The Dissertation Committee for Joseph Jai-sung Yoo Certifies that this is the approved version of the following Dissertation:

Opinion Leaders on Twitter Immigration Issue Networks: Combining Agenda-Setting Effects and the Two-Step Flow of Information

Committee:

Thomas Johnson, Supervisor

Gina Chen

Wenhong Chen

Maxwell McCombs

Dhiraj Murthy

Opinion Leaders on Twitter Immigration Issue Networks: Combining Agenda-Setting Effects and the Two-Step Flow of Information

by

Joseph Jai-sung Yoo

Dissertation

Presented to the Faculty of the Graduate School of

The University of Texas at Austin

in Partial Fulfillment

of the Requirements

for the Degree of

Doctor of Philosophy

The University of Texas at Austin

May 2019

Dedication

To my Heavenly Father and

To my parents, Jung Yul Yoo, and Jeong Yeun Choi

For their everlasting love and support

Acknowledgements

Saying just “thank you” is not enough to express my gratitude during my graduate life. I believe that writing my dissertation is a big achievement in my life, costing my enormous time, and continuous effort. With tremendous supports of my family, friends, and academic colleagues, I could successfully finish my dissertation. Especially, I am so much indebted to my committee members, Dr. Thomas Johnson, Dr. Maxwell McCombs, Dr. Gina Chen, Dr. Wenhong Chen, and Dr. Dhiraj Murthy.

First and foremost, I would like to express my huge gratitude to Dr. Thomas Johnson. We shared a lot of memories since 2011 when I started my academic career. His Theory class sparked me to be interested in social media opinion leaders, my dissertation topic. We worked together, and I could learn his insights, knowledge and passion. We also spent our pastime together, which would help me to refresh my academic life. He is my academic and personal role model. Also, my committee members wholeheartedly provided insightful knowledge for my dissertation. Dr. Maxwell McCombs suggested concise and focused comments that would lead me to think about my research ideas in detail. Dr. Wenhong Chen’s sharp suggestions were fundamental in setting research methodology. I could learn a lot about social media public sphere from Dr. Gina Chen, and computational data analysis from Dr. Dhiraj Murthy.

Further, I want to express my sincere appreciation to my great colleagues, especially Magdalena Saldana, Margaret Ng, Shuning Lu, Kyser Lough, Jeremy Shermak, Ever Figueroa, Clare Boyle, Kelsey Whipple, Martin Johannes Riedl, Jordon Brown, Seokho Lee, Ji won Kim, Hyeri Jung, Taeyoung Lee, Claire Lee, Hogeun Seo, Miki Tanikawa, Saif Shahin, Cindy Pei Zheng, Angela Lee, Danielle Kilgo, Lourdes Cueva

Chacón, Barbara Audet, Logan Molyleux, and Kathleen McEloy. I was especially indebted to Arnold Chung and Myungsang Lee, who helped me learn big data computational analysis skills using R and Python. They emotionally and intellectually supported me, and I would really appreciate it from the bottom of my heart.

I am very grateful to my parents, Jung Yul Yoo and Jeong Yeun Choi, and my younger brother Jaemyung Yoo. My parents heartily supported and prayed eagerly for me so that I was able to complete my dissertation. Whenever I needed emotional supports, my family always helped me out.

Time flies although I think I am a first-year Master's student at the School of Journalism in 2011. Now, I am looking forward to starting my new chapter as an academic scholar who can contribute to the development of Communication and Social Science. I am sure that I could meet great colleagues in the future like great scholars I have ever met in my life.

Abstract

Opinion Leaders on Twitter Immigration Issue Networks: Combining Agenda-Setting Effects and the Two-Step Flow of Information

Joseph Jai-sung Yoo, Ph.D.

The University of Texas at Austin, 2019

Supervisor: Thomas Johnson

This dissertation focuses on opinion leaders on the Twitter issue networks to examine the two-step flow of information and agenda-setting effects. It analyzes the US immigration issue network as a case study because it is controversial on Twitter, and many elites such as lawyers and politicians who can influence others' opinions are engaged in Twitter debates. Twitter is an important platform for active public debates, serving as a networked public sphere that can be used as a source and disseminator of information. Research has shown that communication patterns on the networked public spheres vary, including top-down, bottom-up, and side-by-side communications.

This dissertation asked the following questions: (1) what is the shape of the Twitter immigration issue network? (2) who are Twitter opinion leaders, and what are their characteristics? and (3) who sets the agenda on Twitter: news media, opinion leaders, or the public? To answer those questions, this dissertation employs (1) social network analysis to identify immigration issue networks and opinion leaders, (2) hierarchical

linear regressions to examine factors that can predict opinion leadership, and (3) Granger causality tests to measure the longitudinal agenda-setting effects of each group (news media, opinion leaders, and the public). The author differentiated between the retweet and mention networks because while the retweet network is intended to disseminate information, the mention network is intended to elicit responses, motivating users to participate in Twitter conversations.

Through social network analysis, the author found divisions among clusters. Especially, the retweet network was classified as a polarized network and the mention network was described as a community cluster. The results of hierarchical linear regression analyses indicated that elite status, verified status, the number of followers, and individual issue involvement were common predictors of opinion leadership. The results of time-series Granger causality tests showed a mixture of top-down and bottom-up agenda-setting effects. This dissertation extends our theoretical understanding of opinion leaders based on traditional theories including two-step flow of information and agenda-setting effects. A key practical implication is that active Twitter users can be opinion leaders and can contribute to setting an issue agenda.

Table of Contents

List of Tables

List of Figures

Chapter 1: Introduction

Immigration policy has been one of the most controversial issues in US history, even spurring conflict before the Civil War (Zolberg & Zolberg, 2009). Within the past two decades, various historical events (including the attacks of September 11 and the inauguration of President Donald J. Trump) and legislative actions (including the comprehensive Immigration Reform Act of 2007 and Deferred Action for Childhood Arrivals, known as DACA) have intensified this controversy, generating active debates, protests, and petitions. Within the context of these debates about immigration in the US, there is no doubt that opinion leaders—typically defined as people with elite status and strong reputations who reproduce information from news media and disseminate it to their followers (Katz & Lazarsfeld, 1955)—have played a significant role in shaping public opinion. Before the rise of digital media, opinion leaders relied on traditional news sources such as newspaper, television, and radio. Today, opinion leaders are taking advantage of new media technologies, such as Twitter, for consuming and disseminating information, and this can influence those who can be considered as an opinion leader (Lin, 2003; Nisbet & Kotcher, 2009). By using Twitter, opinion leaders can easily influence followers' opinions and set the agenda for issues among the public and even among professional media outlets. In the era of big computer data, more diverse forms of information sources and information flows can be identified. This diverse circulation of media raises the question: "Who sets the agenda on Twitter?" Is it the news media, opinion leaders, or the public?

This dissertation examines opinion leaders on Twitter networks in order to cast light on the two-step flow of information and agenda-setting effects in Twitter issue network. It focuses on Twitter conversations about US immigration policy because this issue is controversial both online and offline, and many socially respected elites such as lawyers, politicians, authors, activists, and educators who can influence other's opinions are currently engaged in Twitter debates on this topic. In addition, President Trump has accelerated public controversy over immigration through a series of executive orders. President Trump promoted controlling immigration as a major issue in his speech announcing his bid for the presidency in 2015, mentioning "when Mexico is sending its people, they're not sending their best… They're bringing drugs. They're bringing crime. They're rapists. And some, I assume are good people." For opinion leaders, Twitter may operate as both a source and disseminator of information on controversial issues such as the immigration debate (van Haperen, Nicholls, & Uitermark, 2018), gun control issue (Tremayne & Minooie, 2013) and same-sex marriage (Gibson, 2018). Twitter users can consume, distribute, and curate relevant information to support their stances on immigration and the current presidential administration or criticize opponents. They can even encourage their followers to take action to promote their collective views to the general public. In the case of immigration controversies, this study investigates the following questions: (1) what is the shape of the Twitter immigration issue network? (2) who are Twitter opinion leaders, and which factors can predict opinion leadership and the frequency of being retweeted? and (3) who sets the agenda on Twitter: news media, opinion leaders, or the public on Twitter issue network?

In order to answer these questions, the author identified opinion leaders in Twitter immigration issue networks, investigated Twitter users' attributes associated with opinion leadership, and measured longitudinal agenda-setting effects among news media, opinion leaders and the public. Little research has been done to identify opinion leaders on Twitter immigration discourses, one of the most controversial issues in the current presidential administration. Moreover, few researchers have observed the longitudinal agenda-setting effects mediated by opinion leaders. To examine Twitter opinion leadership and its agenda-setting effects, the author employed Discovertext, a third-party Twitter vender, to glean 397,655 tweets by using the search term #immigration from Oct. 1, 2016 to Jan. 31, 2017.

The author conducted a social network analysis, hierarchical linear regression analyses and time-series Granger causality tests on the #immigration retweet and mention networks. Social network analysis can guide the author to examine overall network structures, including clustering based on political orientations and biased distribution of tweets (e.g., right-skewed distribution), and to detect opinion leaders through centrality scores, network measures indicating how specific users are influential. The author conducted hierarchical linear regression analyses to examine predictors of opinion leadership. The opinion leadership was measured as in-degree centrality scores calculated by the frequency of being retweeted and mentioned. In-degree centrality is the number of inbound links sent to a node. Lastly, the author conducted Granger causality tests to measure the longitudinal agenda-setting effects of each group (news media, opinion leaders and the public). The author differentiated first- and second-level agenda-setting analyses. The goal of Granger causality test is to answer the question, "who sets agenda on immigration issue networks?"

Background

Social media connects people in the online sphere (Ellison, Steinfield, & Lampe, 2007). On social media, people can develop strong, weak, and even latent (existing but not developed or manifested yet) connections to others without ever meeting them in person, and they can actively participate in a wide variety of debates about controversial issues like the US immigration policy. Social media can help the public form citizen networks and mobilize civic engagement (Loader, Vromen, & Xenos, 2014) by providing forums for public discussion. Twitter, one of the most popular micro-blogging sites, is also an important platform for active public debates, serving as a networked public sphere. Twitter has become a frequently utilized communication channel for political discussions (Tumasjan et al., 2010). Twitter has various communication affordances to initiate discussions. Among various functions on Twitter, retweets can diffuse information promptly. Users can also mention (@) other users on tweets to let them be engaged in Twitter conversations. A hashtag (#) on Twitter can facilitate discussions by allowing users to become aware of others who share similar interests.

The role of opinion leaders has been an ongoing topic examined in communication scholarship since the term "opinion leader" was first introduced in 1955 (Katz & Lazarsfeld, 1955). Opinion leaders are traditionally defined as people who consume news or information from traditional media (like newspapers, radio and television) and exert personal influences on followers' attitudes and behaviors by transferring information to them (Katz & Lazarsfeld, 1955). They are a few key persons in an entire network, who are actively engaged in discussions, post frequent messages, and have a large number of followers.

Academically, there is no common criterion for determining what percentage of a given network is made up of opinion leaders. Some studies suggest that opinion leaders range from the top 10 (Valente & Pumpuang, 2007), 20 (Park & Kaye, 2017) to 30 (King & Summers, 1970) percentile on the Strength of Personality (SP) scale. This is a survey that measures individuals' perceptions of their influence on others (Noelle-Neumann, 1985).

This study chose social network analysis in order to identify opinion leaders in the network. Unlike self-report surveys, which are vulnerable to individual subjectivity and bias, social network analysis can draw individual relationships inside the whole network using empirical methods (Kim, 2007). Several social network analysis studies examined Twitter networks and found strong evidence of the existence of a two-step flow of information initiated by opinion leaders who mediate the information flow between news media and the public (Cha et al., 2010; Choi, 2015; Xu et al., 2014). Moreover, a multi-step or reversed information flow from followers to leaders and news media which runs counter to the traditional two-step flow of information, has also been found (Brosius & Weimann, 1996; Watts & Dodds, 2007). This means that ordinary users, not only mass media or popular celebrities, can play a significant role in disseminating information. Such a different pattern of information flow suggested the need for researching an “applied” or “updated” two-step flow of information to reflect on the role played by ordinary users.

In 2018, 24% of all US adults used Twitter (Pew Research Center, 2018a) and Twitter tend to be liberal. Thus, twitter population cannot be taken as representative of public opinion in general. However, Twitter can provide an ideal platform for assessing the public reactions corresponding to social issues distributed by its users who take an advantage of various communication affordances. On Twitter, they can distribute information related to social issues and thereby motivate other users to engage with those issues. Twitter’s social utility to the media does not seem to be transferred to other social media platforms (Cision, 2016). Twitter is more open to having more chances to spread information to audiences both directly and indirectly than other social media because most tweets are open to the public and Twitter users do not need permission to follow other users (Giglietto, Rossi & Bennato, 2012). Also, Murthy (2013) argued that Twitter has been examined as a public sphere where democratic engagement happens. Thus, Twitter remains a social media platform that facilitates an investigation of communication patterns regarding specific political issues. Twitter has become the means by which any citizen with access to digital technology can participate in the democratic process (Gil de Zúñiga, Jung, & Valenzuela, 2012).

THEORY

The theoretical motivation of this dissertation was the combination of traditional two-step flow of information and agenda-setting effects on Twitter, a networked public sphere. The first theoretical concept, a networked public sphere, was drawn from communication studies, social network studies and, more broadly, the social sciences. The second and third theoretical concepts, two-step flow of information and agenda-setting, were drawn from the field of communication studies.

First, the author explained communication affordances on Twitter. Twitter offers different functions, including retweets, follower-followee networks (meso layer), hashtag communication (macro layer) and mentioning (micro layer). The default level of Twitter communication is a follower-followee network and Twitter communication flows from follower-followee network, to hashtag communication and finally to mention networks.

A public sphere has been defined as "a constellation of communicative spaces in society that permit the circulation of information, ideas, debates, ideally in an unfettered manner, and also the formation of political will" (Dahlgren, 2005, p. 148). A networked public sphere means a digital shift away from a traditional concept of public sphere allowing diverse participants to produce and disseminate ideas for civic action and disrupting the power of traditional media (Benkler, 2006) through the reliance on platforms such as online discussion boards, blogs and social media. Communication patterns on the networked public spheres vary, including top-down (from the elite to ordinary citizens), bottom-up (grassroots communication from the public to the elite) and side-by-side communications (horizontal communications among all citizens). As social media platforms like Twitter influence the formation of public opinion, a networked public sphere allows its participants to be engaged in the dynamics of interactions and information flows. In contrast to the assumption of traditional information flow which emphasizes the role played by traditional news media, the communicative power of traditional news media can be minimalized due to an influx of new influential members in a networked public sphere.

This dissertation considered agenda-setting effects initiated or mediated by opinion leaders within Twitter debates about US immigration. The evolution of two-step flow of information, which gave birth to opinion leadership was discussed. Katz and Lazarsfeld (1955) found opinion leaders who consumed news media, transferred their personal opinions based on news information to followers. As new media technology developed, the concept of opinion leader has also been updated. Thorson and Wells (2015) introduced a curated flow of information, with five forms of curations: journalistic, social, personal, strategic, and algorithmic curations. Such notions can explain Twitter opinion leaders as curators of information under the condition of abundant information, who filter information and disseminate it to followers through online platforms. A reverse information flow can be expected from Twitter opinion leaders due to an increase in voicing ideas of the public.

Also, the author discussed contextual factors, like verified status, elite status, the degree of activeness, the number of followers and followees to predict opinion leadership. The author assumed that the role of Twitter communication affordance, such as the number of mentions and hashtags and individual issue involvement can predict opinion leadership. Mentions and hashtags can allow Twitter users to expand Twitter conversations, and opinion leaders can use such functions to promote their tweets. Opinion leaders are involved in specific issues (Lazarsfeld, Berelson, & Gaudet, 1948; Sun et al., 2006), leading them to actively distribute information with their personal perspectives. Later, the author focused on content factors and dissected the definition of opinion leadership into (1) a dissemination of (media) messages, (2) an offer of personal thoughts, and (3) a call for specific actions to explain content factors on Twitter predicting the frequency of being retweeted, a measure of influence and popularity of tweets (Dang-Xuan et al., 2013; Zhang et al., 2014).

Political polarization or clustering was also discussed. US immigration policy is politically sensitive for discussants, leading discussion networks into clustered figures: Conservative vs Liberal. The "birds of a feather" phenomenon and selective exposure can explain clustering based on political orientations on this platform (Himelboim, McCreery, & Smith, 2013). The author assumed that in US immigration issue networks, the usage of the political hashtag could represent clustering based on political orientations. Also, algorithmic curation can cause a filter bubble and echo chambers because online algorithm learns preferences of social media users' behaviors, and suggests like-minded information.

Traditional agenda-setting studies measured the transfer of issue salience (McCombs & Shaw, 1972) and suggested that mass media directly influences the public agenda. Brosius and Weimann (1996) combined the two-step flow of information and agenda-setting effects to explain the agenda-setting effects of "early recognizers," influential individuals who firstly identified emerging issues in the news media and diffuse them to public audiences (Brosius & Weimann, 1996). Early recognizers shared similar characteristics with opinion leaders as active audiences and mediators of information flow from the media to the public. Brosius and Weimman (1996) equated early recognizers with opinion leaders because (1) they were mediators between the media and the public agenda and had the agenda-setting ability and (2) they had the high strength of personality (SP) scores. They argued that early recognizers had agenda-setting effects, even though the direction of information flow varied, from news media to the public or from the public to the news media. In the era of big computer data where innumerable human traces are collected through social media, more diverse forms of information flows can be expected, requiring new theoretical approaches to agenda-setting studies. Based on existing theoretical findings, this study questioned whether the original concept of opinion leadership held true in the case of Twitter immigration issue network, or whether a new communicative influence of opinion leaders could be detected.

First- and second-level agenda-setting and longitudinal analysis was also discussed in Chapter 2. While the first-level agenda-setting effect described a transfer of salience about specific topics from the news media to the public, second-level agenda-setting focused more on attribute salience. Because this study combined the two-step flow of information and agenda-setting effects on Twitter, the author explained transfers of salience and attributes among different platforms like mainstream media and Twitter. Longitudinal agenda-setting analyses were required because it can help answer the question "who sets agenda on Twitter?" by tracking the originator of agendas.

METHODS

The aim of this study was three-fold: 1) to identify the Twitter immigration issue network by observing divisions of clusters created by similar characteristics of members, and listing top centrality score users; 2) to examine the factors that predict individuals' likelihood of becoming opinion leaders; and 3) to investigate longitudinal directions of agenda-setting effects initiated by opinion leaders. Methodologically, this study employed (1) social network analysis to identify immigration issue networks and opinion leaders, (2) hierarchical linear regressions to examine factors which can predict opinion leadership and (3) Granger causality to measure the longitudinal agenda-setting effects of each group (news media, opinion leaders and the public) in the network.

First, the author gleaned tweets by using #immigration as a sole search term through a 4-month period from October 1, 2016 to January 31, 2017 (n = 397,655) just before the election, the time leading up to Trump's election and the first days of his new administration. A significant number of discussions and debates related to immigration issues were found on Twitter, allowing the author to test the role of opinion leaders and their longitudinal agenda-setting effects. The author utilized Twitter open API (Application Programming Interface) Firehose in DiscoverText Sifter application to collect tweets which contain #immigration. The author restricted tweets to mentions about general US immigration issue. Tweets for the US immigration issue mostly mentioned migrations from Latin American countries but some of them concerned Syrian refugees and Muslim migration to the US. If individuals from other countries outside of the US posted tweets and used #immigration to discuss US immigration policy, the author included them in this study because such tweets directly talked about US issues, the main issue in this study. The author chose #immigration as a key search term because it was the largest and broadest hashtag used by both political parties and the sole usage of this hashtag can picture the entire network without being polluted by other tweets.

This study differentiated retweet (n = 227, 962) and mention (n = 109,412) networks. While both retweets and mentions are indicators of influence on Twitter, these forms possess different characteristics. Retweeting is oriented to disseminate the messages to one's followers (Barash & Golder, 2010). Mentioning enables other followers to join the Twitter conversation (Honey & Herring, 2009; Chen, Tu, & Zheng, 2017).

Social network analysis can detect opinion leaders and examine the information flow initiated by them. Among centrality measures which are mainly used to find central actors in the networks, in-degree centrality calculated by the number of tweets being retweeted and mentioned, was operationally defined as opinion leadership, the dependent variable in this study. The positive relationship between opinion leadership and centrality measures (Choi, 2012; Lee & Cotte, 2009) supported this assumption. Even though Twitter influential scores like Klout and PeerIndex can measure and publicize the influential users in the entire Twittersphere, this study adopted centrality scores from social network analysis based on the data gleaned by #immigration because influential users between the entire Twittersphere and #immigration network can be different. While users with high Klout scores post tweets about other social issues broadly to earn reputation from followers, opinion leaders on the immigration issue network gain that status through their immigration tweets. In-degree score can explain influential users in the immigration issue network. Also, the author observed shapes of social networks, such as polarized crowds, broadcast network, community clusters or support networks (Pew Research Center, 2014) in the retweet and mention networks. Based on the usage of hashtags, another social network analysis was conducted to observe shapes of hashtag networks. The author assumed that individual usages of hashtags could represent their political orientations, so the co-occurrence between #immigration and other hashtags on individual tweets could help explain how the #immigration network is divided.

