user. In a conversation, 'in-degree centrality' measures the strength of community engage to the user[9]. For instance, @jokowi has a high in-degree centrality in a Covid-19 conversation as he received a huge number of mentions and replies. Then, 'out-degree centrality' refers to the initiative of users to engage with the community[9], such as how many mentions or reply created by the user. These two metrics can describe the level of user engagement within the conversation.

Moreover, this research also identifies users with the highest number of followers, the number of users he/she follows, and the highest numbers of tweet produced by a user. This metrics help to reveal the user's networking activities in Twitter. Finally, this research examines reciprocity of users and edges to find out the mutualism of relationship amongst users. This metric is of importance to understand the strength of conversations will work within the community.

Social Network Analysis will help us visualize the network of conversations. In order to gain an insightful visualization, we implement labelling and visual attribute technique to the network. Vertex' size is measured based on their degree

IV. RESULT

We analyzed 793 unique users and 4441 total relationships established within #BersatuLawanCovid19 conversations as presented in Table III. The relationships are represented by edges. Unique edges refer to the number of relationships if we multiple relationships are counting as one relationship. There were 743 relationships as presented in Table III as unique edges. We then counted all the relationships amongst vertices. There were 3699 relationships within the network, presented as edges with duplicates in Table III. The data indicates that the values of reciprocated edges and vertices are extremely low. This suggests that the mutual engagement within this network was very low. In this regard, we focused on relationships of retweet, replies to, mentions, and mentions within retweet. We excluded all original tweets, or tweets without any mentions to other users, as they do not create any relationship with each other or presented as a self-loop in NodeXL. There were 26 separate group of vertices within this community with no single isolated vertex. The number of vertices in the largest group reached 657 vertices. The maximum path that connected two vertices through intermediate vertices reached 8 two, then the maximum message diffusion through chain reached the next 8 vertices. Based on these findings, we considered that this conversation network had a low mutual engagement. Consequently, the graph density was also extremely low as presented in Table III.

The online community engagement is measured using in-degree and out-degree centrality presented in Table I. The average in-degree centrality reached 1,6, which means every user receives more than one 'mention', 'reply to' or 'retweet'. The maximum in-degree centrality reached 360. This means that the user of hashtag, namely @bnpb_indonesia, received 360 engagement initiatives from others such as mentions, mentions in tweets and retweets and replies. Then, @kemenkesri Twitter account reached the second highest in-degree centrality. Both accounts are the official accounts of the Indonesian Government that are in-charge of various activities to handle the Covid-19 outbreak in Indonesia. Referring to the average number of in-degree that reaches 1,6, it seems that the two accounts are much more popular than other accounts within this topical-based conversation. The minimum in-degree centrality was 0, which means that some users do not receive any mentions or replies to or retweet. Furthermore, the out-degree centrality measures the user's initiative to engage with the community through retweeting another message, mention others and replies to other users. In this case, the average number of out-degree reached 1,6, which means that every user initiated to post a mention, replies to and retweet to others. The maximum degree centrality reached 38 which equals to the number of initiatives to engage with others. If the minimum out-degree centrality reached 0, then some users did not initiate any engagement activities within the community. Tables II demonstrate the top ten users ranked by in- and out- degrees.

TABLE I. IN DEGREE AND OUT DEGREE

	In-Degree	Out-Degree
Minimum	0	0
Maximum	360,000	38,000
Average	1,609	1,609
Median	0,000	1,000

Let us take a closer look at the top ten vertices ranked by the number of tweets and followers as presented at Table II. According to the number of tweets produced by the users, the top ten vertices ranked out by tweets were dominated by several official accounts of institution that has no or minimum relevancy with Covid-19 outbreak, such as the Government of Indonesia' electrical company, Radio Elshinta (a private radio broadcaster company), and the official account of a wireless communication provider. The account actively produced tweets that were different with account which has high in-degree centrality within this online community. Then, according to the top ten users ranked by followers, users with extremely high followers such as @Realdonaldtrump and@ Jokowi, were also involved within this community.

V. DISCUSSION

The present research examines an Indonesia official Twitter hashtag from a network perspective to respond the Covid-19 outbreak. Due to the popularity of this topic, the hashtag is considered as highly active in terms of the high number of users posted messages within this hashtag. The first research question asked about the overall network characteristics within this hashtag. Based upon the network density metrics, we conclude that the density of the conversation-based community was very low, indicating a low engagement level amongst users of the community. This can be inferred that the members of the community might have put efforts to develop a relationship through mentioning others or replying to others; but as the data shows that the value of reciprocated pairs ratio was extremely low, their initiatives to build any engagements were not responded reciprocally by the other users. According to [4] and [5], a conversation is considered work within a community if the community members are reciprocally talking with each other. In other words, this reciprocally talk will affect the level of engagement between the community members in terms of conversational practices. Within a topical-based conversation community, where members of the community are bounded by a similar interest of conversational topic, then the commonly members of the community talked with each other reciprocally. This research found that edge and vertices reciprocated pairs ratio within the hashtag #BersatuLawanCovid-19 were extremely low based on a low edge reciprocated ratio measurement.