Later, the author conducted hierarchical linear regression analyses to measure the predictive powers of Twitter communication affordances, contextual factors and individual issue involvement to opinion leadership in the retweet (Total accounts = 117,040) and mention networks (Total accounts = 50,395). Independent variables were Twitter communication affordances (the average number of hashtags and mentions Twitter users used), contextual factors (general Twitter activities, the number of followers and followees, verified status, elite-status) and the degree of issue involvement.

The author additionally observed content factors on tweets and their influence on the number of being retweeted in the retweet network. For content factors, the author first focused on the definition of traditional opinion leaders: (1) active media users who (2) interpret media messages and (3) influence other's opinion or behavior (Katz & Lazarsfeld, 1955). These three components of the definition of opinion leaders could be dissected into (1) dissemination of media messages and (2) offering personal opinions based on media messages. A positive relationship between Twitter opinion leadership and civic engagement was found (Park & Kaye, 2017), thus the author added a category of (3) a call or mobilization for specific actions. The frequency of being retweeted could represent the influence and popularity of tweets (Dang-Xuan et al., 2013; Zhang et al., 2014). The author manually extracted content factors from randomly selected tweets (n = 1,116) and tested the predictive powers of Twitter communication affordances, content and contextual factors to the number of being retweeted.

After identifying factors predicting opinion leadership, the author conducted Granger causality, a time series-analysis testing to check whether one preceded time series can be connected to the distribution of another time series variable over time. Granger causality fitted the aim of this study because it allowed the author to find the longitudinal direction of agenda-setting effects initiated by (1) news media, (2) opinion leaders, and (3) the public over the four-month period. The author chose the best model determined by time lags and observed causal relationship among clusters at once to figure out whether agenda-setting effects on Twitter issue networks were top-down (from news media to opinion leaders, and then to the public), bottom-up (from the public to opinion leaders, and then to news media), or a mixture of the two processes.

The author gathered 4,981 news articles searched by Lexis-Nexis over the same four-month time period (October 1, 2016 to January 31, 2017) as tweets gathered through Discovertext. The cluster of opinion leaders was decided based on (1) their verification status, and (2) top 10 % of weighted in-degree centrality. If Twitter users belonged to one of these two categories, the author assigned them as opinion leaders. The rest of the tweets (those not posted by opinion leaders) were operationally defined as the public agenda**,** which accounted for the largest numbers in the issue network.

The author conducted Granger causality tests over three different networks: the entire tweets gleaned by #immigration, the retweet network and the mention network. Also, the author examined both first-level and second-level agenda-setting tests. The author assumed that conservative Twitter users would want to establish strict standard of immigration policy and limit the number of migrants into the US. However, Democratic users were favorable toward immigrants and immigration issues (Pew Research Center, 2016). Thus, the author expected different agenda-setting effects among Republican and Democratic Twitter users.

ORGANIZATION

Chapter Two

The second chapter discusses the theoretical foundation of this study. Specifically, the author accounts for the networked public sphere and the application of this concept to Twitter. The author additionally discusses two-step flow of information and agenda-setting theories.

The author introduces Twitter as a communication platform, discussing communication affordances including hashtags (#) as a tool for users to detect others who share similarities, retweets as an affordance to disseminate information, mentions as a default Twitter communication leading other users to be engaged in Twitter discussion, and verified users as influential users who are manually authenticated as trustworthy or popular figures by Twitter. Hashtag can form ad hoc publics, which can be developed into networks with actors who share similar interests, like news topics, news agendas or hobbies. Also, the purpose of retweeting is to spread messages to followers. Retweeting indirectly indicates the reputation of the user being retweeted because retweets are more likely to be viewed and retweeted again by other users (Recuero, Araujo, & Zago, 2011). Mention is a more direct form of Twitter communication to evoke conversations.

This chapter also discusses the history of two-step flow of information and their connection to opinion leaders in both traditional and digital media settings. The combination of agenda-setting and opinion leadership suggested by Brosius and Weimann (1996) is followed to theoretically justify the study of agenda-setting effects of opinion leaders on Twitter issue networks. The history of agenda-setting studies including the first- and second level agenda-setting is examined. The reasons to conduct longitudinal agenda-setting studies are discussed.

Chapter Three

Chapter Three describes the overall methodology of this study to explain three key topics: (1) the characteristics of Twitter immigration issue networks, top centrality-scored users and divisions of clusters, (2) attributes predicting opinion leadership, and (3) the longitudinal agenda-setting effects of each cluster (news media, opinion leaders and the public). In order to answer each of the three topics, the author explains the overall methodology of this study, including social network analysis for Twitter immigration issue network, hierarchical linear regressions for the prediction of opinion leadership and time-series Granger causality tests. The steps of conducting social network analysis, hierarchical linear regressions and Granger causality are explained.

The social network analysis is conducted to investigate the characteristics of overall immigration issue networks by observing kinds of networks (Pew Research Center, 2014) and the presence of opinion leaders based on top centrality score users. The author uses Gephi, an open-source computer-assisted network analysis software launched to conduct social network analysis. This chapter also explains divisions of clusters in the retweet, mention, and hashtag networks. The author calculates modularity scores in the network and modularity classes for each user through Gephi Modularity function, a measure to determine the extent to which calculated clusters are bounded (Himelboim, Smith, & Shneiderman, 2013). Later, the author conducts a hand-coded content analysis to classify political orientation of users in each cluster, labeling them as conservative, liberal, neutral, or unclear groups. The units of analysis are (1) a node (Twitter account) for the retweet and mention networks and (2) the co-occurrence of hashtags with #immigration for hashtag network. The author also measures the degree to which the distribution of networks is skewed by a few users who recorded high in-degree centrality scores or who frequently posted tweets with #immigration.

Later, the author introduces the use of hierarchical linear regressions to examine the predictive power of Twitter communication affordances, contextual factors extracted from Twitter users and their issue involvement to opinion leadership, measured by the weighted in-degree centrality score of each user. The unit of analysis is an individual Twitter user. In terms of contextual factors, the author assumes that jobs of Twitter users including authors, politicians, educational jobs, lawyers, journalists and activists known as elites were positively associated with opinion leadership. Other contextual factors found in users' bio included the degree of activeness, the number of followers and followees and verified status. The author conducts two hierarchical linear regressions on retweet and mention networks.

The author further examines the role of content factors predicting the frequency of being retweeted. This study focuses on three types of tweets based on the definition of opinion leaders: (1) distributing information, (2) offering personal information, and (3) calling for specific actions. While distributing news information basically emphasizes the role of opinion leaders as information distributors, offering opinions based on news information can be opinion leaders' subjective behavior to voice their interpretations about specific issues. Additionally, if Twitter users ask others to join in specific actions like signing a petition and participation in offline protests, the author posits that such tweets included call for specific actions, which could be positively related to opinion leadership (Park & Kaye, 2017). The author randomly selects 1,116 tweets from the retweet network and conducts additional hierarchical linear regression analysis to explain statistical predictions of Twitter communication affordance (average numbers of mentions and hashtags on tweets), content and contextual factors (tweets posted by verified and elite users) on the frequency of being retweeted.

Lastly, the author introduces methodological steps to conduct Granger causality to measure longitudinal agenda-setting effects initiated by news media, opinion leaders and the public. Granger causality can show that the change in the volume of one trend precedes the change of values of another but cannot exhibit to what extent other events outside the model trigger both time trends (Russell Neuman et al., 2014). In this chapter, the author tests which clusters (news media, opinion leaders and the public) could initiate longitudinal agenda-setting effects. The author tests whether traditional concept of agenda-setting effects (from news media to opinion leaders, and then to the public) held true or whether a different type of agenda-setting relationship was found.

The author utilizes Lexis-Nexis to glean news articles related to US immigration policy issue (n = 4,981) over the four-month period (October 1, 2016 to January 31, 2017). Later, the author divides Twitter users into two clusters: opinion leaders and the public. Opinion leaders are operationally defined as (1) verified users and (2) users who have top 10% of in-degree centrality scores in the issue network. The unit of analysis is the daily volume of news articles for news media and total number of daily tweets for opinion leaders and the public agenda.

Chapter Four

The fourth chapter discusses the results of social network analyses to investigate the overall network, the presence of opinion leaders based on centrality scores, and divisions of clusters. The results of social network analysis illustrate the overall structure of the Twitter immigration issue network and influential users calculated by centrality scores. The author examines shapes of networks suggested by Pew Research Center (2014), including polarized crowds, broadcast network, community clusters or support networks. The author also investigates hashtag network created by co-occurrence with #immigration, assuming that such a co-occurrence can represent similar political orientations. Lastly, the author observes whether Twitter users who recorded high in-degree centrality scores and who posted a lot of tweets dominated each network.

Chapter Five

Chapter Five explains the results of hierarchical linear regression analyses predicting opinion leaderships in the retweet and mention networks and the frequency of being retweeted in the randomly selected retweets. The author examines the predictive powers of Twitter communication affordances (average number of mentions and hashtags users posted), contextual factors (general Twitter activities, the number of followers and followees, verified status, and user's elite occupations), and individual issue involvement to opinion leaderships. In addition, the author focuses on content factors defined by traditional opinion leaders (distributing information, offering information, and calling for specific actions), and their associations with the frequency of being retweeted.

Chapter Six

Chapter Six discusses the results of Granger causality tests to investigate the longitudinal agenda-setting effects of each group (news media, opinion leaders and the public). Steps to find the best model and conduct longitudinal analyses are also mentioned. The author presents the first- and second-level longitudinal agenda-setting effects on Twitter immigration issue network. Based on the results of Granger causality tests, the directions of agenda-setting effects on Twitter issue networks such as top-down (from news media to opinion leaders, and then to the public) or bottom-up (from the public to opinion leaders, and then to news media) are discussed.

Chapter Seven

The seventh chapter discusses findings of this study. This chapter integrates the findings of each preceding chapter into the theoretical, methodological and practical contributions. The author discusses some limitations of this study. Considering contributions and limitations, the author proposes suggestions for further research to expand upon the current study.

SIGNIFICANCE OF THE STUDY

The contribution of this dissertation is three-fold. First of all, this study can theoretically validate traditional theories of communication: two-step flow of information and agenda-setting theory in the Twitter issue network. Brosius and Weimann (1996) first introduced the combination of agenda-setting theory and the two-step flow of information, and this dissertation tests the validity of this combination on Twitter. Weimann and Brosius (2017) emphasized the role of interpersonal communication as an agenda-setter in the digital media environment and the necessity of combining agenda-setting theory and two-step flow of information. In the era of digital media, this study can explain new phenomena based on two important communication theories. Additionally, this study measures the longitudinal agenda-setting effects of about 400,000 tweets by conducting Granger causality to go beyond cross-sectional data and describes more elaborated agenda-setting effects on Twitter issue networks.

Second, this study combines more than three methods to understand Twitter issue network, characteristics of opinion leaders and the longitudinal information flow. Social network analysis, hand-coded content analysis, hierarchical linear regression analyses, and time-series Granger causality tests can be combined to draw clearer pictures of Twitter issue network and the presence of opinion leaders.

Lastly and practically, this study can provide guidelines for immigration activists or immigration issue stakeholders to understand the network structure by focusing on possible relationships between news media, opinion leaders and the public. The immigration activists or leaders can identify opinion leaders first and strategically contact them or media workers to promote immigration issue-specific information. Therefore, they can promote their ideas, mobilize the public and ultimately, contribute to the society in a desired way.

Chapter 2: Literature Review

Studies of the networked public sphere and two-step flow of information emphasize the communicative power of individuals. In their study of the combination of two-step flow of information and agenda-setting, Brosius and Weimann (1996) discussed the central role of early recognizers, who share similarities with opinion leaders, as mediators of information flow. Opinion leaders in the network cannot be neglected, especially in Twitter networks, where a wide range of information is provided and opinion leaders seek to capture other users' attention by curating that information. In order to be influential in the network, such actors should have persuasive power to grasp others' attention. On Twitter, the frequency of being retweeted represents how such tweets are disseminated among followers, and the frequency of being mentioned indicates how many times Twitter users are engaged in given discussions. Thus, it is important to examine who is taking a central place and influencing the agenda-setting process and which kinds of tweets are retweeted or mentioned frequently on Twitter, a new form of networked public sphere.

The author relied on communication affordances on Twitter, networked public sphere, two-step flow of information, agenda-setting theory and social network to help explain the results. Twitter communication affordances (Twitter's specific properties and how they are used by Twitter users) explain the specific roles of hashtags, retweets and mentions in the immigration issue networks. The author argued using hashtags can contribute to the formation of issue networks. Retweeting is a way to disseminate messages on Twitter and mentioning can allow others to join Twitter conversations. Currently, Twitter can perform as a virtual public sphere where diverse individuals can join in public discussions. Traditional public sphere scholars argued the presence of elites on the society leading discussions and mediating communications between the state and the public. Similar to elites in public sphere, the two-step flow of information gave birth to the concept of opinion leaders, a small number of influential individuals who consume information from news media, curate it with their filtering activities, and distribute messages to followers. The author explains historical development of opinion leaders and compares similar and different characteristics between traditional opinion leaders, and online and Twitter ones. The author emphasizes curating role of online opinion leaders and the importance of the grassroots communication process on Twitter. Several factors to explain opinion leaders are discussed, based on the definition of opinion leaders, and Twitter communicating characteristics including the number of tweets, verified status, and the number of followers and followees.

Social network analysis explains the relational patterns and forms of structures among various actors, which are divided due to different political perspectives. Selective exposure and political polarization can explain divisions of clusters on Twittersphere. Also in social network analysis, actors with higher in-degree centrality scores have a high level of popularity, due to their curating and disseminating activities. In addition, agenda-setting theories explain the transfer of issue salience from news media to the public, and first- and second-level agenda-setting theories explain how issue salience and affective attributes in specific issues can initiate agenda-setting process, respectively. The author combines two-step flow of information and agenda-setting theories and assumes that opinion leaders who are located in the center of issue network can set the agenda on Twitter issue networks. The author emphasizes the necessity of longitudinal approaches in agenda-setting studies for more elaborate investigations explaining causal relationship among news media, opinion leaders and the public.

COMMUNICATIONS ON TWITTER

Social media has served as a platform where synchronous online political discussions with a large number of participants are joined together (Russell Neuman, Bimber, & Hindman, 2011), and social media platforms such as Twitter provide important venues to examine within the context of civil democracy (Mutz & Young, 2011). Twitter is the fourth largest social networking site, following Facebook, YouTube, and Instagram globally (DreamGrow, 2018). Twitter has more than 330 million active users worldwide. These users send approximately 500 million tweets of 280 characters per day, up from original limit of 140 characters. Twitter is well-known for providing conversational information to its users via a public forum in real time, and users can create diverse topic ecosystems based on their shared interests and concerns (Twitter, 2018a). Twitter is widely used among political journalists as a news source for reporting and a platform for communicating with audiences (Broersma & Graham, 2012). Its characteristics, which allow users to disseminate information promptly, make it an ideal platform to influence the news-consuming process. Journalists can post short news facts, hyperlinks, images or video that may not be fit to print but can be considered as newsworthy information. Also, politicians or political reporters can strategically launch scoops to generate buzz on Twitter (Murthy, 2015).

Twitter has unique combination of communication affordances that affect how it can be used in the immigration debate. Gaver (1991) defined affordances as “the interaction between technologies and the people who will use them” (p. 80). Like his definition, scholars have argued that technology affordance is an interaction between technology itself and users’ social construction of the meanings of that technology (Treem & Leonardi, 2013; Valenzuela, Correa, & Gil de Zúñiga, 2018). Twitter offers asymmetrical connections to users, indicating that mutual approval is not required to follow other users, and it is possible to follow others without knowing them personally (Valenzuela, Correa, & Gil de Zúñiga, 2018). Twitter is valued more for its immediacy than for interactions; tweets show up instantly. This immediacy affordance indicates that Twitter is appropriate for disseminating information quickly. Several scholars argued that the primary function of Twitter is to spread information, including personal information or breaking news (Kwak et al., 2010; Murthy, 2011). Any individual, from citizens to journalists, can utilize Twitter to disseminate information.

Twitter can coordinate the circulation of information across different online platforms through tweets, retweets and mentions (Parmelee & Bichard, 2012). Retweeting is rebroadcasting others' tweets to disseminate the messages to one's followers (Barash & Golder, 2010). Retweeting empowers Twitter users to spread information and proliferate it to receivers who do not need to have a direct relationship with original Twitter users being retweeted. A retweet is a prompt and interactive tool to spread information (boyd, Golder, & Lotan, 2010; Suh et al., 2010). Twitter users retweet other tweets to share interesting content with their followers and to give comments on others' tweets (Wang et al., 2016), but sometimes they retweet to criticize others. Information diffusion is closely related to follower-followee relationships on Twitter, which can be further developed into information networks because tweets posted by users are visible by default on the accounts of those users (Barash & Golder, 2010). Li, Dombrowski, and Brady (2018) found three key strategies of using retweets for immigration-focused nonprofit organizations: (1) disseminating contents about immigration-related issues, (2) calling for participation and (3) engaging in conversations with political actors and news media.

Besides retweets, Twitter users show different self-representation strategies based on their audiences. Bruns and Moe (2013) argued that there are three structural layers of communication on Twitter: the meso layer of follower-followee networks (the default level of

Twitter communication), the macro layer of hashtag-based exchanges, and the micro layer of interpersonal communication. The most relevant affordance to determinine the flow of information on Twitter is users' capacity to follow other users. Following is not necessarily reciprocal on Twitter. Tweet dissemination across the follower-followee network upon which Twitter is based shapes the meso layer of communication. Most tweets are publicly open; thus, tweets on the meso layer of communication can reach a wide variety of followers who are unknown even to the original Tweet posters. Basically, Twitter users cannot control the meso layer of communication. Anyone in their Twitter network can selectively observe their tweets. Such a wide range of meso layer communication can be complemented by the macro level of Twitter communication, initiated by hashtags, which indicates a user's intention to narrow down the range of Twitter communication (Bruns & Moe, 2013).

A hashtag (#), a type of metadata tag used on social media, is utilized to identify messages on a particular topic or event. It is mainly used to mark tweets as being relevant to specific topics and make them easily discernible to other users. It also allows users to receive (for consumers) and forward (for producers) relevant and timely information. The use of a hashtag emphasizes the importance of widely communicated information on Twitter, which means that a tweet has the potential to reach a large audience even well beyond users' existing followers. Hashtags allows users to shape ad hoc groups related to specific issues or themes on a daily basis, contributing to the formation of a larger information network (White, 2016). Anyone can join hashtag feeds, and discussants perceive that hashtags increase the visibility of their posts. A hashtag can contribute to the formation of issue public networks, which are rapidly assembled (Bruns & Burgess, 2011). Twitter hashtags can perform "as a vehicle for otherwise unconnected participants to be able to join in a distributed conversation" (Bruns & Burgess, 2011, p. 49).

Issue networks shaped by hashtags can be dynamic and even ephemeral while an issue is still developing offline, but they can also solidify into long-standing discussion networks, such as the controversy around WikiLeaks (#wikileaks) in 2010 and the Occupy Wall Street protest (#OWS) in 2011 (Gleason, 2013; Penney & Dadas, 2014). Williams et al. (2015) argued that social network-related phenomena can be observed across all hashtags and are likely to be generalized in network patterns. These patterns introduce a homophily, a tendency to gather like-minded individuals into closed communities, or "echo chambers," that reinforce their own opinions on issue networks. However, such a likeminded echo chambers are open to their opponents, triggering trolling (O'Hara & Stevens, 2015). The macro level of hashtag communication is usually less predictable than the meso level of follower-followee communication, and it is the most topical use of the hashtag syntax based on shared interests.

Hashtag communication takes users from the meso to the macro layer. Ultimately, however, another communicative convention leads users to proceed in the opposite direction toward the micro layer of communication because it is the most targeted communication on Twitter. An "@mention" reply can highlight a tweet to specific users, and such an "@mention" reply is usually reciprocal, like an interpersonal communication, which shows multi-turn exchanges. Bruns and Moe (2013) argued that Twitter infrastructure is in a process of narrowing down the focus of communication and the micro layer of communication in Twitter, termed as an "@mention" reply**.** This micro layer is similar to offline conversations, including those with close friends or family. Such a directed communication can be more easily detected by targeted users than ephemeral hashtag communications (macro level). Sometimes, multiple users can form a small group of networks by joining "@mention" conversations. However, regardless of the fact that both users are connected based on follower-followee networks (meso level), any

Twitter users can be addressed in an “@mention” reply. Not all @mentions may strike up conversations like hashtag conversations, especially when referred accounts are owned by celebrities, brands or institutions. For example, Twitter users mention celebrities or brands in the hope that it may result in following conversations (Marwick & boyd, 2011b).

Active and deliberate transition between layers exists in the Twitter platform. Twitter Communication flows from the default meso layer to the more familiar micro layer or the more public macro layer. However, the reverse is also possible: the conversation in response to an “@mention” reply allows tweet senders to move from the micro back to the meso layer, while the choice to refrain from adding a hashtag to a topical tweet can be considered as an intentional move from the macro back to the meso layer. Hashtagged tweets and @mentions are always visible to the senders’ followers.

MOTIVATIONS TO FOLLOW OTHER ACCOUNTS, RETWEET OTHER TWEETS, AND MENTION OTHER USERS

Twitter users have motivations to (1) follow other accounts, (2) retweet other tweets and (3) mention other users. First of all, one key motivation for following other accounts is that Twitter is often a partisan arena, so users tend to follow politicians and political parties that they support (Mirer & Bode, 2015), leading to a high degree of homogeneity on a user’s Twitter feed (Peng et al., 2016). Another motivation for following is that users can follow celebrities or athletes as fans, following their daily lives (Marwick & boyd, 2011b). The motivation for interacting directly with public figures could be also found in following an athlete’s Twitter accounts (Hambrick et al., 2010).

Twitter users also have diverse motivations for retweeting other users’ tweets. They normally retweeted breaking news and trending topics (boyd, Golder, & Lotan, 2010), produced by Twitter accounts of news organizations or journalists. Users retweet other tweets to share interesting or like-minded content with their followers and to give feedbacks on others' tweets (Wang et al., 2016). Lastly, Twitter users mention others for several purposes. Poell and Rajagopalan (2015) argued that the main purposes of mentioning other users can be classified into promoting contents, engaging in conversations and information-exchanges to connect activists, organizations, journalists, friends and family and collaborate in actions around particular issues.

In sum, all 3 of these activities including retweeting, mentioning (macro layer activity) and following (micro layer activity) shares similar motivations: the desire to connect with well-known political figures, journalists, celebrities, activists or social movement organizations. Ausserhofer and Maireder (2013) found that journalists, political experts and politicians are the main actors who dominated the political public sphere. Paßmann, Boeschoten, and Schäfer (2014) termed Twitter users whose tweets were referred by mainstream media and retweeted by others frequently as "Twitter elites" (p. 337).

In this study, three forms of Twitter conversations are playing a significant role in gleaning tweets and extracting relationships among participants. The author chose US immigration policy as a case study on Twitter issue networks, and collected tweets based on #immigration, a broad term to shape the micro level of communication which is appropriate to observe the whole issue network. Later, the author created two forms of network—retweet and mention networks—to examine which factors grasp more attention from users by measuring the frequency of retweets and mentions. While a retweet network can observe how specific tweets are disseminated, a mention network can measure how many users got nominations from others. @mention, the micro layer of Twitter conversation, is a way to invite other users to become engaged in US immigration conversations. The default layer of Twitter conversation, follower-followee relationships, can be a clue for detecting mutual connections with other users.

ISSUE PUBLIC: US IMMIGRATION POLICY

Adopting the terminology used by Papacharissi and de Fatima Oliveira (2012), this study uses the term "networked publics" to refer to individuals who connect with others on the web based on their similar interests. Twitter publics can be defined as users who post tweets with relevant hashtags or keywords based on shared interests, encompassing activities of politically vocal Twitter users. They are more likely to be informed about specific issues from Twitter streams rather than be well-versed on a variety of issues gained through using mainstream media.

The author used the term "issue networks" throughout this study. These networks are organized around issues, which are defined as contestable matters of concern regarding facts, values, and policies (Young & Leonardi, 2012). Issues are topics that elicit the attention of highly motivated individuals who use media to monitor topics that they are especially committed to following, such as abortion (Kim, 2007) and immigration policies. Publics can be divided into several issue publics (Krosnick, 1990). McCombs (2002) defined an issue as the object "on which the attention of the media and the public are focused" (p. 5). This public interest gives journalists an incentive to cover issues that are widely considered as newsworthy.

The term "publics" refers to the separation of the mass audiences into interest-based gatherings. The study of networked public spheres aligns closely with that of issue networks because both of these constitute sets of actors with issue-based relationships directed by hashtags (Bruns & Burgess, 2011). Some activists or influential individuals can constitute the issue public networks and have millions of followers. Issue networks can be shaped by active users who participate in political discussions on Twitter (Park et al., 2016). With the aid of digital media, issue networks can expand over time, which suggests that public attention to any given issue is not static. Thus, this study chooses a specific issue, the US immigration, to examine the longitudinal change of networks and information flow.

Topics refer to general categories that guide people to structure the complexity of their reality, working as a reference point for the communication (Luhmann, 1971). The difference between issue and topic can be explained by how people can take sides; unlike topics, issues are contentious, "with individuals and groups taking opposing positions" (Miller & Riechert, 2001, p. 108). Heclo (1978) coined the term "issue network," which was defined as the broadening process of organizational participation in policy-making by issue activists, or issue experts, who can come together to form networks.

On Twitter, hashtags play a significant role in producing issue networks as issue publics are formed, reshaped, and coordinated. Publics gathering around hashtags can become ad hoc issue publics, brought about by breaking news or important current issues. But further, those publics can discuss specific issues and organize events. It is therefore important to note that the issue networks, shaped by issue publics, refer to a particular subset of Twitter users who use related hashtags under different circumstances. US immigration policy is an example of an issue network because it is continuously and considerably reported by news media (Gil de Zúñiga, Correa, & Valenzuela, 2012). Also, many publics who can be influenced by the change of Presidency and its aftereffects (e.g., rescinding DACA) are constantly paying attention to this presidential administration's actions and organizing offline protests.

The author chose US immigration policy as a case study to examine opinion leadership for several reasons. First, immigration policy has long been a salient and politically controversial issue in American politics. It has emerged in national headline news and at the top of the national policy agenda, and it has been also discussed on Twitter. Large amounts of tweets were created to discuss US immigration policy, and opinion leaders were active participants of Twitter discussions (Chung & Zeng, 2016). Second, the result of the 2016 presidential election was considered a game-changer for the immigration issue because President Trump has continuously expressed support for strict immigration policies that privilege American citizens at the expense of immigrants. Several studies examined the US immigration issue during the 2016 Presidential election campaign (e.g., Flores, 2018). President Trump promoted controlling immigration as a major issue in his campaign through announcement speech in 2015. During the presidential campaign, Trump attacked Mexican immigrants and Muslims. He has used Twitter to arouse controversies during the campaign, criticizing media bias and illegal immigration and receiving more favorites and retweets than Clinton (Lee & Xu, 2018).

Also, immigration policy is a divisive and polarized issue in politics (Johnston, Newman & Velez, 2015) and in the networked public sphere, and it generated a wide range of discussions among both liberals and conservatives. According to Pew Research Center (2016), the disparity in perspectives about immigration is widening among conservatives and liberals. A 2016 poll found that 59% of the public agreed that immigrants in the US can strengthen the country through hard work and talent, while 33% of Americans described immigrants as a burden to the country because they perceive them as taking jobs, housing, and health care away from American citizens. Opinions about immigrants have dramatically shifted from 1994, when 31% of poll respondents were favorable to immigration and 63% of them said immigrants were burdensome, when they answered question: “do immigrants strengthen the country?” Among Democrats and liberal-leaning individuals, 78% stated that immigrants strengthened the US, but only 35% of Republicans or conservative-leaning individuals agreed with that idea.

Timeline of US immigration policy from the 2016 presidential election

The focus on this four-month time period enabled the author to gauge public reactions about immigration issues during the 2016 presidential election and the early Trump administration. Both presidential candidates, Donald Trump and Hillary Rodham Clinton, opined about immigration during the election campaign. While Clinton presented herself as an advocate for immigration legislation and emphasized her commitment to keeping immigrant families together, Trump wanted to raise the bar for refugees and asylum seekers to enter the country (Valverde, 2016). During the presidential campaign, Trump made demeaning remarks about immigrants from Latin American countries and repeatedly claimed the country needed to build a wall to keep Latin American immigrants out and that Mexico would be forced to pay for the wall (Valverde, 2016). At the third presidential debate, which was held on Oct. 19, 2016, presidential candidate Trump mentioned that illegal immigration was related to the drug trade and made an impassioned argument for building the border wall. Hillary Clinton disagreed with him about building a wall but agreed that all criminal immigrants should be deported from the US (Valverde, 2016).

Deferred Action for Childhood Arrivals (DACA), which offers renewable deportation deferrals and work permits to undocumented immigrants who were brought to the US as children, was a controversial topic between two candidates during the presidential campaign. Former President Obama initiated DACA as an executive action in 2012. Hillary Clinton proposed comprehensive immigration reform, which could create pathways to legal citizenship for more immigrants and defended DACA. On the other hand, Trump supported rescinding DACA. After the election, he mentioned the executive action as “one of the most unconstitutional actions ever undertaken by a President” on his personal Twitter, criticizing former President Obama’s stance and foretelling some changes in DACA (Rudalevige, 2016).

After the election, on Jan. 27, 2017, President Trump signed an executive order titled "Protecting the Nation from Foreign Terrorist Entry into the United States." The stated purpose of this order was to move "radical Islamic terrorists out the United States of America" from the executive action (Fishel et al., 2017). This order took effect to bar entry to the US for all people from Iraq, Iran, Libya, Somalia, Sudan, Syria and Yemen for 90 days. It also ordered the suspension of the US refugee program and a ban on Syrian refugees (McGraw, Kelsey, & Keneally, 2017). Also, President Trump declared "The Executive Order on Border Security," which announced plans to construct a border wall, increase border patrol personnel, expand construction of detention facilities for immigrants, and limit access to asylum in the US. After President Trump declared these orders, nationwide protests against those orders occurred throughout the week.

TWITTER AS A NETWORKED PUBLIC SPHERE

On Twitter, activists and influential people on the immigration issue networks may perform the role of opinion leaders to fight for their stance, persuade opponents, or reinterpret the news media. Basically, Twitter has been considered as a public platform, which allows users to read relevant content (Marwick & boyd, 2011a) without a requirement to follow each other. Twitter users can easily follow public figures, such as journalists, politicians, singers and actors. Such characteristics lead Twitter to become a venue for public discussion and to operate as a networked public sphere. In the digital age, the original concept of a public sphere, as conceived by Habermas (1991), has given rise to the concept of a networked public sphere. A public sphere is defined as "a network for communicating information and points of view" (Habermas, 1991, p. 360) and "a realm of our social life in which something approaching public opinion can be formed" (Habermas, Lennox, & Lennox, 1974, p. 49). Dahlgren (2005) developed the concept of public sphere into “a constellation of communicative spaces in society that permit the circulation of information, ideas, debates – ideally in an unfettered manner – and also the formation of political will” (p. 148). The German term *öffentlichkeit* is a root of public sphere, translating into “the public” as the collective of speakers and listeners and “publicness” as the state of being visible to the public (Friedrichs, Lepsuius, & Neidhardt, 1994). The public sphere is a mediated sphere between society and state, organized by the public who exchanges public opinion.

The goal of the public sphere is public agreement and it also pursues the facilitation of unrestricted and diverse discussions of public issues. Habermas (1991) argued that public discourses in public sphere should be distinguished from mere opinions. There have been several measurable criteria for a public sphere: (1) Political communication about similar issues under similar aspects of relevance among discussion participants (Eder & Kantner, 2000), (2) The communicative relations and interactions between speakers who can be either media themselves or political actors who use media and public sphere as a platform to express their thoughts (Adam, 2008), (3) Participants who were willing to ask questions and modify their positions in light of other relevant thoughts and reasons (Dahlgren, 2005), and (4) Equal opportunity to express their ideas to every participant (Habermas, 1991).

Mass media like newspapers, magazines, radio and television support communication in the public sphere, and journalists and elite actors like scholars, politicians and celebrity perform a mediating role by transmitting information with their perspectives from the mass media to the public in the public sphere. Traditionally, physical sites like salons and coffee houses were public sphere where elites gave their ideas to the public. Ordinary people known as the public were mere audiences who could watch events unfolding on “the virtual stage of mediated communication” (Habermas, 2006, p. 415). Public spheres remained a hierarchical top-down model from mass media and elites to the public and elites played a prominent role in distributing their own ideas through mass media platforms. The public was mere consumers of information, rather than producing ideas in traditional public sphere.

However, due to the development of information and communication technologies like the Internet, the communicative power of ordinary citizens has improved, freeing them to pursue and exchange information with less mediation from traditional mass media or elites in the public sphere. Friedland, Hove, and Rojas (2006) introduced the networked public sphere where any individual can express their opinions on blogs and in personal sites open to the public. Benkler (2006) defined the networked public sphere as an important avenue for discussions and debates of public interest. He argued that a range of practices, organizations, and technologies can be engaged in a networked public sphere for public discourses, political debates, mobilization, and interaction with traditional media. A network public sphere is created when a shift from analog to digital platforms enables more individuals from more diverse backgrounds to create, curate, and circulate information and ideas; it also allows these individuals increased opportunities to participate in civic and political actions. The decentralized, egalitarian, and participatory nature of social media, characterized by the minimal cost of participation and a low entrance barrier, enables users to join a wide variety of interactions, which can lead them to engage in discussions and form social network structures. Moreover, like-minded individuals can easily find each other and gather together to form clusters or groups (Benkler, 2006). On Twitter, hashtags might help them to find like-minded others, but sometimes users intentionally follow others who are in line with their opinions (Vickery, 2016). Thus, active political discussions can be expected on the networked public sphere.

Papacharissi (2008) suggested a concept of the virtual public sphere, which was alienated from the traditional public sphere. The advent of Internet gave birth to the virtual public sphere. Papacharissi (2008) enumerated several components of the Internet that distinguishes itself from the traditional public sphere: civic narcissism, pluralistic agonism, and hybridity of commercial and public interest. Technically, the Internet provides media consumers with the chance to become producers simultaneously. Blogs stimulated civic narcissism, which can be understood as "the introspection and self-absorption that takes place in blogs and similar spaces" (Papacharissi, 2008, p. 253). Individuals who value their thoughts and feelings (self-expression) and who expect others' interest in their self-expressions tend to publicize themselves on blogs and similar places, which fuels narcissism. Blogs emphasized issues that were originally marginalized by mainstream media, stimulating the public agenda. After becoming popularized through blogs or the Internet among the public, such issues were covered in mainstream media.

The Internet and digital media also allowed (1) political elites to publicize news releases, (2) non-profit organizations or activists to get their agenda into the mainstream media and (3) ordinary citizens to directly present their opinions. Direct representation of ideas through the Internet led to a plurality of information, created and consumed by its users from every social stratification. Mouffe (2005) argued that agonism is a we/they relationship assuming that conflicting ideas were common on the Internet. While a public sphere pursues public agreement, the direct representation through the Internet resulted in agonistic expression, boosting diversity of ideas and democracy. On the other hand, the we/they relationship may result in political polarization, an ideological gap between liberals and conservatives because individuals in the virtual public sphere were less concerned with public agreement, voicing more disagreement (Papacharissi, 2008).

Networked public sphere as a hybrid space refers that the Internet as a place where commercial and civil interests co-exist. Information technology was subsumed into the capitalist market, becoming commodified to be a mainstream content platform. The goal of such information technology is to attract audiences. Internet platforms like YouTube are examples of commercial spaces pursing public interest by offering on-demand content and creating public spaces like comment sections that users can engage in political discussions (Papacharissi, 2008). The hybridity of commercial and public interest on online provides audiences with spaces where anyone can participate in democratic practices, such as offering political opinions, while the Internet is viable within a capitalism simultaneously.

In sum, civic narcissism, pluralistic agonism and hybridity of commercial and public interest can distinguish the online sphere from the traditional concept of public sphere, in which public access was restricted due to lower opportunity for general public to physically participate in public discussions. Twitter can be considered as having all three elements: users post tweets to feel better than others, known as the superiority feeling (Panek, Nardis, & Konrath, 2013). They may have a desire to express their thoughts and feelings on Twitter, assuming that Twitter can be used to demonstrate their perceived superiority to others Also, a large amount of information is being produced on Twitter, which can be utilized to support their views and offer political disagreement to argue against cross-cutting viewpoints (Papacharissi, 2008). Finally, Twitter can be a marketing platform for companies (Hutchings, 2012) to promote products and for political parties to ask supporters to donate. Such functions lead Twitter to be characterized as a virtual public sphere, being apart from traditional public sphere.

Twitter has been established as an important platform for information exchange and for the formation of opinions and debates on a wide range of issues. The emergence of social media as a connected, rapid, diverse and mediating space for the dissemination and discussion of news and information has increased the complexity of media ecology. As the concept of a networked pubic sphere would lead one to expect, Twitter users gather together in highly connected networks around shared interests and specific discussions about issues or events (Bruns & Highfield, 2015). The characteristics of a networked public sphere can be achieved by specific communication affordances of Twitter, including follower-followee relationships, # (hashtags) and @ (mentions). Any figures—including members of the public and government, media, organizations, corporations, and activists—can participate in a wide variety of interactions, like information searches and calls for action related to social issues.

Twitter allows a wide range of relationships which is similar to broadcast and interpersonal communication. It has the functions of broadcast media allowing one-to-many relationships (Marwick & boyd, 2011a), and face-to-face and reciprocal communication. Twitter users can express their opinions, attitudes, and emotions about polarizing controversial issues like US immigration. Like broadcast television, Twitter can flatten diverse social contexts into one. This process, known as context collapse, enabling content creators (Tweeters) to manage images for multiple audiences and distribute content through a networked structure. Broadcast and networked audiences are found: while broadcast audiences are mass, networked audiences have similar interests. Content creators want to present themselves appropriately, based on the communication affordance. They consider imagined audiences to whom they think they are speaking (Marwick & boyd, 2011a). For example, Twitter users who want to promote their works may use hashtags representing their works, and tweets about their works to invisible others on Twitter. Authors or artists may conjure up invisible followers as their fan communities. Viewers are interconnected with each other including content creators and latent participants (existing but not yet activated), further shaping social networks (Marwick & boyd, 2011a). In terms of interpersonal communication, an "@mention" reply is usually reciprocal having multi-turn exchanges. Known as the micro layer of communication in Twitter, it is similar to offline communication with family and close friends (Bruns & Moe, 2013).

A networked public sphere requires social network analysis in order to study it due to the role of social networks in shaping flows of public opinion and influence (Beck et al., 2002). Networked forms of communication consist of the gathering of connections among diverse social networks. The Internet facilitates the structural diversity of connections and offers more public spaces. Specific network structures in networked public spheres need to be examined, and potential clustering between network structures can be expected.

Selective exposure, polarization, and opinion leaders

The ideological differences between the Republican and Democratic parties form the center of American politics. These two parties are polarized over most contemporary issues: gay marriage, gun control, welfare spending, tax increases, immigration issues, and so on (Schier, 2016). Those issues are discussed on Twitter and users can easily join such discussions, forming issue networks. Individuals tend to join homogenous interpersonal groups and seek information from likeminded users because such information give them a sense of assurance and social unity (Stroud, 2010). By seeking favorable information only, individuals can become more polarized.

Polarization, a politically vast gap between liberals and conservatives can occur when people who lead discussions on the network exhibit extreme views, thereby intensifying divisions between members of the network who identify with those views and members who oppose them and creating echo chambers. Thus, Twitter conversations about US immigration tend to feature clustered discourse among participants. When they consume arguments that favor and support their sides, members are persuaded to develop more straightforward attitudes in the direction of groups. Conover et al. (2011) found evidence of political polarization or clustering on Twitter. Sunstein (2018) developed his ideas about polarized online spheres, arguing that today's Internet and social media are driving political fragmentation, and extremity. Like his assumption, Himelboim, Smith, and Shneiderman (2013) found that members in Twitter discussions followed users from their own clusters rather than other clusters.

The role of opinion leaders can be related to polarization or clustering at the audience level. The concept of reinforcement overlaps with the definitions of opinion leadership and selective exposure. Lazarsfeld, Berelson, and Gaudet (1948) basically argued that opinion leaders were self-assured enough to assert why they were right, and they were reminded that other people agreed with them. Currently based on the concept of selective exposure and algorithmic curation of social media, Soares, Recuero and Zago (2018) found echo chambers on Twitter during the impeachment process of the ex-Brazilian president, and opinion leaders who had numerous followers in the network reinforced clustering by generating a considerable number of retweets. While few studies have examined the relationship between opinion leaders and clustering based on political orientation, it is probable that opinion leaders have the most extreme views, leading followers to adjust to their ideas. Echo chambers on Twitter networks can reinforce political perspectives of partisans.

Scholars have examined Twitter networks and articulated various forms of communication patterns (Himelboim, Smith & Shneiderman, 2013; Pew Research Center, 2014; Bastos et al., 2018). Conversation patterns on Twitter included polarized crowds, tight crowds, brand clusters, community clusters, broadcast network and support network. Pew Research Center (2014) found polarized crowds representing two big and dense groups which were rarely connected. Polarized crowds, two groups (liberal and conservative) with few cross-connections to others, can be explained by clustering based on political orientation. Himelboim, Smith, and Shneiderman (2013) found evidence of selective exposure clusters, those who were densely connected. Hub users, who have a large number of in-degree centrality, occupied the center of each cluster which was ideologically homogeneous. Himelboim, Smith, and Shneiderman (2013) relied on the modularity, a measure of clusters disconnected from one another, and argued that polarized crowds have a high level of density and low level of modularity. They proposed that the combination of density and modularity can distinguish unified or divided network structures.