TABLE II. LIST OF USERS RANK BY IN-OUT DEGREE, FOLLOWERS AND TWEETS

	In-Degree	Out-Degree	Followers	Tweet
1	bnpb_indonesia	jokowinomics_id	realdonaldtrump	pln_123
2	kemenkesri	nyiurnyiur	flotus	radioelshinta
3	lawancovid19_id	ratihtwijaya1	jokowi	myxlcare
4	fadjroel	fadjroel	who	aepishere
5	jubirpresidenri	sunandarps	najwashihab	sonorafm92
6	jokowinomics_id	pedoman_id	ridwankamil	indonesiagaruda
7	pedoman_id	brigade01arwan1	radioelshinta	dms_ambon
8	kemenbumn	irvinmenyenx	indonesiagaruda	cnnindonesia
9	bppt_ri	mimiweeka	kpk_ri	blackpink828
10	perekonomianri	progjo	kemenristekbrin	mudha_satriya

TABLE III. OVERALL NETWORK METRICS

Graph Metric	Value
Graph Type	Directed
Vertices	793,000
Unique Edges	743,000
Edges With Duplicates	3698,000
Total Edges	4441,000
Self-Loops	8,000
Reciprocated Vertex Pair Ratio	0,006
Reciprocated Edge Ratio	0,0126
Connected Components	26,000
Single-Vertex Connected Components	0,000
Maximum Vertices in a Connected Component	657,000
Maximum Edges in a Connected Component	4234,000
Maximum Geodesic Distance (Diameter)	8,000
Average Geodesic Distance	2,9208
Graph Density	0,0020

The second research question is about the type of users involved within this network. The network is dominated by two extremely popular vertices or users, @bnpb_indonesia and @kemenkesri. However, those users did not reply any engagement effort to them. Two popular users serve roles as core actors who's responsible to manage various efforts to fight against this pandemic. They served as a source of information and the key actor to enhance the engagement amongst community members from a social movement perspective[11]. As a popular hashtag, #BersatuLawanCovid-19 had several users having extremely huge number of followers involved within this conversation-based community.

However, it looks like those users did not actively participate within the conversation. The low density and low reciprocity amongst members of the community, in particular the core actors, impact to flow of information within this community. On the other words, the information flow within this community may face barriers due to the low reciprocity of the core actors. Moreover, as the community discussed a common and well-known topic, most of the members could be not interconnected with each other's. This findings align with the work of [10] that emphasizes that users of a discussion of common health issues is disconnected from one another. Then, during this emergency crises, as the core actors have their own audiences, we suggest to enhance engagement between core actors and other of the community, in particular their own audiences. This perhaps can impact to the flow of information to the society.

VI. CONCLUSIONS

Derived from the discussion above, this study shows that the hashtag #BersatuLawanCovid-19 has worked well in attracting the number of users and in developing further messages within the conservation-based community. However, this research also demonstrates that the level of engagement amongst the community members is extremely low, or indicating low mutual relationships amongst its community members. Based on these indicators, we interpret that the messages posted to the hashtag could not invite reciprocal conversations, and consequently resulted in a low level of engagement amongst its members. This can be caused by the hashtag's characteristic as a one direction message or a public message, which is initiated by the Indonesian Government to fight against the Covid-19 pandemic as its main purpose. In this regard, despite the one-direction characteristic, we propose that the level of engagement should be developed, as this can help the hashtag creator gains a better understanding about any changing behaviours and opinions from the community members that may represent the Indonesian society in general during a crisis. We thus suggest that the official account of the Indonesian Government can improve its strategy of Twitter conversational-based online community to build higher level of engagement with the Twitter communities in Indonesia. In particular, this can help monitor the evolving situation during this Covid-19 pandemic through the Indonesian society's point of view.

REFERENCES

[1] L. Rossi and M. Magnani, "Conversation Practices and Network Structure in Twitter," in ICWSM, 2012.

[2] A. Bruns, "How long is a tweet? Mapping dynamic conversation networks on Twitter using Gawk and Gephi," Information, Communication & Society, vol. 15, no. 9, pp. 1323-1351, 2012.

[3] L. Hong, G. Convertino, and E. H. Chi, "Language matters in twitter: A large scale study," in Fifth international AAAI conference on weblogs and social media, 2011: Citeseer.

[4] D. Boyd, S. Golder, and G. Lotan, "Tweet, Tweet, Retweet: Conversational Aspects of Retweeting on Twitter," in 2010 43rd

[5] Hawaii International Conference on System Sciences, 5-8 Jan. 2010 2010, pp. 1-10, doi: 10.1109/HICSS.2010.412.

[6] C. Honey and S. C. Herring, "Beyond microblogging: Conversation and collaboration via Twitter," in 2009 42nd Hawaii International Conference on System Sciences, 2009: Ieee, pp. 1-10.

[7] F. Suwana, "What motivates digital activism? The case of the Save KPK movement in Indonesia," Information, Communication & Society, vol. 23, no. 9, pp. 1295-1310, 2020/07/28 2020, doi: 10.1080/1369118X.2018.1563205.

[8] M. H. Walker and F. B. Lynn, "The embedded self: A social networks approach to identity theory," Social Psychology Quarterly, vol. 76, no. 2, pp. 151-179, 2013.

[9] P. Roy, A. Martínez, G. Miscione, M. Zuidgeest, and M. van Maarseveen, "Using Social Network Analysis to profile people based on their e-communication and travel balance," Journal of Transport Geography, vol. 24, pp. 111-122, 2012.

[10] D. Hansen, B. Shneiderman, and M. A. Smith, Analyzing social media networks with NodeXL: Insights from a connected world. Morgan Kaufmann, 2010.

[11] I. Himelboim, M. A. Smith, L. Rainie, B. Shneiderman, and C. Espina, "Classifying Twitter topic-networks using social network analysis," Social media+ society, vol. 3, no. 1, p. 2056305117691545, 2017.

[12] [D. Isa and I. Himelboim, "A social networks approach to online social movement: Social mediators and mediated content in# freeajstaff twitter network," Social Media+ Society, vol. 4, no. 1, p. 2056305118760807, 2018.