While political discussions were an example of polarized crowds, other types of discussions gave birth to different Twitter networks. For example, professional topics and hobby groups could create tight crowds, which were highly interconnected individuals with few members being isolated. Also, when Twitter users talked about celebrities or famous products, brand clusters were shaped around many disconnected individuals. Members in brand clusters only focused on a topic like products or celebrities, and they did not have interested in connecting to others. Community clusters were developed by some popular topics, such as global media topics that triggered multiple conversations and create multiple smaller groups. Broadcast network was defined as a hub and spoke structure, caused by Twitter commentary of breaking news. Members in the broadcast network tended to talk to each other to share thoughts about news. Hubs in broadcast networks have a similarity with opinion leaders, because they are a small number of individuals who are located in the center of networks. A support network has a large number of outward spokes because a hub account replies to other disconnected individuals, resulting in outward spokes. Support networks are in contrast with broadcast networks that have a hub user with inward links. Customer complaints can be an example of support networks.

Bastos et al., (2018) analyzed the network of agricultural expertise and found evidence of centralization when members shared specialized information. Governmental agencies and news outlets were located at the center of such Twitter network as information resources.

In this study, the first four research question asked about the overall structure of retweet and mention networks. Visual graphs of retweet and mention networks were drawn to map the network's overall structure. Pew Research Center (2014) indicated different types Twitter networks based on characteristics of topics: polarized crowds, tight crowds, brand clusters, community clusters, broadcast network and support network. Centrality scores are reported to detect opinion leaders in the two networks. Visual networks, centrality scores and the distribution of tweets for retweet and mention networks can explain network structures. Based on this information, the author formulated two research questions:

RQ1a: What does the Twitter #immigration issue retweet network visually look like?

RQ1b: What does the Twitter #immigration issue mention network visually look like?

RQ2a: How are clusters in the retweet network divided from each other?

RQ2b: How are clusters in the mention network divided from each other?

RQ3a: Who are influential users in the retweet network?

RQ3b: Who are influential users in the mention network?

While the retweet and mention networks were created to investigate network structures among Twitter users, the author additionally drew hashtag co-occurrence networks, based on hashtags embedded in the entire network to examine politically clustered patterns of word usage. The "birds of a feather" phenomenon and homophily are clearly connected to political polarization or clustering on Twitter (Himelboim, McCreery, & Smith, 2013). The author assumed that hashtag co-occurrence could represent each political ideology and that two (or more) ideological clusters (conservatives and liberals) could be found on the #immigration network. Twitter users' choice of hashtags can represent the user's political orientations or other characteristics. Hashtag co-occurrence networks can be produced from each tweet containing a number of hashtags, posted by a single Twitter user. Scholars argued that hashtag co-occurrence can explain topical structure of Twitter networks (Bode et al., 2015). Two hashtags in a tweet can share similar characteristics more than two randomly selected hashtags (Pöschko, 2011). In terms of Twitter conversations regarding the US immigration policy issue, the co-occurrence patterns among hashtags in the same cluster can be closer than others in different clusters. For example, if users add #hugnotwall along with #immigration, a hashtag co-occurrence is created, showing favorable attitudes or liberal ideas to the US immigration policy. Based on the assumption of hashtag-occurrence networks, the author asked a research question:

RQ4: Does a hashtag network created by hashtag co-occurrences with #immigration show divisions of clusters?

The following section defines opinion leaders, who play a significant role in shaping networks and setting media agenda.

TWO-STEP FLOW OF INFORMATION AND OPINION LEADERSHIP

Lazarsfeld, Berelson, and Gaudet (1948) conceptualized the two-step flow of communication, arguing that the flow of information from mass media to the less active public is mediated by a small number of opinion leaders. Individuals who paid closer attention to news media and their messages received this information. Then, they passed on their interpretations, in addition to media content, to followers. These leaders are more exposed to media resources, and they transfer the influence of their personal opinions and attitudes to the rest of their whole networks (Katz & Lazarsfeld, 1955). They have been shown to process and handle new information effectively (Rogers, 2010). As a result, opinion leaders can influence opinions, attitudes, beliefs, motivations, and behaviors of their followers in a desired way (Rogers, 2010; Park, 2013). While the traditional definition of opinion leaders emphasizes their access to information through traditional news media, subsequent definitions focus on the extent of influence, including the impact of public opinion, attitudes, and behaviors that they could exert on their followers.

According to Katz and Lazarsfeld (1955), there are four major traits of opinion leaders: having a following, being regarded as an expert, being knowledgeable, and holding a position within their community to influence social pressure and support. Opinion leaders have been found to have more interpersonal interconnections, higher socio-economic status, and greater degrees of education than their followers in the social system (Rogers, 2010). On the other hand, opinion leaders and followers have similar traits like political orientations or shared interests like hobbies. Opinion leaders tend to share their knowledge with followers in the network. They are greatly involved in social activities and organizations, being active in such events and socializing with others, which is referred to as gregariousness (Weimann, 1994). In sum, opinion leaders are well-embedded in the network, highly connected with, and very visible, to others.

In the two-step flow of information, influential citizens have played a significant role in conveying information. The two-step flow of information could represent the minimal effects of media, emphasizing the role of interpersonal communication and supplementing the limitation of mass media's direct reach toward audiences. Hong and Shemer (1976) found that interpersonal communication was an intervening variable between media and personal agendas, which either facilitated or reduced the importance of the media's effects on personal agendas. Erbing, Goldenberg, and Miller (1980) argued that interpersonal communication was necessary to make audiences understand news media content, increasing issue salience for news topics. Thus, interpersonal communication initiated by opinion leaders can reinforce media messages.

Criticism of the two-step flow of information and opinion leadership originated from the idea of a one-step flow of information from news media to the public. Specifically, Deutschmann and Danielson (1960) argued that initial news media information flowed directly to the public, without being filtered by opinion leaders. Such assumption is based on the "magic bullet" or "hypodermic needle" model, assuming that audiences were passive in consuming information and that mass media effect was strong and impactful (Lasswell, 1927). Also, Gitlin (1978) argued that the influence of interpersonal communication was largely gathered before the advent of television programs. After consuming television programs, individuals did not rely on other influentials to interpret information, directly consuming information. Also, Robinson (1976) suggested a multi-step flow of information which includes direct flow of information from mass media to the public. However, the advent of the Internet has brought up more detailed examinations of opinion leaders.

ONLINE OPINION LEADERS: (1) SIMILARITIES AND DIFFERENCES WITH TRADITIONAL OPINION LEADERS

The emergence of the Internet and digital media has raised the question of whether traditional models of two-step flow of information and theories about the role of opinion leaders remain valid for analyzing online networks. The Internet provides an unlimited amount of information at low cost, and users can personalize their news resources. However, several studies found evidence of opinion leaders on the Internet and social media (Ko, Yin, & Kuo, 2008; Choi, 2014; 2015; Park & Kaye, 2017; Xu et al., 2014).

While traditional and online opinion leaders share similarities especially in their social gregariousness, an amount of knowledge and information filtering activities, they had different characteristics in terms of information consuming behaviors. Basically, traditional opinion leaders were socially gregarious, having a large social networks. Also, online opinion leaders synthesized others' online contents, like a filtering role of traditional opinion leaders (Cassell et al., 2006). In addition, online opinion leaders were perceived as knowledgeable and innovative (Lyons & Henderson, 2005) like offline opinion leaders. On the other hand, while traditional opinion leaders were defined by their frequency of news consumption, online opinion leaders can be decided by several ways, including the frequency of producing and distributing information (Choi, 2012).

Online opinion leaders possess additional unique characteristics. Online opinion leaders, especially in discussion groups were active posters who often wrote more detailed contents (Cassell et al., 2006). They had high perceived expertise and knowledge and their posts are perceived as accurate and thorough (Golder & Donath, 2004), Lastly, they were long-time members of discussion groups (Himelboim, Gleave, & Smith, 2009). Huffaker (2010) argued that long-time members in online discussion groups were more experienced and they were perceived to possess reputations and credibility.

The Internet is widely assumed to be an egalitarian forum that facilitates many-to-many interactions and reduces inequality by increasing opportunities for participation in online discussions. On the other side, power law distributions, defined as disproportional distribution of links among nodes (many nodes with few links and few nodes with many links), can explain the small number of influential users on online discussion platforms such as Usenet newsgroups (Himelboim, 2008) and Wikipedia discussion pages (Laniado et al., 2011).

Preferential attachment can explain long-tail distributions. Long-tail distribution means there are a large number of commentsfar from the head or central part of the distribution. Both distributions implicate disproportional distributions of members in the network. Preferential attachment means that the more connected with followers a node is, the more likely it is to receive new connections, resulting in heavily skewed distribution (Ravid & Rafaeli, 2004) in the online discussion groups. Further examination is required to understand how discussions on Twitter issue networks take place in synchronous settings. By examining the structure of the #immigration issue network, the author can examine the degree to which discussions are concentrated on a few opinion leaders.

A long-tail distribution indicates a form of probability distribution that has a large number of occurrence far from the central part of the distribution. On Twitter, it explains an unequal distribution of posts created by all users in the network, assuming that opinion leaders created more tweets than others. A long tail distribution can be one form of network structures. To examine distributions of discussions on retweet and mention networks, the author asked a research question:

RQ5a: Are the structures of the discussion group on the #immigration retweet network concentrated on a few individuals, based on individual in-degree centrality scores?

RQ5b: Are the structures of the discussion group on the #immigration mention network concentrated on a few individuals, based on individual in-degree centrality scores?

RQ6a: Are the structures of the discussion group on the #immigration retweet network concentrated on a few individuals, based on the number of tweets posted by individual users?

RQ6b: Are the structures of the discussion group on the #immigration mention network concentrated on a few individuals, based on the number of tweets posted by individual users?

Online opinion leaders: (2) the presence of curators

Active audience theory could support the role of opinion leaders. This theory assumes that audiences actively negotiate the meanings of media contexts, rather than blindly consuming information. Such audiences may possess interpretive perspectives and bring individual experiences when adding personal meanings to media (Fiske, 1989). Opinion leaders are individuals among active audiences who continuously consume information from various resources and curate the information on their online platforms, including social media and personal blogs. The term 'curation' is an activity where individuals find information, filter it from their perspective and distribute this information to others. The concept of active audiences prompted a framework to discuss curated flows of information in digital media (Thorson & Wells, 2015).

Opinion leaders play an important role in information flow by providing a wide spectrum of perspectives based on abundant information and ease of use of digital media technology. While traditional opinion leaders had a greater access to information than followers, digital media changed the dynamics of information flow: online opinion leaders can produce information and broadcast it to mass audiences. Also, while social and demographic characteristics of individuals were determinant factors to be offline opinion leaders, online opinion leaders were freer from such restrictions: online is a sphere that offers limited participants' identities. Discussion groups on the Internet like BulletinBoards.com have been an anonymous environment in which little is known about Internet users (Rhoades & Rhoades, 2013). Individuals who are active in influencing other's opinions can become opinion leaders regardless of economic or educational status. Online opinion leaders could be determined by the quality of arguments they made (Lu, Jerath, & Singh, 2013) and the degree of activeness they contribute to online discussions (Kwak et al., 2010).

Thorson and Wells (2015) introduced the concept of a curated flow of information, conducted by individuals who were active selectors and creators of content. These curators mediated the information flow from mass media to the public and from the public to mass media. They are active selectors of relevant information by filtering out messages they receive and promoting those that they perceived as important under the condition of abundant information (Thorson & Wells, 2015). This act is similar to journalistic gatekeeping, a process in which information is filtered for distribution through several levels of journalists and editors. The notion of an active audience among the ordinary public can support the study of opinion leaders and curators. Both opinion leaders and curators share similarities: they actively consume messages, filter them out, search out more information, and reframe it with their personal perspectives. While traditional opinion leaders were famous figures who had a large number of followers, Thorson and Wells (2015) did not mention curator's popularity or large number of followers. Also rather than direct and clear-cut flows from news media to the public, the current networked public sphere may feature multiple and intertwined information flows which contain personal interpretations like jokes, criticism, or other expressions of users' attitudes toward issues. Such diverse information flows can build up each individual's communication experiences. Exposure to any given message thus depends on an individual's position within intertwined message flows; this dependence highlights the importance of social networks in information flow.

Thorson and Wells (2015) introduced the concept of social curation among five forms of curated flows of information: journalistic, social, personal, strategic, and algorithmic curations. Journalistic curation is a secondary gatekeeping process undertaken by journalists, who maintain an important role in new media environments by deciding which issues and events to report.

Social curation is performed by the social network of which an individual is a member. Personal curation originates from the multi-channel and multi-device media ecology, where the role of individuals in curating messages is becoming increasingly powerful. Personal curators have a capacity to curate messages within their own media environment, but they only curate for themselves. Strategic curation occurs when actors like politicians, corporations, governments, and interest groups strategically address their messages to the public. This form of communication usually bypasses the process of gatekeeping by newsmakers and journalists. Algorithmic curation, is an information process selection managed by computational algorithms. Technological actors employed by corporations or political parties create algorithms to dictate information flows.

Among the five types of curation, journalistic, social and strategic curations are the most pertinent concept for this study. Journalistic curation focused on the role of journalists in the gatekeeping process as a creator of news content. Journalists post links to stories written by themselves or their organizations on personal blogs, playing a promotional role. Twitter is a platform for them to post news stories, add commentaries to the stories they post, and interact with audiences (Lasorsa, Lewis, & Holton, 2012).

As mentioned, social curation is performed by the social network of which an individual is a member (Thorson & Wells, 2015). The classic model of two-step information flow emphasized the role of interpersonal communication in disseminating information and mediating the information flow from mass media to the public. The rise of social media has brought interpersonal communication to the forefront of academic focus because the affordances of social media enable users to consume news distributed by their friends, share common interests and lifestyles with other users, and create their persuasive content. Thorson and Wells (2015) argued that the two-step flow of information can still exist in social curation as a form of information exchange in homogeneous networks shaped by shared interests and common characteristics among members. Social curation shares common concepts with the broadcasting role of Twitter: active content creators can flatten diverse social contexts into one and strategically distribute them to followers who share similarities. Social curation and the broadcasting role of Twitter users can influence the re-interpretation and distribution of information on Twitter. Opinion leaders who consume information actively can post tweets with their perspectives to curate information, and they can disseminate their opinions about that information on social media. For example, opinion leaders actively utilized Weibo, the Chinese social media that is like a hybrid of Facebook and Twitter, to disseminate information about organ donation by retweeting (Shi & Salmon, 2018).

Strategic curation can be actively utilized by strategic actors like politicians, corporations, governments and interest groups to address their ideas directly to the public. Like online opinion leaders who used the Internet to effectively distribute their ideas, strategic actors relied on the Internet and social media including Facebook and Twitter to reach the public who were in line with their ideas. Also, they can interact directly with their followers. Strategic curations can bypass journalistic curations and narrow down targeted audiences based on homogeneity. Political actors also redistributed stories from the news media, which can be defined as an inversion of traditional gatekeeping relationship. Political actors selected stories they wanted to spread to followers and they even tried to argue for their opinions to persuade others who were not in line with them.

Algorithmic curation, the last form of curating activities, is a process of information selection driven by computational algorithms. Algorithmic curation prioritizes shared information by learning what social media users like or post comments about. As a result, this form of curation can cause a filter bubble, a state of isolation caused by personalized searches when an algorithm selectively suggests information based on users' information. Within a filter bubble, individuals are exposed to information that confirms their existing beliefs (Pariser, 2011). For example, a Democrat stops seeing conservative posts because social media algorithms have learned from this user's previous social media behaviors. This process is in line with personalization and fragmentation of individual media consumption, which have ultimately resulted in polarization based on political orientations or other divisions. While individuals have a tendency to consume media that aligns their perspectives, known as selective exposure (Stroud, 2010), new media technologies based on algorithmic curation can foster selective consumption of information.

TWITTER OPINION LEADERS

Scholars have identified characteristics of Twitter network and opinion leaders by conducting social network analysis. Traditional (Katz & Lazarsfeld, 1955) and online (Bodendorf & Kaiser, 2009) opinion leaders have been located in the center of their networks. Xu et al. (2014) examined social connectivity of opinion leaders in the Twittersphere. Results indicated that the degree of connections based on betweenness centrality (a proxy of opinion leadership that measures a Twitter user's strategic location and ability to reach every user in the network) could predict the frequency to be retweeted (a measure about distributing information). This finding suggested that opinion leaders have a larger number of connections that involve in specific issues more than followers. Dubois and Gaffney (2014) emphasized a network position of users to be influential in the network based on the high centrality scores of political elites like media outlets, journalists and politicians. In terms of US immigration issue network, opinion leaders might have a large number of connections, a high interest and knowledge in immigration issues. Also, they can be located in the center of Twitter networks.

On Twitter discussion networks, a small fraction of heavy users, about 4% of all Twitter users in Germany, accounted for more than 40% of message interactions on Twitter (Tumasjan et al., 2010). In the US, less than 0.05 % of Twitter users attracted almost 50% of attention within Twitter (Wu et al., 2011).

Some findings supported new opinion leaders, which contrasted with traditional ones. Park (2013) found that opinion leaders did not depend more on news media contents than followers, which is in contrast to traditional opinion leaders. Also, Park and Kaye (2017) found that socio-economic status did not predict opinion leadership. Twitter opinion leadership relied on leaders' internal motivations of information seeking and mobilization (Park, 2013). Also, while Twitter opinion leaders are also active users who post tweets frequently, opinion leaders are not determined by socio-economic status like intelligent and higher social positions.

Twitter opinion leaders can be determined by their followers. This idea originated from a multi-step flow model, offered by van den Ban (1964). This model argued that social influence started from informal and interpersonal communication rather than formal ways like professional media. Domingos and Richardson (2001) even argued that people made choices based on opinions of their peers rather than a few influentials, emphasizing the importance of ordinary people. Information flow on social media like Twitter may differ from the traditional two-step flow of information model, which creates more complex forms of information flow. This means that unlike traditional model of opinion leadership characterized by top-down process, social media opinion leaders are determined by their follower, a bottom-up process. Cha et al. (2010) found that Twitter users who had a large number of followers, like celebrities (e.g., actors, musicians, athletes and models), did not necessarily trigger many retweets, the content value of tweets and the popularity of tweets (Dang-Xuan et al., 2013; Zhang et al., 2014). Such celebrities could not have an expertise in specific topics. Ordinary users could be influential by concentrating on single topic and posting insightful tweets perceived by followers.

Twitter studies have found strong evidence of the intermediary actions of opinion leaders (Cha et al., 2010; Wu et al., 2011), such as curating activities (receiving, filtering and disseminating messages). Wu et al. (2011) found that Twitter can bypass intermediated relations from traditional media. Twitter opinion leaders have high expertise in their specific domain, not heavily relying on news consumption. Some contents created by an influential user can drive press coverage, reversing the top-down process initiated by traditional media (Lessig, 2005). When a specific actor is mentioned frequently by others in the network, such an actor is likely to be influential (Bakshy et al., 2011). Twitter has unique characteristics that make it ideal for rapid diffusion of information compared to other kinds of social media (Hansen et al., 2011) and opinion leaders can take advantage of this function. In terms of Twitter activists for US immigration policy, van Haperen, Nicholls, & Uitermark (2018) investigated social movement known as the #not1more campaign against immigrant deportations from 2013 to 2014, and found that this movement was supported by organizers and activists who are highly active in tweeting, and well connected with others in building online protests. The author assumed that such active users are highly involved in specific issues they have interests.

The concepts of agenda uptake (Gruszczynski & Wagner, 2017), a condition in which the salience of an issue is transferred between multiple actors, emphasize the role of ordinary citizens, arguing that personalized public interest and the development of niche media (personalized and specialized interest-based media) can affect the agenda of mainstream media.

Current audiences were likely to follow politically like-minded information through niche media. In addition, niche media and the public interacted mutually, setting the agenda of niche media (Gruszczynski & Wagner, 2017).

Issue involvement: a key to be an opinion leader

Traditional opinion leaders were intensely involved with specific issues or topic (Lazarsfel et al., 1948). They paid a great level of attention to news media and had specific knowledge about given issues or topics. In the marketing term, involvement was defined as "a person's perceived relevance of the object based on inherent interests, values, or needs that motivate one toward the object" (Zaichkowsky, 1985, p. 342). Like an assumption of Lazarsfeld et al. (1948), Flynn, Goldsmith and Eastman (1994) found a positive relationship between product involvement and opinion leadership. Opinion leaders had a high level of knowledge and expertise, which led them to be involved in specific issues (Lazarsfeld et al., 1948; Sun et al., 2006). Such a high level of involvement can be exemplified by communication behaviors like distributing information with their personal perspectives. Personal relevance is a key characteristic to be involved in specific issues. When individuals believe that specific issues or topics had an "intrinsic importance" (Sherif et al., 1973, p. 311) or "significant consequences for their own lives" (Apsler & Sears, 1968, p. 162) to them, they were likely to have high psychological involvement.

Social media activities can indicate a varying level of involvement to specific issues and topics. For example, Twitter users can reveal their political orientations on their bios, which can suggest their political affiliations with specific issues. Basically, "intrinsic importance" (Sherif et al., 1973, p. 311) and personal interest can be psychological involvement. Xu et al. (2014) argued that individual issue involvement was reflected by the number of engaging tweets such as tweets to give comments and call for actions. They found that engaging tweeting activities were significantly associated with Twitter opinion leadership measured by the number of retweets. Like their findings, the number of tweets can refer to issue involvement: users who post tweets about specific issues are more likely to be involved in given issues. By posting a large number of tweets, users can contribute to the formation of discussion networks and become central actors in such networks. Based on this argument, the author assumed that the number of tweets posted by Twitter users can refer to individual issue involvement, which means that such users are highly involved in the US immigration policy. The author additionally assumed that such a high level of involvement is positively associated with Twitter opinion leadership.

CONTEXTUAL FACTORS TO BE OPINION LEADERS

In this study, the author examined Twitter users' contextual factors to predict opinion leadership. Contextual factors are signals that enable audiences to make judgments of messages. Chaiken (1987) argued that characteristics of message's authors can form judgments for behavioral decisions. Specifically, users understand messages based on their evaluations of message's contextual factors, like characteristics of online communities (Watts & Zhang, 2008), including argument quality and source credibility. In social media, the personal attributes of Twitter users, like verified status, the numbers of followers and tweets, and occupations mentioned on their bios, can influence audiences to believe that specific content creators are worth following.

Several contextual factors of Twitter users can influence audiences' future actions on Twitter. Kwak et al. (2010) found that author-related factors on Twitter include degree of activeness, experience, and authoritativeness. The degree of activeness refers to the level of contribution authors made. The number of messages users posted can belong to this category.

Additionally, the number of Twitter users' followers can be a proxy of popularity. Traditionally, opinion leaders have had gregarious social relationships and a large number of followers may connote that the user's information is widely perceived as worth following (Jin & Phua, 2014). If political figures interact more with the public, they might have more followers. Followers can perceive that users with a large number of followers can disseminate information efficiently.

Also, due to Twitter's potential to reach large audiences, a positive relationship has been found between opinion leadership and the number of other accounts a user follows (Shi & Salmon, 2018). A large number of followees can offer users with a wide range of information. Based on the argument, users who are mutually well-connected on Twitter are likely to be more influential than others.

The traditional definition of opinion leaders argued that opinion leaders were knowledgeable and well-educated (Katz & Lazarsfeld, 1955). Opinion leaders with a huge amount of knowledge may consume news or information from media or resources and articulate their knowledges to others. While there is no exact method to measure individual knowledge of Twitter users, their occupations on bios can imply a user's elite status. Traditionally, occupations of opinion leaders include journalists, politicians, authors and educators, which require large amounts of knowledge on subjects. Wu et al. (2011) operationally defined elite users as celebrities (e.g., Hollywood stars and political figures), media (e.g., news media such as CNN and New York Times), formal organizations (e.g., corporations and NGO) and blogs, and found that such elite users performed as an intermediary role from the media to the public. Also, they generated more retweets than ordinary users.

In addition, Twitter has offered a verification process, confirming that an account of public interest is authentically verified by Twitter. Verified users make up a small percentage of the entire Twitter sphere, about 0.061 percent of total daily active users in 2016 (Navarra, 2016) but they can influence other users due to their high level of credibility, resulting in a large number of reactions (Zhang et al., 2014). When Twitter users in several public interest areas (e.g., music, acting, fashion, government, politics, religion, journalism, media, sports, business and other key interest areas, Twitter 2018b) request their accounts to be verified, Twitter administrators review information they submit. If administrators confirm that an account is of public interest, then a blue badge is added to that account's Twitter profile.

The author focused on contextual factors of Twitter opinion leaders. Also, the author differentiated retweet and mention networks because the author assumed that they have different intentions to be created. While retweeting aims at rebroadcasting others' tweets in order to disseminate the messages to one's followers (Barash & Golder, 2010), mentioning leads other followers to join Twitter conversations, being considered as a direct form of communication (Honey & Herring, 2009; Chen, Tu, & Zheng, 2017). Due to different purposes, influences of contextual factors to opinion leadership can be expectedly different. Twitter users or opinion leaders mainly retweet to disseminate information or their ideas, so more mutual relationships can be beneficial for them to distribute information. By mentioning others, they might focus more on maintaining ties or expanding Twitter conversations. Zhang et al. (2014) examined the influence of contextual factors on the number of retweets and comments received by posts on Weibo, and found that the number of followers and authors' authoritativeness (verified status on Twitter) were significantly associated with the number of retweets and comments.

Twitter offers a function called verified accounts, owned by users with the blue checkmark badge next to their names for the purpose of letting others know that such accounts of public interest are authentic (Twitter, 2018b). Twitter manually authenticates users of public interest. These users may be celebrities or organizations from different areas including music, acting, government, politics, religion, journalism, media, sports, business, and other key interest areas (Twitter, 2018b).

Verified status can increase an account's influence over other Twitter users. Castillo, Mendoza, and Poblete. (2011) found that posts by Twitter administrators were considered by Twitter users as more trustworthy and authoritative than posts by non-verified users. Zhang et al. (2014) found that verified users were perceived as more credible and could initiate more retweets than unverified ones. Before Twitter, Internet users presented many verifiable elements (e.g., occupations, relationship status, and gender) in their profiles on personal websites. Those elements increased the reliability of each user's identity and facilitated the formation of online networks (Lampe, Ellison, & Steinfield, 2007). Such verified accounts share similarities with opinion leaders: (1) they make up a small percentage of the entire network, and (2) they can drive a large amount of reactions from followers due to their credibility.

THE DEFINITION OF OPINION LEADERS, TWEETS AND TWITTER USERS

In this study, the author examined Twitter contents to understand which kinds of tweets were circulated most in immigration issue retweet and mention networks. First, content characteristics of tweets can reflect on intentions of tweet posters. Twitter users create a lot of user-generated contents (UGC) to imagined audiences, an imagined group of potential viewers in a larger social network to self-promote themselves (Marwick & boyd, 2011a). Before explaining content factors of tweets, it is worth examining the tradition definition of opinion leaders: active media consumers who interpret media messages and influence other's opinion or behavior (Katz & Lazarsfeld, 1955). They consumed information from news media, filter and curate it, and disseminate it with their perspectives, influencing others opinions. Twitter can be an information transfer platform for opinion leaders and information consumers. First, Twitter can distribute information like breaking news through retweet functions. Second, users can post tweets arguing for their personal ideas and retweet other tweets to endorse or criticize others' ideas. Lastly, Twitter can be used as an online mobilization platform to motivate users to engage in social movement activities (Theocharis et al., 2015). A study that explored the relationship between opinion leadership and political engagement supported this finding (Park & Kaye, 2017). Tweets for the purpose of mobilization were oriented to ask readers to doing specific actions, like petitions, donations and participation in offline activities such as Occupy Wall Street movement (Penney & Dadas, 2014).

Tweets can have several communicative functions. Lovejoy and Saxton (2012) introduced a typology to categorize tweets into three classifications: information, communities and actions on Twitter usages for nonprofit Organizations. Tweets under the category of information included information about general activities. Community tweets were aimed at building a community of followers. The third function, "action," was oriented to lead followers to do something, like donating money or participating in events or protests. Categorizations of Lovejoy and Saxton can be associated with the tweets users and opinion leaders who wish to show intentions on their tweets. Opinion leaders, or other Twitter users can manifest their intentions on their tweets, including dissemination of factual information, transfer of personal opinions and request for doing actions. While the category of community function developed by Lovejoy and Saxton (2012) did not exactly explain offering personal information, this category included some personal opinionated contents, such as giving recognition and thanks to others. Lu et al., (2018) also termed such personally opinionated tweets as commentarial tweets that contained original posters' feeling about specific issues. Lovejoy and Saxton's (2012) study offers criteria to classify tweet contents, based on the original poster's intention.

The author dissected the definition of opinion leadership into three components: distributing information, offering personal information and calling for specific actions. Active media users interpreted media messages and disseminated them to others. Also, activists used Twitter as a mobilization tool (Theocharis et al., 2015; Vicari, 2017) and tweets posted by activists or opinion leaders may include messages calling others to do specific actions. These elements of the definition of opinion leaders were dissected into (1) a dissemination of (media) messages, (2) an offer of personal thoughts, and (3) a call or mobilization for specific actions. Opinion leaders can successfully disseminate immigration news, and offer personal thoughts to persuade others and express their feelings about issues to others. Also, they can use Twitter to mobilize followers to join in protests or sign petitions.

TWITTER COMMUNICATION AFFORDANCES AND OPINION LEADERSHIP

Besides contextual factors, the author examined Twitter communication affordances embedded on tweets and their relationship with opinion leadership. Activists or influentials on such issue networks can perform the role of opinion leaders to distribute information, reinterpret the news media, and persuade others including opponents. While mentioning is a direct way to nominate potential conversation participants, hashtags can cause tweets reach latent audiences (existing technically but not yet have been activated). Located in the micro layer of Twitter communication, mention (@) can highlight tweets to other users, enlarging Twitter conversations. Opinion leaders who wish to distribute information and offer personal information can mention other users a lot to let others be engaged in discussions. Guille and Favre (2015) argued that mentioning others could lead to more accurate detection of events or topics from noisy Twitter posts, filtering spam and resulting in more in-depth discussions. Also, it is an interactive and mutual way of conversation. Mentioning can represent users' active behavior in igniting conversations. Lee, Cha, and Yang (2011) found that influential Twitter users in South Korea were more likely to mention other users when their names were mentioned by others because they consider mentioning behavior as a social etiquette, building mutual relationships. Also, a high level of Twitter activities including total number of tweets posted and total number of mentions sent was positively associated with mentions and retweets received (Borge Bravo & Dell Valle, 2017). However, political elites or Twitter users may not mention others because they might avoid excessive engagement (Otterbacher, Hemphill, & Shapiro, 2012).

Hashtags on Twitter also allow users to search for relevant users and to consume relevant information. By using hashtags, Twitter users can actively engage in public discussions about common issues (Dahlgren, 2005) and contribute to the formation of an ad hoc issue network (a Twitter network formed for a particular purpose only) (Bruns & Burgess, 2011). Using hashtags can be also considered as an active behavior of Twitter users: they wish to be free from irrelevant distractions and maximize their tweets to other users (Bruns & Burgess, 2011). Using hashtags is a way to express their opinions to imagined audiences who discusses similar topics. Users who post hashtags on their tweets can function as a potential bridge between ad hoc publics and Twitter users they are following by adding visibility of tweets to latent audiences. For opinion leaders, more usage of hashtags on one tweet means the possibility of reaching more readers, expanding their influences. Several studies found the significant relationship between the use of hashtags and the frequency of being retweeted due to a higher chance to be seen by other Twitter users (Suh et al., 2010; Dang-Xuan et al., 2013). However, like the usage of mentions, political actors or celebrities may not use more hashtags because of their perceived popularity.

In this study, the author investigated the influence of several factors on opinion leadership. Factors included Twitter affordance (the number of mentions and hashtags), contextual factors (the number of total tweets, the number of followers and followees, elite occupations and verified status), users' issue involvement. The US immigration policy can be an example of testing Twitter opinion leaders based on contextual factors, users' issue involvement, and the role of Twitter communication affordances. Based on arguments about contextual factors, the author tested the following five hypotheses and four research questions to examine the influence of Twitter affordances and contextual factors on opinion leadership.

RQ7: What is the relationship between mentioning other users and opinion leadership in the a) retweet network & b) mention network?

RQ8: What is the relationship between the number of hashtags and opinion leadership in the a) retweet network & b) mention network?

H1: There is a positive relationship between activeness of Twitter users in terms of number of tweets and opinion leadership in the a) retweet network & b) mention network.

H2: There is a positive relationship between the number of followers and opinion leadership in the a) retweet network & b) mention network.

H3: There is a positive relationship between the number of followees and opinion leadership in the a) retweet network & b) mention network.

H4: Twitter users whose accounts are officially verified by Twitter are more likely to be opinion leaders in the a) retweet network & b) mention network.

RQ9a: What is the relationship between Twitter users whose tweets were retweeted by others and their elite-job status?

RQ9b: What is the relationship between Twitter users who were mentioned by others and their elite-job status?

Also, the author paid attention to issue involvement as a predictor of opinion leaders. The author defined issue involvement by measuring the number of tweets with #immigration posted by users in the sample. The number of tweets with #immigration is differentiated from the general number of tweets because some users can post tweets which do not relate to the US immigration issue. For example, Twitter users can post tweets about Affordable Care Act (ACA, Obamacare) to show their support or opposition to this issue, along with US immigration issue.

H5: Those who were more involved in the US immigration issue are more likely to be opinion leaders in the a) retweet network & b) mention network.

RQ10a: What is the strongest predictor of opinion leaders in the retweet network?

RQ10b: What is the strongest predictor of opinion leaders in the mention network?

The author additionally focused on content factors to understand which kinds of tweets were distributed most in the issue networks, and examine the influence on opinion leadership. In terms of content factors, the author focused on the definition of traditional opinion leaders: individuals who are more exposed to media resources and transfer personal influence of opinions and attitudes to the rest of members of the whole networks (Katz & Lazarsfeld, 1955). The author divided this sentence into three components: (1) active media consumers who (2) interpret media messages and disseminate them and (3) influence other's opinion or behavior. Also, Park and Kaye (2017) found that Twitter opinion leadership was positively associated with civic engagement. Thus, Twitter can be utilized as a mobilization platform for opinion leaders to ask others to doing specific actions. Thus, the author assumed that opinion leaders encourage their followers to call for specific actions on Twitter, like retweeting specific tweets and participating in offline events. In order to measure the predictive power of content factors, the frequency of being retweeted is required. While contextual factors focus on the users' characteristics, the unit of analysis measuring content factors is a tweet. The frequency of being retweeted can show the influence and popularity of tweets (Dang-Xuan et al., 2013; Zhang et al., 2014).

Twitter communication affordances like the number of hashtags and mentions in a tweet can influence the frequency of being retweeted. More numbers of hashtags and mentions on a tweet indicate a higher chance to be detected by other users, leading them to retweet it when they consider it is worth sharing with their followers (Wang et al., 2016). In addition, tweets posted by verified users or elite-status users contain more information that is perceived as credible than others posted by ordinary users (Zhang et al., 2014). The author expected associative relationships between contextual factors like verified status, and originator of tweets who have knowledge-intensive occupations, and the frequency of being retweeted.

The author posed seven research questions to test the influence of Twitter communication affordances, contextual factors of Twitter users, and content factors of tweets on the frequency of being retweeted.

RQ11: What is the relationship between the number of mentions in a tweet and the frequency of being retweeted?

RQ12: What is the relationship between the number of hashtags in a tweet and the frequency of being retweeted?

RQ13: Is there a positive relationship between tweets posted by verified users and the frequency of being retweeted?

RQ14: Is there a positive relationship between tweets posted by knowledge-intensive users and the frequency of being retweeted?

RQ15: Is there a positive relationship between tweets that were oriented to disseminate information and the frequency of being retweeted?

RQ16: Is there a positive relationship between tweets that were oriented to offer personal information and the frequency of being retweeted?

RQ17: Is there a positive relationship between tweets that were oriented to call for specific actions and the frequency of being retweeted?

AGENDA-SETTING: WHO SETS THE AGENDA AND HOW?

Since its first emergence in the late 1960s, agenda-setting theory has evolved and is now regarded as one of the most prominent theories to empirically explain media's effects on audiences (DeFleur, 1998). Starting from the coverage of the 1968 US presidential election, agenda-setting theory has examined the transfer of issue salience from the media to the public (McCombs & Shaw, 1972). Scholars of agenda-setting theory assume that if traditional media covered and highlighted some issues in their news presentations frequently (the volume of news coverage), then those issues were perceived as important in the audiences' minds (the audience perception about the issue). Known as first-level agenda-setting, this theory tests the hypothesis of issue transfer, arguing that "the mass media set the agenda for each political campaign, influencing the salience of attitudes toward the political issues" (p. 177). The first-level agenda-setting can also happen on nonpolitical issues covered in the news media. At this level, the public agenda is determined by a set of objects. It measures the media effect based on both news media and the audience in a balanced manner. The salience of an object in the public can be explained mainly by how frequently the object appeared or was mentioned in the media agenda (McCombs, 2014, p. 52).

While the first-level agenda-setting effect describes the capability of news media to affect the salience of specific topics on the public agenda (Reynolds, 2002), second-level agenda-setting focuses more on attribute salience. At this level, the attributes of a public agenda become much more important than they are in first-level agenda-setting. The object in the agenda-setting process possess attributes, defined as a variety of characteristics and traits that describe objects. For example, in one object (such as politicians), some attributes are mentioned frequently (such as leadership), while other attributes are less emphasized (such as corruption). Thus, researchers who study second-level agenda setting try to measure the transfer of attribute salience. McCombs (2005) argued that “the media not only can be successful in telling us what to think about, they also can be successful in telling us how to think about it” (p. 546). For example, while the transfer of issue salience about presidential candidates occurs during first-level agenda-setting, research on second-level agenda-setting examines the transfer of presidential candidate images (attributes) from news media to the public.

In the US immigration issue network, first- and second-level agenda-setting can be examined. First, comparing the differences in issue salience, the general volume of tweets about immigration reflects a first level agenda-setting study. On the other hand, comparing the differences in the volumes of issue attributes between news and tweets measures second level agenda-setting. McCombs (2014) argued that attributes can be divided into (1) substantive (e.g., characters of politicians such as trustworthiness or electability) and (2) affective attributes (e.g., positive or negative evaluations to politicians). US immigration policy is a polarized issue among liberals and conservatives. Political conservatives generally hold more negative views toward US immigrants than liberals do (Chandler & Tsai, 2001) because they have been found to be more sensitive to threats to their group identity than liberals (Inbar, Pizarro, & Bloom, 2009; Vigil, 2010). While it is rash to stereotype differences of agenda-setting effects between conservatives and liberals, differences in Twitter usage between the two political groups have been examined. Conservative Twitter users exhibited higher levels of political activity, by posting a larger proportion of tweets than liberals (Conover et al., 2011; Barberá, 2015). Thus, different Twitter activities and agenda-setting effects can be expected in discussing US immigration policy.

This study focuses on longitudinal intermedia agenda-setting effects, measuring the transfer of the issue salience and affective tones (positive or negative attitudes toward US immigrants) between traditional news media and Twitter platform. The author tested first level agenda-setting by examining longitudinal differences in volumes of news articles and tweets posted by opinion leaders and the public. In addition, the author tested the second-level agenda-setting by focusing on affective tones of US immigration issue. The US immigration policy is a polarized topic, and there are supporters and opponents of this issue on the Twitter network. Pew Research Center (2016) found a divisive public attitude toward US immigrants (59% of supporters and 33% of opponents). Some users reveal their political orientations and their attitudes to US immigrants on their Twitter profiles and post or retweet other tweets to show their beliefs. Each group might have different second level agenda-setting process in the retweet and mention network.

THE COMBINATION OF TWO-STEP FLOW OF INFORMATION AND AGENDA-SETTING THEORY

Brosius and Weimann (1996) combined the two-step flow of information and agenda-setting and presented four models: the classical two-step flow, the reverse two-step flow, initiating the classical agenda-setting process, and initiating the reverse agenda-setting process. They outlined the functions of the early recognizers who have higher degree of the Strength of Personality (SP) which is still utilized to measure opinion leadership. Brosius and Weimman

(1996) equated early recognizers with opinion leaders because (1) they mediated message flows between the news media and the public, having the agenda-setting ability and (2) they had the high strength of personality scores, a survey evaluating individuals' perceptions of their influence on others such as a reflection of individual confidence in their leadership roles, their ability to shape other's opinions, and their self-perceived influence on social and political outcomes. The reverse two-step flow model reversed the direction of information flow from the classical two-step model and suggests that the public's interests and issues pass from the public to the media through early recognizers. Early recognizers could serve as mediators between the news media and the public in the classical and the reversed two-step flow of information models. They could be initiators of agenda-setting processes. They could initiate traditional agenda-setting process that news media influenced the public agenda (early recognizers -> media agenda -> public agenda) and reverse agenda setting that the public influenced the agenda of news media (early recognizers -> public agenda -> media agenda).

A reverse agenda-setting effect has been discussed by scholars. Traditional agenda-setting theory measured the direct transfer of issue salience (McCombs & Shaw, 1972) from mass media to the public, indicating that issue salience is greatly influenced by the news media. Through these classical and reversed agenda-setting processes, interpersonal communication initiates the agenda-setting process. Supporting this reversed flow of information, Wanta and Wu (1992) found that interpersonal communication reinforced media messages and enhanced agenda-setting effects when the issues in the discussion were covered in the news media. McCombs (2014) argued that the concept of reverse agenda-setting simply implied that journalists responded to perceived public interests, and as a result, the public agenda can be reported as preceding and influencing the media agenda. Beneath the notion of a reverse agenda-setting process, interpersonal communication plays a significant role in shaping public issues, being one of the most important elements of the traditional public sphere (Habermas, 1991). Opinion leaders can be defined as individuals who can initiate reverse agenda-setting processes.

The study of reverse agenda-setting effects has recently given rise to the concept of agenda uptake. Gruszczynski and Wagner (2017) proposed the theory of agenda-uptake, which explains that public interest and niche media (specialized media outlets designed to attract specific audiences, such as Breihtbart, a rightwing syndicated American news website founded in 2007 and Daily Kos, a liberal political blog that began in 2002) attention to specific issue could influence the agenda of mainstream media. In the digital media environment, communication technology allows multiple paths of influence on the media and the public agenda, with direct effects from independent actors through YouTube and social media like Twitter. Significantly, these social media technologies also blur the line between news media and interpersonal communication. For example, news organizations on Twitter have been keeping touch with their audiences by updating the latest news, but Twitter ordinary users could break news and others might retweet them for the purpose of distributing information. Reporters kept on watching Twitter feeds, covering them if such news broken by ordinary users are worthwhile to report. On the other hand, journalists can still maintain their influence on agenda-setting process, because they can report and promote their news stories through Twitter. Also, they can interact with audiences, by offering personal perspectives on the news (Lasorsa, Lewis, & Holton, 2012).

A similar principle of agenda uptake can be applied to the two-step flow of information, which assumes that opinion leaders can also influence the agenda of mainstream news. For instance, Farrell and Drezner (2008) argued that blogs can initiate a bottom-up agenda. Elite actors like politicians paid attention to a few bloggers known as A-list bloggers (Trammell &

Keshelashvili, 2005), who have a large number of readers, resulting in a large number of in-links to their blogs and bringing in bloggers' ideas on their policy-making decisions. They found a power law distribution, an unequal distribution of readership in blogger sphere. Based on these findings, Twitter grassroots activities initiated by their followers can be utilized for a few Twitter opinion leaders to organize bottom-up activities to exert agenda-setting effects to their followers. Agenda-uptake indicates that the agenda of the public and niche media could influence the mainstream media to cover issues (Gruszczynski & Wagner, 2017).

The author assumed that opinion leaders could exert agenda-setting effects upon both news media and the public. Generally, people who receive nominations from their followers as influentials, such as the top 10% or 15%, can be identified as opinion leaders (Valente & Pumpuang, 2007). In the marketing, Cakim (2007) suggested a term "e-fluentials" to refer to those who spread information via the Internet and found that 10% of adult US citizens were e-fluentials who were active at generating buzz about products and companies. Moreover, positions developed in social network analysis can be used to identify those who are most central (Freeman, 1979). To mediate information flow, opinion leaders should be strategically located on the central position in the network. The study of opinion leadership on Twitter is required to find the role of opinion leaders by mapping and examining relational on the network.

Reasons to conduct longitudinal agenda-setting studies for opinion leadership

In order to understand agenda-setting effects, longitudinal studies need to be conducted between news media and the public. The term 'longitudinal' means such a causal relationship happens over time. This form of analysis would assist researchers in the attractive but challenging task of finding the route of information flow, which originated from the traditional two-step flow of information study.

Major sources of news information continue to stem from the mass media and are often embedded in tweets with hyperlinks. All those processes require a causal relationship among the agenda of the media, opinion leaders, and the public over time. Guo (2012) also argued for the necessity of examining longitudinal data in the agenda-setting process over different time periods to understand the evolution of agenda networks. Generally, the time lag for traditional agenda-setting effects has been measured as one month (Brosius & Weimann, 1996), but the lag between traditional news and online discussion varies from one to seven days (Roberts, Wanta, & Dzwo, 2002). The lag of transfer from news media to Twitter discussion has been identified as just one day (Groshek & Groshek, 2013). Thus, the examination of longitudinal directions of information flow is required to investigate causal inference.

In the time-series data, there should be a statistically significant correlation between cause (x) and result (y). A cause should happen earlier than a result, and other noises that can influence statistical relationships and make longitudinal patterns difficult to identify, such as external variables not related to x and y, should be eliminated for analytical rigorousness. Several studies conducted longitudinal agenda-setting effects among online media platforms and found mutual interactions from different media platforms (Meraz, 2011; Vargo et al., 2014). Such studies argued that the sources of agenda can be diversified.

Granger causality is a statistical test to examine whether one time-series variable can forecast another one (Granger, 1969). Specifically, time-series variable X Granger-cause future values of Y if a series of t-tests and F-tests on lagged values of X and Y are statistically significant. Granger causality can calculate more accurate and clearer results than other time-series tests including ARIMA (Auto-Regressive Integrated Moving Average), which is prone to error (Freeman, 1983). Russell Neuman et al., (2014) found a complex and intertwined interaction between traditional media and Twitter agendas by conducting Granger causality tests and suggested that both traditional news media and social media could set agendas.

This study is one of the few studies to utilize a mixed methodology that combines social network analysis and the Granger causality test. The study of opinion leadership and longitudinal information flow in the Twittersphere is required to determine the role of opinion leaders and to examine how the longitudinal influences of news media on the public are connected to relational patterns like centrality and direction. Several scholars ascertained the presence of opinion leaders who initiated a reversed agenda-setting effects from the public to the news media (Brosius & Weimann, 1996; Weiss-Blatt, 2015). This study can provide a more accurate and comprehensive picture of opinion leadership than previous studies because it identifies opinion leaders through social network analysis and analyzes the causal relationship of agenda-setting effects initiated by traditional news media, Twitter opinion leaders and Twitter ordinary users.

PREDICTING LONGITUDINAL AGENDA-SETTING EFFECTS

The analysis of longitudinal agenda-setting effects is necessary for answering the question, "who sets agenda on Twitter networks?" By adding an analysis of an opinion leader cluster to the investigation of information flow between news media and the public, this study can answer whether the traditional two-step flow of information model holds true or whether other clusters (opinion leaders or the public) set a reversed agenda-setting effect. Historically, news media set the agenda within the traditional concept of agenda-setting. Recently, social media (Russell Neuman et al., 2014) have been found to set the agenda for traditional news media. Opinion leaders can be selected based on nominations from other users (Kilgo et al., 2016), emphasizing the role of a grassroots process in shaping issue networks and assigning opinion leaders. Thus, a reversed agenda-setting process can be expected.

Based on arguments for longitudinal agenda-setting effects, the author tested two research questions and three hypotheses by measuring the volume of news articles published by news media and the number of tweets posted by opinion leaders and the public on the US immigration issue. The author first examined the transfer of salience by measuring volumes of news articles and tweets on each cluster and second the transfer of attributes by measuring volumes of tweets with affective attributes (tone of tweets: liberal-leaning groups supporting more lenient attitudes to US immigrants *vs* conservative leaning groups supporting stricter attitudes to immigrants) for each cluster. The author created two groups (conservative opinion leaders and the public & liberal opinion leaders and the public) based on their profiles on Twitter bio and conducted second-level agenda-setting tests comparing the volume of news media and the number of tweets posted by each political opinion leaders and the public. The author tested three alternative hypotheses because three hypotheses argue conflicting relationships.

RQ18: What is the causal relationship among news media, opinion leaders, and the public in terms of issue salience in US immigration issue networks?

RQ19: What is the causal relationship among news media, opinion leaders, and the public in terms of affective attributes in US immigration issue networks?

H6: News media are more likely to set the issue agenda of opinion leaders on the #immigration issue network on Twitter in the a) retweet network & b) mention network.

H7: Opinion leaders are more likely to set the issue agenda of the public on the #immigration issue network on Twitter in the a) retweet network & b) mention network.

H8: The public is more likely to set the issue agenda of the news on the #immigration issue network on Twitter in the a) retweet network & b) mention network.

Chapter 3: Methodology

This study combined the two-step flow of information and agenda-setting theory to examine the characteristics of opinion leaders and their influence in setting agendas on the Twitter immigration issue network. The author employed Discovertext, a third-party Twitter vender, to glean 397,655 tweets by using the search term #immigration. Due to different characteristics of retweeting (disseminating information) and mentioning (expanding conversations), the author created two different networks: retweet (n = 227,962) and mention (n = 109,412) networks based on the frequency of being retweeted and mentioned for Twitter users. To address hypotheses and research questions, the author conducted a social network analysis, a hierarchical linear regression analysis, and a time-series Granger causality test based on each networks. The analysis will consist of four steps: 1) establishing the retweet, mention and hashtag networks, 2) identifying opinion leaders by conducting social network analysis and measuring centrality scores, 3) predicting opinion leadership by conducting hierarchical linear regression analyses, and 4) conducting Granger causality tests to examine the longitudinal direction of first- and second-level agenda-setting effects on the #immigration issue network (e.g., from opinion leaders to news media / from news media to opinion leaders).

CASE SELECTION, DATA COLLECTION AND ANALYTICAL PROCEDURE

The author collected tweets containing #immigration using Twitter open API (Application Programming Interface) Firehose in DiscoverText Sifter application which is a data reseller providing access to big social data, being defined as voluminious, unstructured and non-linear (Slavakis, Giannakis, & Mateos 2014). The author conducted a keyword search because a keyword can shape “broad topics” related to specific events (Thelwall et al., 2010). This search allowed the author to find a broad range of relevant contents like accounts, tweets and hashtags.

After empirically testing a wide range of search queries, the author decided to choose #immigration to generate a sample for this study, because #immigration is the most general hashtag to glean tweets related to the US immigration issue. Hashtags (#) can shape ad-hoc publics for specific issues by serving as a signifier that can invite any Twitter user to comment. (Bruns & Burgess, 2011). While some studies have examined Twitter discourses on US immigration reform by gathering tweets with keywords such as "immigration policy," "illegal immigration," and "immigration reform" (Chung & Zeng, 2016), few studies have analyzed these immigration discourses by directly examining a Twitter hashtag. Because some studies relied on one hashtag to examine Twitter issue networks in terms of an environmental issue like PM 2.5, an indicator of air pollution in China known as atmospheric particulate matter (PM) that have a diameter less than 2.5 micrometers (Chen, Tu, & Zheng, 2017) and Wisconsin recall election in 2012 (Xu et al., 2014), this study utilized #immigration to gather tweets about US immigration discourses.

The author examined issue networks gathered by #immigration which focused on US immigration news and discussions. Because this study is interested in the longitudinal information flow of Twitter issue networks, the author examined tweets created over a time period of four months: Oct.1, 2016 to Jan. 31, 2017. This date range includes the 2016 US presidential election and President Trump's announcement of an executive order for US immigrants, titled 'Protecting the Nation from Foreign Terrorist Entry into the United States' which lowered the number of refugees into the US and suspended the entry of immigrants from Iran, Iraq, Libya, Somalia, Sudan, Syria and Yemen. The author assumed that a four-month period was sufficient to observe the dynamics of Twitter discussions about immigration issues and to detect the role of opinion leaders and the change of information flow based on previous research. Jang and Park (2017) conducted a time-series analysis of intermedia attention transfers from news media to Twitter based on a four-month period. Also, Meraz (2011) conducted a time-series intermedia agenda-setting effect from traditional news media to political blogs based on about a three-month period. A total of 397,665 tweets were gathered from Oct. 1, 2016 to Jan. 31, 2017, based on the keyword #immigration.

Using one hashtag for the social network analysis could describe an overall network structure better than using multiple hashtags because #immigration was the main hashtag in mentioning immigration issues and it was used in a neutral and consistent way by supporters and opponents of the US immigration policy. That was, both supporters and opponents of immigration used #immigration to signify the topic and often used other hashtags to indicate their position on the issue. The hashtag #immigration provided virtual communities on Twitter with a tool to discuss up-to-date immigration news and show their support or disagreement with current US immigration policy. In addition to #immigration, other hashtags such as #illegalimmigration, #wall, and #immigrationpolicy also explain the US immigration issue. However, #illegalimmigration (n = 25,189 from Oct. 1, 2016 to Jan 31, 2017) and #wall (n = 205,417) were clearly biased and skewed, and #immigrationpolicy (n = 603) was not actively utilized compared to other hashtags. #DACA (n = 77,597) was not highly mentioned during the 2016 presidential campaign and #proimmigration (n = 272) also suggested bias, so the author selected #immigration only in order to minimize bias in the tweet sample. Even though #immigration could not fully cover all Twitter discourses related to the US immigration issue, the author decided to use #immigration only because this hashtag had been actively used by Twitter users across a wide range of the political spectrum and showed higher frequency of usage compared to other hashtags.

Tweets gathered through DiscoverText's Datasift were metadata, known as ancillary information embedded in each tweet and gathered in the corpus of data. DiscoverText is a social media data reseller that has historical Twitter data. Several third-party data reseller such as Gnip sells 100% of historical population of historical tweets. The author chose DiscoverText because some providers like Crimson Hexagon offer limited social data access, like a maximum of 50,000 tweets to be crawled in one day. If more than 50,000 tweets with specific hashtags were produced in a day, data gleaned by Crimson Hexagon could not represent the whole population of tweets. DiscoverText aims to provide complete Twitter data, in a given period by searching through specific keywords. This data set did not include deleted (by users) and officially suspended (by Twitter officials) tweets determined by the Twitter Terms of Service. Some scholars have conducted Twitter textual or network analyses in which tweets were gleaned by DiscoverText (Theocharis et al., 2015; Chung, 2017; Vicari, 2017). Metadata include a tweet ID (a unique numerical identifier assigned to each tweet), the username and profile of the account, geolocation, the number of followers, the number of followees, hashtags, Twitter's messages, URL links, and multimedia contents (video, images or other media), users' bios, and verified status attached to each tweet. The raw form of metadata is a Comma Separated Value (csv), in which all Twitter interactions like retweets and mentions were recorded.

MEASURES

Social network analysis and structure of issue retweet and mention networks

The author conducted social network analysis to examine the structure of US immigration issue network and the presence of opinion leaders. Four research questions are addressed based on the result of social network analysis. RQ1 asked: "What do the twitter immigration issue a) retweet and b) mention networks look like?" RQ2 asked: "How are clusters in the a) retweet and

b) mention networks divided from each other?” RQ3 inquired: “Who are influential users in the a) retweet and b) mention networks?” RQ4 inquired: “Does a hashtag network created by hashtag co-occurrence with #immigration show divisions among clusters?” In this study, retweet and mention networks were shaped by the frequency of being retweeted (rt) and mentioned (@) among members.

In order to answer this study’s research questions, the author conducted a social network analysis and examined the retweet and mention networks and measured centrality scores of individual Twitter users. Social network analysis is a set of relational methods used to systematically understand and identify connections among actors (Wasserman & Faust, 1994). It posits that social lives are created and maintained largely by social relationships and the patterns they form. Social network analysis examines nodes (actors, persons or organizations or status), ties (edge among nodes), dyads (groups of two nodes), triads (groups of three nodes), sub-networks (parts of a larger network) and the network itself as essential elements of social phenomena (Wasserman & Faust, 1994; Ward, Stovel, & Sacks, 2011). Network models can investigate such relational patterns in network data and identify outcomes of multiple associated processes. For the social network analysis, the unit of analysis network is an individual Twitter account. This is operationally treated as a single node in the entire network.

Opinion leaders emerge from the give-and-take transmission of information, and they account for a large amount of information transmission. Katz and Lazarsfeld (1955) argued that opinion leadership is “an integral part of the give-and-take of everyday personal relationships” (p. 33), suggesting that opinion leadership is a socially constructed relationship. Nisbet (2005) argued that opinion leadership is a combination of social embeddedness (density) and persuasion (information giving), emphasizing the importance of combining social relations and opinion-giving behaviors of individual members in the network. Opinion leaders are usually placed in the center of information flow in the network. Several scholars (Choi, 2012; Lee & Cotte, 2009) have found a positive relationship between opinion leadership and degree centrality, calculated by the number of retweets (rt) and mentions (@).

The author assumed that opinion leaders possess higher in-degree centralities than other nodes in the issue network. Centrality refers to the number of connections that a node has within a network and implies the node's level of importance within that network (Hanneman & Riddle, 2005). Measurements of centrality calculate how highly concentrated links are around a small number of central nodes (Borgatti, 2006; Wasserman & Faust, 1994; Ward, Stovel, & Sacks, 2011). Valente (2012) argues that node centrality indicates a measure for identifying opinion leaders in social networks. Nodes with a higher centrality are considered as more important than others (Barabási, 2003).

In-degree centrality measures the number of links sent to a node, while out-degree centrality measures the number of links sent by a given node. In this study, each in-degree centrality was measured by the frequency of being retweeted (rt) and mentioned (@). Some scholars measured influences from opinion leaders to the public by focusing on retweets (Choi, 2014) and mentions (Chen, Tu & Zheng, 2017). The author treated retweet and mention networks separately. Two network structures have its own distinct characteristics to define centralities and network formation. For example, while the tweets of news organizations, journalists or any informative resources can be retweeted more to spread information or breaking news (Marwick & boyd, 2011b; Wei et al., 2013), mentioning leads other users who have already known each other to be engaged into the conversation.

Twitter users may retweet to stimulate specific audiences by simply passing on information, giving additional comments on someone's tweet, or publicly agreeing or disagreeing with someone's ideas (boyd, Golder, & Lotan, 2010). Larsson and Moe (2012) mentioned that a retweet was an effective measure for the extent to which tweets were understood as important in the network. Also, a retweet can bolster the credibility and reputation of the person whose tweets were retweeted (Recuero et al., 2011). Such retweeting behavior can empower Twitter users to spread tweets beyond the reach of followers and proliferate them across the network to receivers who do not have direct relationships with the creator of the original messages (Lee & Sundar, 2013). However, the author found that some Twitter users, especially journalists' Twitter accounts, mentioned that 'retweets are not endorsements' on bios, indicating the discrepancy of opinions between their organizations and their personal opinions.

Mentioning or targeting other users, the most direct communication channel on Twitter, is another way to measure opinion leadership. The @ symbol is utilized to nominate other users for mentioning, which is an actual form of communication. Twitter accounts with higher in-degree centrality in mention networks can receive potentially greater attention due to a high chance to be detected by others. González-Bailón, Borge-Holthoefer, and Moreno (2013) argued that the mention network is sparser than the followee-follower network because only a small fraction of actors is engaged in direct communications with others. The mention network has a lower level of clustering with densely connected nodes that are sparsely linked to other clusters.

The unit of retweet and mention network is a tweet. The author cleaned raw csv files from DiscoverText by extracting sources and targets of two networks and converted source and target relationships into directional networks (from sources to targets). The filtering functions in Microsoft Excel and Python scripts were utilized to clean and organize directional retweet and mention networks. The author used Gephi, an open-source computer-assisted network analysis and visualization software launched in 2010 to calculate centrality scores.

Other centralities—like betweenness centrality, closeness centrality and eigenvector centrality (Hanneman & Riddle, 2005)—are also measured for the descriptive analysis. Measures of centrality can be categorized into betweenness centrality, degree centrality (in and out), closeness centrality, and eigenvector centrality. Betweenness centrality indicates the amount of flow in the network that would not occur if the node were not present (or were choosing not to transmit (Everett & Borgatti, 2005). An actor with high betweenness centrality functions as an information broker: a bridge and gatekeeper who strategically controls the information flow in the network by connecting "unconnected" nodes (Freeman, 1979), over which news or information is transmitted through the principal paths of a social network. A node with high betweenness centrality can have considerable influence within a network because it maintains a high level of control over information. Brokers can filter or distort resources, providing benefits in the form of control but inhibiting the overall flow of resources (Burt, 2004).

Degree centrality indicates the share of edges attributable to each actor by measuring the number of edges. Total degree centrality is calculated by the sum of in-degree and out-degree centrality. In-degree centrality is the number of links sent to a given node, while out-degree refers to the number of links sent by that node (Hämmerli, Gattiker, & Weyermann, 2006). In contrast, nodes with higher in-degree scores have greater prestige and popularity, because these nodes are sought after by others. Twitter users who have a large number of followers can be considered as prestigious, while an individual with a large number of followees can be regarded as socialite.

Despite the value of degree centrality for measuring influential users in the network, it is problematic because it only measures immediate ties, rather than indirect ties to all others (Hanneman & Riddle, 2005). One actor can be tied to a large number of others, which are disconnected from the network in the aggregate. Moreover, whether a central position itself in the network is structurally unique or not remains questionable. In order to solve this problem, closeness centrality measures an actor's distance from others in the network in the form of geodesic distances (the shortest paths among actors). It can reflect an actor's freedom from being controlled by others. As mentioned above, the central point is more powerful than others because the power originates from a reference point. This central point is evaluated by other actors, whose views are then taken up by a larger number of actors in the network. The sum of geodesic distances for each actor in the network can be named as the farness of the actor from others. The degree of farness can be converted into a measure of closeness centrality. Still, in a larger and more complex network, it is possible to misinterpret the measures. To solve this problem, measurements of eigenvector centrality find the most central actors, who have the smallest degree of farness from others in the overall structure of the network. It assigns higher weights to links that connect a node to central nodes.

To answer RQ1, the author displays the entire network structures of retweet and mention networks with several clusters consisting of directional network edges (mutual relationships) to display all ties. In order to exclude inactive Twitter accounts, the author deleted Twitter accounts that recorded only single value of degree centrality (degree ≥ 2) for the retweet and mention network. The author chose degree centrality as a criterion for network visualization because it is a sum of in- and out-degree centrality scores, which allowed the author to examine mutual interactions among nodes clearly.

Gephi was used to visualize nodes and graphs, calculate modularity and centrality scores. Gephi is an open source software that provides intuitive understanding of the layout of large network data (Jacomy et al., 2014). The Force Atlas 2 layout, a force-directed algorithm (an algorithm assigning forces among nodes and edges) developed by Gephi, was chosen to visualize networks. A Computational algorithm created by Blondel et al. (2008) was used to calculate modularity scores on large networks and to enumerate clusters produced by similarities of members in each cluster. The modularity scores range from -1 to 1 (Li & Schuurmans, 2011). The modularity scores closer to 1 have dense connections between nodes within clusters but sparse connections between nodes in different clusters (Li & Schuurmans, 2011). In the retweet network, total 34,892 (29.8% of users in the entire retweet network) nodes and 97,417 edges were found and in the mention network, total 23,304 (46.2 % of users in the entire retweet network) nodes and 61,507 edges were found.

To answer RQ2, the author measured the number of clusters in two networks. The author conducted cluster analysis, which uses modularity as a metric to enumerate groups in social networks, based on the study done by Himelboim, Smith, & Shneiderman (2013) who created a term ‘Selective Exposure Cluster.’ A modularity is a measure to determine the extent to which calculated clusters are bounded, resulting in a structure of where selective exposure can happen (Himelboim, Smith, & Shneiderman 2013). The higher score of modularity means that when connections within a group are denser, connections within other groups are also denser. Modularity score can be used to highlight divisions of clusters in the network. According to Newman and Girvan (2004), most modularity scores have been recorded in the range from 0.3 to 0.7. Garcia et al. (2015) argued that low modularity scores range from -1 to 0.3, implying that no polarization exists in the network, while high modularity scores range from 0.3 to < 1, indicating the existence of polarization. Himelboim, Smith and Shneiderman (2013) argued 0.6 as a threshold for detecting high modularity and 0.4 as a sufficient threshold to be a medium level of divisions among clusters. The author used modularity function in Gephi, whose computational algorithm was created by Blondel et al. (2008). Such algorithm works best to detect communities in the large network.

The author measured divisions among clusters with several processes. First, the author calculated modularity scores in the network and modularity classes for each user through Gephi modularity function. Then, the author ranked Twitter accounts by degree centrality scores in descending order and chose top 10 and few more accounts who had the highest degree scores in each modularity cluster (*n* of Twitter accounts in the retweet network = 404, *n* of Twitter accounts in the mention network = 600). The author assigned a political orientation to each user and cluster, labeling them as conservative, liberal, neutral, or unclear groups. The author classified political ideology of each cluster based on their users' profiles. For example, the author assigned Twitter users as 'liberal' when they described their liberal ideology on their profiles (e.g., #Uniteblue #Hillary2016 Uruguayan immigrant mother). A hand-coded content analysis with another coder was conducted to measure the reliability of classification (506/34,892, 1.5 % of the sample in the retweet network & 622/23,304, 2.7 % of the sample in the mention network). Few studies have offered a proper criterion to analyze clusters in large networks. Because the modularity test results in a large number of clusters, the author chose to examine prominent clusters that included at least one percent of the entire users (Guo, Rohde, & Wu, 2018).

After finding out politically biased clusters, the author conducted the second hand-coded analysis for those clusters (conservative-leaning or Republican and liberal-leaning or Democratic). The author chose more than 60 accounts (the top 50 accounts that had the highest degree scores + 10 randomly selected accounts) in politically opinionated clusters (*n* of Twitter accounts in the retweet network = 574, *n* of Twitter accounts in the mention network = 1,178) to figure out whether the rest members in each cluster had similar political orientations with the top 10 Twitter accounts.

The author conducted Krippendorff's alpha test to measure inter-coder reliability between two coders. Krippendorff suggested criteria for the inter-coder analysis test: tentatively conclusive (0.67 - 0.80) and conclusive (above 0.8) agreements (Krippendorff, 2004). The inter-coder reliability tests among two coders showed a conclusive agreement .91 for the retweet network and .92 for the mention network.

Lastly, the author also observed shapes of social networks, such as polarized crowds, broadcast network, community clusters or support networks (Pew Research Center, 2014). Polarized crowds are two distinctive groups that rarely interact with each other. Polarized crowd can be determined by the visual representation of two ideologically distinct groups (conservative vs liberal or Republican vs Democratic). Broadcast network has a hub that performs as agenda-setters or conversation starters located in the central position of the network to broadcast messages to many disconnected audiences. Community clusters indicate multiple smaller groups around few hubs with their own audiences and information resources. Support networks produces "a hub-and-spoke structure (Pew Research Center, 2014)," in which hubs are connected with many unconnected users, shaping outward spokes.

To answer RQ3, the author measured the verified and elite status of the top 50 Twitter accounts in each network. Specifically, the author coded users' occupations on profiles to determine whether they worked in knowledge-intensive occupations or social movement organizations by observing their Twitter bios. This study is a very first trial to determine whether knowledge-intensive occupations are related to Twitter opinion leadership, based on the characteristics of traditional opinion leaders who had more knowledge than followers (Katz & Lazarsfeld, 1955). Knowledge-intensive occupations include (1) academic position (Twitter users who worked for educational institutions), (2) politicians (users who were professionally engaged in politics and hold offices previously and currently), (3) lawyers (users who practically applied laws as an attorney, advocate, judge or barrister), (4) journalists (users who collected, wrote and distributed news for certified news organizations), (5) authors (users who created any written works involving the publication of novels or other books), (6) celebrities (users who are famous and celebrated persons, like singers and actors), (7) bloggers (users who wrote informal or conversational stories regularly on personal and organizational websites) and (8) organizations (Twitter accounts managed by any social organizations, including news companies, research institutions and NGO). Such individuals possess a high level of professional knowledge and offer personal opinions regularly. While other positions like scientists, engineers or doctors are also knowledge-intensive occupations, they have typically offered their personal thoughts to the public less frequently, focusing on their main occupations. Also, such users were not directly related to the US immigration discussions. Such categorization is developed from the study of Chen, Tu and Zheng (2017) which measured the role of several actors in PM 2.5 Twitter networks and the observation of user profiles in the US immigration policy networks.

The author differentiated such knowledge-intensive (elite) and celebrated occupations with others to create a dichotomized variable (users having knowledge-intensive occupations vs ordinary citizen which was a proxy of the public). If Twitter users did not belong to one of those positions, the author coded them as the public. The author used the variable which indicates that

Twitter users are knowledge-intensive and celebrated users as a single binary variable (1 = yes, 0 = no).

Research question 4 inquired: “Does a hashtag network created by hashtag co-occurrences with #immigration show divisions among clusters?” To examine divisions of clusters in the hashtag network, a cluster analysis measuring modularity scores (the number of communities) in the hashtag co-occurrence network was conducted. The author assumed that two hashtags share similar nuances if they co-occur in one tweet than the similarity between two hashtags, which were randomly selected (Muntean, Morar, & Moldovan, 2012). A hashtag co-occurrence network is created when a specific hashtag was used with #immigration on a tweet. The co-occurrences between two hashtags are represented as a tie with a hashtag representing as a node. Such a co-occurrence also casts light on Twitter’s topical structure (Bode et al., 2015). The author considered hashtags in tweets as proxies for topics related to the immigration issue. Because this study chose #immigration as the search keyword in order to minimize bias in the sample of tweets, the author observed the main #immigration and the degree to which it is connected to other hashtags, assuming that such a hashtag usage (co-occurrence) with #immigration may express a particular point of view. Specifically, the author assumed that both liberal and conservative hashtag co-occurrence networks are created based on individual political ideologies. For example, #immigration is sometimes accompanied by #freedom, #hugsnotwalls, or #DACA, hashtags that indicate a positive view of immigrants and support for immigrants’ rights. Also, some hashtags like #Imwithher and #hillary were leading liberal hashtags during the presidential election period, paired with #immigration. On the other hand, #tcot (top conservative on Twitter), #buildthewall and #maga (Make America Great Again) are prominent conservative hashtags that suggest negative attitudes toward immigrants and support for stricter US immigration policies. Because these hashtags are widely used in discussing US immigration issues, the author could detect them at a glance.

The author utilized Gephi to visualize hashtag co-occurrence networks and calculated modularity scores for the hashtag network and modularity classes for each hashtag. The author did not include #immigration for the analysis because it is the main hashtag co-occurred with other hashtags. From the entire hashtag network, total 1,118 communities with 26,875 hashtags were detected. Based on a recommendation about reducing the large network into a reasonable one suggested by Borgatti, Everett, and Johnson (2013), the author extracted hashtag nodes which appeared at least 200 times in the #immigration hashtag network (degree ≥ 200), based on Blondel, et al. (2008)'s algorithm again for the hashtag network. A total of otal 212 hashtags and 10,314 edges were found. Then, the author assigned a political orientation and themes to each hashtags and cluster, labeling them as conservative, liberal, neutral, other, or unclear groups, by observing hashtags and their associations with others in each cluster.

Research question 5 asked: "Are the structures of the discussion group on the #immigration a) retweet and b) mention network concentrated on a few individuals, based on individual in-degree centrality scores?" Research question 6 asked: "Are the structures of the discussion group on the #immigration a) retweet and b) mention network concentrated on a few individuals, based on the number of tweets posted by individual users?" The author measured the distribution of in-degree centrality scores and the number of tweets in each network, to observe whether the large portions of occurrence were far from the central part of the network. The degree of concentration in the overall network structure can be measured by the Gini coefficient. Gini coefficients are used to identify whether or not information dissemination originated from a small number of opinion leaders in the retweet and mention networks. A zero value means that perfect equality was achieved, and a coefficient value close to 1 means that only a few individuals were concentrated on each network. Gini coefficient was measured by the proportion of in-degree centrality scores each user earned divided by total number of relationships (RQ 5) and the proportion of tweets individual users posted divided by total number of tweets in each network (RQ 6). The Lorenz curve, visualizing Gini coefficient in the graph, was also drawn for each network. The Lorenz curves visually represent unequal distribution of in-degree centrality scores and tweets posted by individual users in each network. A computer language R was used to calculate Gini coefficient values for retweet and mention networks and draw Lorenz curves. Distribution graphs were also used to observe distribution of in-degree centrality scores such as long-tail distributions posted by participants in each network.

Predicting opinion leadership on Twitter issue networks

The author conducted hierarchical linear regression analyses to measure the predictive powers of Twitter communication affordances, contextual factors and the degree of issue involvement to opinion leadership (Zhang et al., 2014; Shi & Salmon, 2018). The author posited that in-degree centrality scores are direct measures of opinion leadership. In social network analysis, in-degree centrality scores measured the degree of connectedness by measuring inbound links they got through Gephi. The unit of analysis is the Twitter account (*n* of retweet network = 117,040, *n* of mention network = 50,395).

Eleven research questions and five hypotheses were tested based on three hierarchical linear regression analyses. Research question 7 asked: “What is the relationship between mentioning other users and opinion leadership in the a) retweet network & b) mention network? Research question 8 asked: “What is the relationship between the number of hashtags and opinion leadership in the a) retweet network & b) mention network?” Research question 9 asked:

“What is the relationship between a) Twitter users whose tweets were retweeted by others b) Twitter users who were mentioned by others and their job status?” Research question 10 asked: “What is the strongest predictor of opinion leaders in the a) retweet network & b) mention network?” The first hypothesis examined: “There is a positive relationship between activeness of Twitter users in terms of number of tweets and opinion leadership in the a) retweet network & b) mention network.” The second hypothesis examined: “There is a positive relationship between the number of followers and opinion leadership in the a) retweet network & b) mention network.” The third hypothesis tested: “There is a positive relationship between the number of followees and opinion leadership in the a) retweet network & b) mention network.” The fourth hypothesis examined: “Twitter users whose accounts are officially verified by Twitter are more likely to be opinion leaders in the a) retweet network & b) mention network.” The fifth hypothesis measured: “Those who were more involved in the US immigration issue are more likely to be opinion leaders in the a) retweet network & b) mention network.”

Research questions 11 and 12 asked: “What is the relationship between Twitter communication affordances (the average number of mentions and hashtags in a tweet) and the frequency of being retweeted?” Research question 13 asked: “Is there a positive relationship between tweets posted by verified users and the frequency of being retweeted?” Research question 14 inquired:” “Is there a positive relationship between tweets posted by users who had knowledge-intensive occupations and the frequency of being retweeted?” Research question 15 asked: “Is there a positive relationship between tweets which were oriented to disseminate more information and the frequency of being retweeted?” Research question 16 asked: “Is there a positive relationship between tweets that were oriented to offer more personal information and the frequency of being retweeted?” Research question 17 asked: “Is there a positive relationship between tweets that were oriented to call for more specific actions and the frequency of being retweeted?”

To answer research questions 7, 8, 9, and 10, and test hypotheses 1, 2, 3, 4, and 5, the author set independent variables as Twitter communication affordances (the average number of mentions and hashtags per user), contextual factors (overall numbers of tweets per user, the number of followers and followees, verified status and elite status), and issue involvement (the number of tweets with #immigration per user) and the dependent variable as an in-degree centrality scores per user.

In answering research questions 7 and 8, the author sought to measure the relationship between the number of hashtags and mentions and opinion leadership. Excel and Tableau were used to sort respective users and measure the total number of mentions and hashtags posted by each user. The author deducted one for the total number of hashtags because #immigration was a default for every tweet. After getting the total number of mentions and hashtags respective users posted, the author divided such numbers with the total number of tweets they posted with #immigration to get an average of hashtags and mentions they posted in one tweet.

The author defined contextual factors as signals that enable audiences to make judgments about who opinion leaders are. In social media, the personal attributes of Twitter users, like elite occupations mentioned on their bios and verified status, can influence audiences to believe that specific users are credible and reliable. Kwak et al. (2010) found that author-related factors on Twitter include degree of activeness and authoritativeness. Opinion leaders are renowned as knowledgeable and credible figures from whom others seek interpretations of information (Valente & Pumpuang, 2007). Also, having a large number of followers enabled Twitter users to disseminate information effectively, and having a large number of friends (followees) offers a wide source of information to users. Both numbers of followers and followees are related to mutual interactions with other Twitter users. Some social media users had verified badges on their profile, which implies that they were well-known and authoritative individuals or organizations. Users have to manually submit their personal information to Twitter to be confirmed as verified users. Castillo, Mendoza, and Poblete (2011) found that posts by official sources such as news organizations were considered as more trustworthy and authoritative by Twitter users. Zhang et al. (2014) also found that verified users such as elite members and celebrities were more credible than unverified ones.

The author measured general Twitter activities by investigating the number of entire tweets posted by users to test hypothesis 1. Also, both numbers of followers and followees, and verified status of individual Twitter users were recorded to test hypotheses 2, 3 and 4.

To answer research question 9, the author observed Twitter users' occupations mentioned on their bio to measure the statistical association between elite-job status and opinion leadership. Specifically, the author extracted elite occupations and social organizations of Twitter users through searching their bios by using Boolean search (e.g., filtering Twitter users with keywords such as author "OR" writer "OR" blogger). Excel, the Data managing software Tableau and hand-coded content analysis were utilized to extract users' occupation. The author extracted Twitter users with (1) academic positions, (2) politicians, (3) lawyers, (4) journalists, (5) authors, (6) celebrities, (7) bloggers, and (8) organizations, and coded as a single binary variable (1 = yes, 0 = no).

In order to validate hypothesis 5, the author operationalized the issue involvement of individual users as the number of tweets which contained #immigration posted by them over the four-month period. This number is differentiated from general Twitter activities, the entire number of tweets posted by individual users. The author assumed that differences in contributing to the expansion of #immigration networks between users who post other topics such as same-sex marriage and gun control issues, and others who only posted about the US immigration policy can be expected. The #immigration network is an issue-specific discussion group, so opinion leaders in #immigration issue networks are heavily involved in the US immigration issues discussed on Twitter.

Research question 10 asked the strongest predictor of opinion leaders in the retweet and mention network. The author chose the highest standardized beta value (β) among significant predicts in hierarchical linear regression analyses of each model.

With independent variables (the average number of hashtags and mentions Twitter users used, general Twitter activities, the numbers of followers and followees, verified status, elite-status and the degree of issue involvement), the author conducted two hierarchical linear regression analyses on retweet (Total accounts = 117,040) and mention networks (Total accounts for the mention network = 50,395) were conducted, respectively. In two hierarchical linear regressions, the first block of hierarchical linear regression analyses is Twitter communication affordance, and the second block included contextual factors of Twitter users. The individual issue involvement was added in the third block. In-degree centrality scores, the dependent variable of this study, were highly skewed having a lot of zeroes. Thus, square-root transformation was conducted only for in-degree centrality to reduce skewedness.

Hierarchical linear regressions on the random samples

With contextual factors, the author focused on content factors on tweets and their influence to the number of retweets in the retweet network. The retweet can be a proxy for measuring diffusion of information, assuming that more retweeted tweets can attract more attention from other users (Gruzd, Wellman, & Takhteyev, 2011; Park & Kaye, 2017). Also, the number of retweets can represent the influence and popularity of tweets (Dang-Xuan et al., 2013; Zhang et al., 2014). For content factors, the author first focused on the definition of traditional opinion leaders: (1) active media users who (2) interpret media messages and (3) influence other's opinion or behavior (Katz & Lazarsfeld, 1955). These three components of the definition of opinion leaders can be dissected into (1) dissemination of media messages, (2) offering personal opinions based on media messages, and (3) a call or mobilization for specific actions.

The author differentiated dependent variables as in-degree centrality for the first two hierarchical linear regression models and the frequency of being retweeted for the hierarchical linear regression model to measure the influence of contextual factors to concentrate because the unit of analysis among two models were different: Twitter account and a tweet. Opinion leaders can post tweets with different purposes, which led authors to determine that types of tweets users posted cannot represent Twitter users. Opinion leaders can post tweets to distribute information and persuade others with their opinions in different tweets. Thus, the dependent variable measuring the influence of contextual factors was the frequency of being retweeted in additional hierarchical linear regression analysis.

To measure the influence of content and contextual factors on the number of retweets (Zhang et al., 2014), the author randomly selected total 1,116 tweets from the entire retweet network and extracted content factors from tweets and conducted hierarchical linear regression analysis. There is no exact rule about determining targeted sample size from the entire population. Several studies conducted manual content analysis based on 1,575 tweets (Lee & Xu, 2018), 1,962 (Hambrick et al., 2010), and 1,617 (Small, 2011). The author calculated what would be a desirable sample size through Surveymonkey, an online survey development software. The author set confidence level as 99% and margin of error as 5% (https://www.surveymonkey.com/mp/sample-size-calculator/). As a result, the minimum sample size was 664 for the retweet network (n = 227,962), which means that the sample size for this study would be larger than 664. The author randomly selected 1,116 tweets from the retweet. More than 664 calculated for desirable sample size is enough to represent the population and conduct studies based on random sampling process. The first block of hierarchical linear regression models predicting the frequency of being retweeted was twitter communication affordances. The second model included contextual factors, and three content factors were added in the third block.

Tweets that belong to the dissemination of media messages are ones that distribute factual information to others. Such tweets are used to select or curate a story among various resources and disseminate them to others users. Tweets that are oriented to offer personal opinions convey subjective and persuasive information to others. Such tweets should contain personal opinions to persuade other users. Tweets that call for specific actions are asking readers to join petitions and offline protests or events. Lastly, tweets which do not belong to these three categories are coded as 'the other.' The author read each tweet and manually coded whether each tweet belongs to one of the three categories (1 = yes, 0 = no). The author added the third category, a call for specific actions because Park and Kaye (2017) found a positive relationship between Twitter opinion leadership and civic engagement. The opinion leaders as mobilizers for social issue can affect others' actual behaviors such as donations and participations in protests. Such textual categories which have not been tested before can be manifested within tweets. In Twitter conversations like the #immigration network, such textual cues can draw attention to others, leading them to retweet information.

Inter-coder reliability tests

The author conducted manual content analyses for users' elite occupations and content factors. While the author relied on the big data computational analysis for the first two hierarchical linear regression analyses, the human observation for users' occupations and content factors is required to interpret nuances in the texts. The author and a trained coder coded (1) Twitter users' occupations (from their bios) and (2) types of tweets they posted (disseminating information, offering opinions and calling for actions). The author conducted measured inter-coder reliability between two coders. The author randomly selected 80 tweets (7.1% of the sample) from the randomly selected 1,116 retweets for the inter-coder reliability tests. Krippendorff's alpha score was recorded as 0.91 for user's elite status, 0.83 for user's non-elite status, 0.77 for the category of disseminating information, 0.86 for the category of offering personal information, 1 for the categories of calling for action and others, showing tentatively conclusive and conclusive agreements (Krippendorff, 2004).

To answer research questions 11, 12, 13, 14, 15, 16, and 17, the author conducted additional hierarchical linear regression analyses on randomly selected retweets from the entire retweet network. Independent variables are Twitter communication affordances (the number of mentions and hashtags on tweets), contextual factors (tweets posted by verified users and elite-status users) and content factors (tweets which were oriented to disseminate information, offer personal information and call for specific actions). The frequency of being retweeted representing the degree of influence for tweets was operationally defined as a dependent variable in the third hierarchical linear regression analysis.

Time-Series Granger causality

The author additionally focused on the longitudinal agenda-setting effects among news media, opinion leaders, and the public groups. Historically, before the rise of social media, the answer to the question, “who sets the agenda?” was news media based on the traditional concept of agenda-setting. However, Broersma and Graham (2012) argued that social media provided an alternative to traditional media as a news outlet during the 2010 British and Dutch elections. Recent studies have found that political blogs (Meraz, 2011) and social media (Russell Neuman et al., 2014) also set the agenda for traditional news media, indicating multiple dynamic interactions among issue setters. This study added opinion leaders as a part of longitudinal agenda-setting process, due to the emphasis on the role of opinion leaders as a mediator of information flow between news media and the public (Katz & Lazarsfeld, 1955) and the importance of interpersonal communication on social media (Weimann & Brosius, 2017). In doing so, the author tried to examine the validity of the traditional concept of agenda-setting and two-step flow of information (from news media to the public, from news media to opinion leaders and from opinion leaders to the public). Also, the author tried to observe reversed agenda-setting effects (from opinion leaders to news media, from the public to news media and from the public to opinion leaders).

The author tested two research questions and three hypotheses to test longitudinal agenda-setting effects among news media, opinion leaders and the public. Research question 18 asked: “What is the causal relationship among news media, opinion leader and the public in terms of issue salience in US immigration issue networks?” Research question 19 asked: “What is the causal relationship among news media, opinion leader and the public in terms of affective attributes in US immigration issue networks?” Hypothesis 7 tested: “News media are more likely to set the issue agenda of opinion leaders on the #immigration issue network on Twitter in the a) retweet network & b) mention network. Hypothesis 8 tested: “Opinion leaders influence the agenda of the news media and the public in the a) retweet network & b) mention network. Hypothesis 9 tested: “The public is more likely to set the issue agenda of the news media and opinion leaders in the a) retweet network & b) mention network. Granger causality tests measure how one group influenced another (that is, how influence flows from news media to opinion leaders/opinion leaders to the public/news media to the public) and also detect reverse relationships (when influence flows from the public to opinion leaders/opinion leaders to news media/the public to news media). The author operationally defined opinion leaders in the time-series analyses based on two criteria: (1) verified Twitter accounts and (2) Twitter users who scored within the top 10 % of in-degree centrality scores in the entire network.

The author conducted both first-level and second-level agenda-setting tests. While the first-level agenda-setting focuses on the transfer of issue salience, the second-level agenda-setting emphasized the transfer of issue attributes among each entity (McCombs, 2005). The author measured the transfer of news articles (for news media) and tweets (for opinion leaders and the public) for the first-level agenda-setting. The author assumed that Republican and conservative Twitter users would want to establish strict standard of immigration policy and limit the number of migrants into the US. On the other hand, Democratic users are favorable toward immigrants and immigration issues (Pew Research Center, 2016). Thus, the author expected different agenda-setting effects among Republican and Democratic Twitter users. The author created Republican and Democratic groups of opinion leaders and the public, based on their political ideologies listed on their profiles and their tweets. The filtering function in Excel and computer language Python scripts were used to sort users who explicitly described their political preferences on their Twitter profiles based on politically opinionated keywords.

The Granger causality test is a statistical analysis to determine whether the time lag of one variable can forecast the distribution of another one over time (Granger, 1969). It has been mainly utilized in economics but communication scholars have paid attention to it, particularly for agenda-setting studies (Groshek & Groshek, 2013; Meraz, 2011; Tan & Weaver, 2007). In the agenda-setting studies, scholars measure the associations of topic saliences between news media outlets and the public. Specifically, Granger casualty in agenda-setting effects occurs when the distribution of topic salience in one group can precede and predictively explain a significant amount of variance of topic salience distribution in another one. As a form of a systematic time series analysis, Granger causality can explain the real nature of relationships between agendas across different time periods.

Granger causality can show that the change in the volume of one trend preceded the change of values of another, but cannot exhibit to what extent other events outside the model trigger both timely sets (Russell Neuman et al., 2014). In this test, a measure x is said to “Granger-cause” a measure y if y can be better predicted from past values of x and y together than from past values of y alone (Freeman, 1983). The Granger causality test can also identify mutual reciprocal Granger causations (Kellstedt, 2003). The Granger causality test was appropriate for this study because it focuses on the dynamic responsiveness of traditional media and Twitter opinion leaders and the public to specific issues by examining correlations of longitudinal data, so that it is considered as a more accurate way to conduct time series analysis, compared to Auto Regressive Integrated Moving Average (ARIMA) (Meraz, 2011).

To create groups of users who possibly set the agenda, the author made a media group that covered the US immigration issue. Separate from the first study--which measured the issue network structure, found opinion leaders, and analyzed the causal relationship between opinion leadership (in-degree centralities) and user attributes-- the author utilized Lexis-Nexis to glean US news coverage of immigration issues. The term "#immigration" within the same period (October 1, 2016 to January 31, 2017) was applied to a Lexis-Nexis search. Daily volumes of mainstream and national news coverage (New York Times, The Washington Post, ABC, CBS, CNN, FOX, MSNBC and NBC, n = 4,981) were found through Lexis-Nexis search. Traditionally, New York Times and Washington Post were regarded as an agenda setter for other media (McCombs, 2014). Also, because USA Today is distributed in all the US along with New York Times and Washington Post, it has been considered as one of three national newspapers. For television news, ABC, CBS and NBC are national network news, which are airing their news nationally. The author chose CNN, MSNBC and FOX as indicators of news media because those three cable news channels are fully devoted to television news broadcasts.

Time-series groups for opinion leaders and the public in the #immigration network were created for retweet (n = 227,962) and mention (n = 109,412) networks separately. The author additionally created time-series groups of the retweet and mention networks (n of entire Republican network = 121,262, n of Republican retweet network = 94,885, n of Republican mention network = 11,661, n of entire Democratic network = 31,395, n of Democratic retweet network = 30,014 & n of Democratic mention network = 13,612). Then, the author calculated time-series first-level and second-level agenda-setting effects of each group based on daily volumes of being retweeted and mentioned by other users. The originators and time stamps of each tweet were strictly recorded in order to determine which sources (opinion leaders or the public) posted tweets at specific moments. From the record of time stamps, this study created time-series data vectors for social media data.

The author operationally defined opinion leaders as (1) any verified Twitter accounts and (2) users who scored within the top 10 % of in-degree centrality scores over the four-month period. The accounts that were verified as official Twitter accounts with badges on their bio were operationally defined as opinion leaders. The 2016 record indicated that they were only 0.061 percent of all Twitter users (Navarra, 2016). In addition, the criteria (top 10% of in-degree centrality) for defining opinion leaders in the Granger causality test were originated from the first study: network analysis and the following hierarchical linear regression analyses. In order to maintain strictness in selecting opinion leaders, the author decided to define opinion leaders as users in the top 10% of high centrality scores and verified accounts. Previous studies (Brosius & Weimann, 1996; Valente & Pumpuang, 2007) argued that opinion leaders were recorded as the top 10% of individuals in the network, which is in line with the current study. Even though accounts were verified and were not owned by media workers, accounts belonging to the top 10% of high in-degree centrality measures in retweets and mention networks were assigned as opinion leaders for Granger causality analyses. If Twitter accounts met one of two criteria, the author classified them as opinion leaders. If accounts were both verified and within top 10% of centrality scored, they were treated the same as other opinion leader accounts. Thus, tweets posted by verified users and within top 10% of high in-degree centrality scores were defined as tweets posted by opinion leaders. The rest of Twitter accounts, which did not belong to opinion leader group, were categorized as the public.

Some impulses in time-series graphs were expected in longitudinal agenda-setting tests. An impulse is a sudden and unreflective urge or spike in time series data and gradually returns to the long-term average. In this study, an impulse originated from any news related to US immigration policy such as the election of President Trump and the declaration of strict immigration rules in one group can raise the level of attention in another group (news media, or opinion leaders, or the public) for a while, and then the attention level gradually regresses to the long-term average, known as asymptotic status. Most newsworthy events that create impulses on Twitter are rare and sporadic. For example, when the election of President Trump and the following executive order that got rid of privacy protections for DACA recipients were announced, audiences could pay a lot of attention to the immigration issue and tweet about it promptly. As a result, we can observe DACA and US immigration issues in Twitter 'trending' sections, and expect a lot of impulse in Twitter discussion.

Several conditions are required to meet before conducting Granger causality tests. The author preliminarily conducted Augmented Dickey-Fuller tests to examine the presence of stationarities in each vector auto-regression (VAR). Stationarity means that any statistical properties like mean and variance are all constant for each group (news media and Twitter issue network) over time (Amiri & Ventelou, 2012; Toda & Yamamoto, 1995). All time-series variables should achieve stationarity, and the Augmented Dickey-Fuller (ADF) test identifies whether impulses, trends, cycles and seasonal variations result in unrecoverable (not able to be recovered later) deviations from the average or not. For Augmented Dickey-Fuller tests, the null hypothesis tests whether a unit root, a feature of some stochastic process that results in non-stationarity of time-series variables, exists in the time-series analysis. The alternative hypothesis is that all variables maintain the stationarity among them to meet statistical validity of time-series analyses. Time-series models in this study should reject the null hypotheses in ADF tests.

Second, the Granger test should determine the appropriate number of lagged independent variables in the regression. Some agenda-setting studies (Roberts, Wanta, & Dzwo, 2002) found that agenda-setting effects occur in a week or less. Roberts, Wanta and Dzwo (2002) found that a lag between traditional news and online discussion varies from one to seven days, and Day 7 produced the most effects. But currently, time lag between traditional news and Twitter discussion was compressed into one day (Groshek & Groshek, 2013). In order to confirm this assumption, this study assessed the proper number of lags to validate the suitability of the choices. While too short of a time lag could not grasp the temporal order of attention to an issue between traditional media and Twitter opinion leaders, a time lag that was too long could be ineffective due to the dissipating effects over time (Chaffee, 1972). Based on these arguments, the author conducted statistical tests to confirm the appropriate number of lag with the log likelihood function and a criterion applied for lag selection, such as Akaike's information criterion (AIC) of each group in a 4-month span (Becketti, 2013). Those measures suggest the appropriate time lag for Granger-causality tests for three groups (news media, opinion leaders and the public) separately. Time lag for the entire #immigration network was 5 days, the retweet network was measured by the time lag of 5 days and the mention network was measured by 4-day time lag. Other times lags were also calculated (entire Republican network: 5 days, Republican retweet network: 2 days, Republican mention network: 3 days, entire Democratic network: 3 days, Democratic retweet network: 5 days, & Democratic mention network: 1 day).

The author then conducted Portmanteau tests to examine any autocorrelation in time-series data (Arranz, 2005). A Portmanteau test is oriented to verify a model's match to datasets. Specifically, it tests whether any time-series groups have autocorrelation issues (the degree of similarity between a given time-series value and a lagged value of it over time) or not. Autocorrelation indicates that there are significant correlations between specific points separated by different time lags (Box et al., 2014). Time-series data should not have autocorrelations, which means that residuals in time-series analysis are independent up to time lag calculated by

AIC scores maintaining asymptotic status. As a result, autocorrelation values have to record zeros because standard errors of regression coefficients can seriously underestimate the true standard deviation of estimated coefficients and statistical inference processes cannot be strictly applicable (Kutner, Nachtsheim & Neter, 2004). The null hypothesis of Portmanteau tests assumes that residuals in time-series variables are independent (no autocorrelations), while the alternative hypothesis argues that autocorrelations exist in each time-series variable. Portmanteau tests should support the null hypotheses.

Lastly, the author tested whether the past time lag of the attention of two groups could predict the next day of attention significantly better than the previous days of levels of one group, by conducting a Wald test which assesses the validity of Granger causality. The Wald test calculates the value determining whether the restricted model that excludes any vectors is significantly outperformed by the non-restricted model that has the lagged values of all variables (Granger, 1969). Chi-square tests measuring Granger causality indicate the magnitude of the reduction in error term variance caused by the corresponding variables. When the test yielded a statistically significant Chi-square scores, this study could reject the null hypothesis testing, so that the restricted model was not adopted and argue that a vector could Granger-cause the dependent variable. The R computational command “vars” and “tseries” were used for the longitudinal time-series test.

The author examined possible trends, cycles and seasonal variations by computing one VAR model in which prior values in outcome variable Y were the only independent variables to predict the latter values in Y in the first model and a second model in which prior values of an independent predictor X were added to the first model. X was a time-series variable performed as a cause to Y, a lagged time-series variable that happened later than X. If the ratio of the variance of the first VAR model's error term to the second error term was larger than 1, then time-series factor X Granger-caused Y. The Wald test for Granger causality calculated Chi-square scores based on the entire time-series variables over the four-month period, not being separated by smaller periods of times such as a month.

The comparison between the volume of news articles related to the issues and the public discourses on Twitter was visualized as a line graph across time to reflect on any trend including impulses and spikes in the four-month period data. Later, if the spikes in Twitter accounts of opinion leaders on issue networks in preceding days could predict the levels of Twitter accounts of traditional media on that issue, this result could detect that the attention of Twitter opinion leaders Granger-caused the level of attention of traditional media or the public for US immigration issue. The same processes were then applied to other relationships between news media, opinion leaders and the public.

Research question 18 examined the first level agenda-setting in each three networks (the entire, retweet and mention groups) Research question 19 measured the transfer of salience of affective attributes among three networks (the second-level agenda-setting). The affective attributes were categorized by the political orientation of Twitter users, into Republican and Democratic mentioned on their bios. Hypotheses 6, 7, and 8 are possible tests to find significant agenda-setting effects among three networks. Hypothesis 6 posited that news media are more likely to set the issue agenda of opinion leaders and the public on the #immigration issue network on Twitter, assuming a top-down process of agenda-setting effects. Hypothesis 7 assumed that opinion leaders influence the agenda of the news media and the public. It tests both top-down and reversed agenda-setting processes, exploring the mediated role of opinion leaders between news media and the public. Hypothesis 8 assumed that the public is more likely to set the issue agenda of the news media and opinion leaders on the #immigration issue network on Twitter, testing the reversed agenda-setting effects, arguing a reversed agenda-setting process for the alternative tests from hypothesis 6. Based on significant coefficients of six kinds of directions (news media to opinion leaders/opinion leaders to the public/the public to news media/the public to opinion leaders/opinion leaders to news media/the public to news media), this study can figure out longitudinal directions of agenda-setting processes by testing whether the information flow follows the traditional top-down agenda setting process (from news media to the public, from news media to opinion leaders and from opinion leaders to the public) or has a reversed relationships (from opinion leaders to news media, from the public to news media and from the public to opinion leaders) over the 4-month #immigration issue network on Twitter.

Chapter 4: US immigration issue networks and social network analysis

This chapter examines characteristics of issue networks and investigates opinion leaders through a social network analysis on the retweet and mention issue networks. First, the author examined overall characteristics of the retweet and mention networks by drawing visual network graphs and measuring divisions of clusters. In order to predict the political orientations or traits of each cluster, the author manually coded the top degree centrality scored Twitter accounts in each cluster to find out similarities like political orientations among members of clusters. Also, the author operationally defined in-degree centrality scores as measures of opinion leadership because Twitter accounts with higher in-degree centrality scores were located at the center of the social network (Choi, 2012; Guo, Rohde, & Wu, 2018), indicating a higher level of popularity in the retweet and mention network. The result of social network analysis offers the ranking of in-degree centrality scores, proposing that higher ranking of in-degree centrality scores means opinion leaders.

The author additionally observed a hashtag network that was produced by co-occurrences with #immigration and other immigration-related hashtags to observe divisions of hashtag clusters. Hashtag co-occurrence could explain topical structure of networks, based on the assumption that two hashtags in a tweet share similar characteristics. Specifically, the author observed whether the use of political hashtags shows support or opposition to US immigration policy issues. Lastly, the author measured the distribution of in-degree centrality scores and tweets individual users posted in the retweet and mention networks to observe whether #immigration issue networks were dominated by a few users or whether several participants equally contributed to the formation of Twitter issue networks.

Descriptive analysis

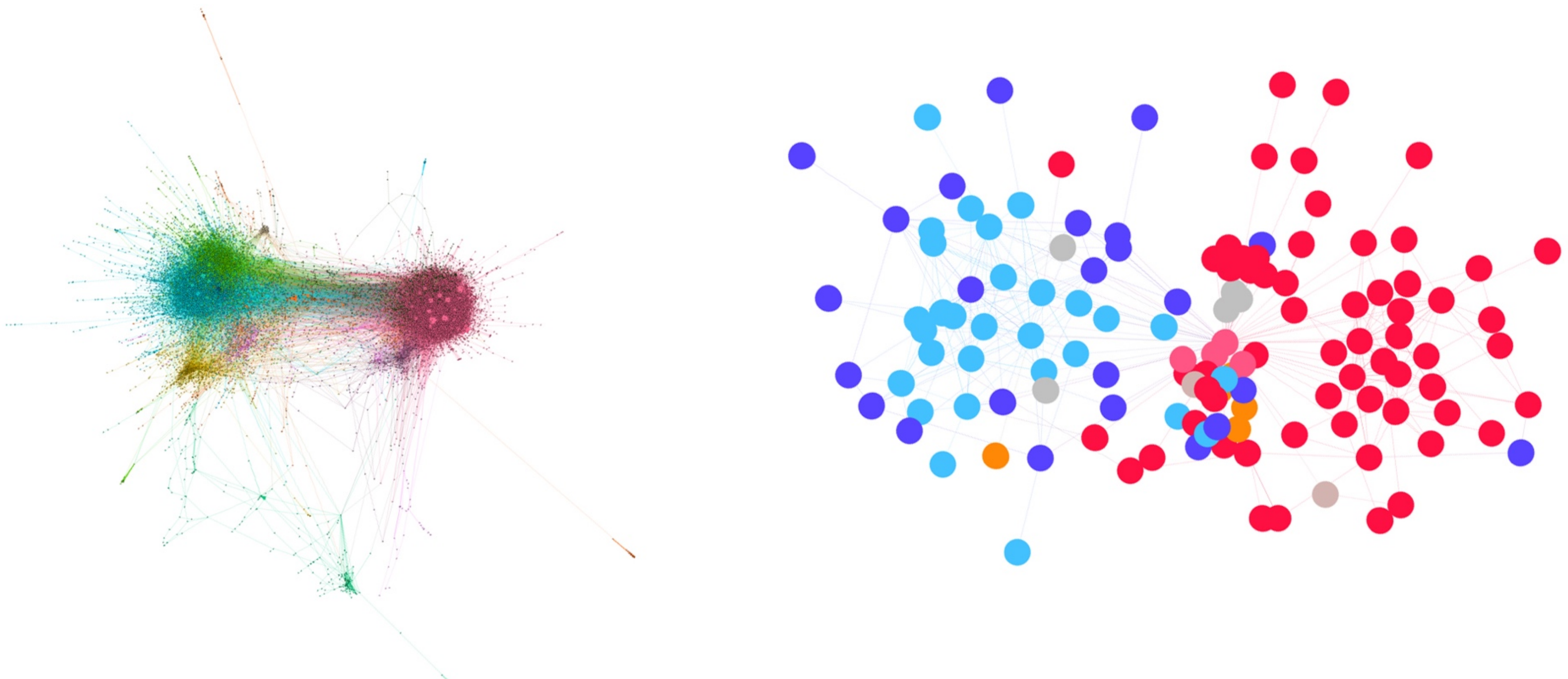
The total number of tweets which used #immigration from Oct. 1, 2016 to Jan. 31, 2017 (before and after the 2016 Presidential election) was 397,555. Among these, 9,502 of tweets (2.4% of the total) were retweeted or mentioned by officially verified accounts. The total number of accounts who created tweets with #immigration was 156,971, and the number of verified accounts among them was 7,335, accounting for 4.7% of the sample population. The total number of tweets that were retweeted was 227,956, and among them, 3,225 tweets were posted by verified accounts which accounted for 1.4% of the entire retweet network. The total number of accounts who were in the retweet network was 117,040, and among them, 1,821 accounts (1.6%) were verified. The total number of tweets which mentioned other accounts was 109,412 and among them, 2,905 tweets were mentioned by verified accounts (2.7%). A total of 50,395 accounts were detected in the mention network. Among them, 1,206 verified accounts were found (2.4%). Based on 2016 information, officially verified users made up 0.061% of Twitter users (Navarra, 2016). In this study, the percentages of verified accounts were higher than this officially reported percentage of verified users, suggesting a greater percentage of verified users participated in the immigration debate.

Shapes of the retweet and mention networks

The first research question, "How #immigration issue retweet and mention networks are visually represented?," was explored by observing the shapes of retweet and mention networks and categorizing networks based on the findings of Pew Research Center (2014). Pew Research Center (2014) argued that Twitter discussion patterns included polarized crowds (two groups with few cross-connections to others), tight crowds (highly interconnected individuals with few members being isolated), brand clusters (a type of clusters with many disconnected individuals) community clusters (a type of clusters with multiple smaller groups), broadcast network (a hub and spoke structure) and support network (a large number of outward spokes). An open-source network analysis software Gephi was used to draw networks and calculate modularity scores.

The modularity scores were 0.665 with 15 clusters for the retweet network and 0.720 with 47 clusters for the mention network. Specifically, among 34,892 Twitter accounts and 97,417 edges after being filtered to exclude less active Twitter accounts (degree centrality ≤ 2) in the retweet network, a total of 15 clusters were found. Visually, two noticeable communities (each comprising several clusters) were found. In the mention network, a total of 47 clusters were detected among the 23,304 Twitter accounts and 61,507 edges which recorded degree centrality scores higher than 2. Twitter accounts were coalesced to form several clusters in which accounts with high degree centrality scores were located in the center of clusters. For instance, @realDonaldTrump (degree centrality score = 6,719) and @HillaryClinton (degree centrality score = 2,397) managed by 2016 Presidential candidates Donald Trump and Hillary Clinton scored high degree centrality scores in the mention network. In answering research question 1, Figures 1 and 2 show visualized representations of the retweet and mention networks.

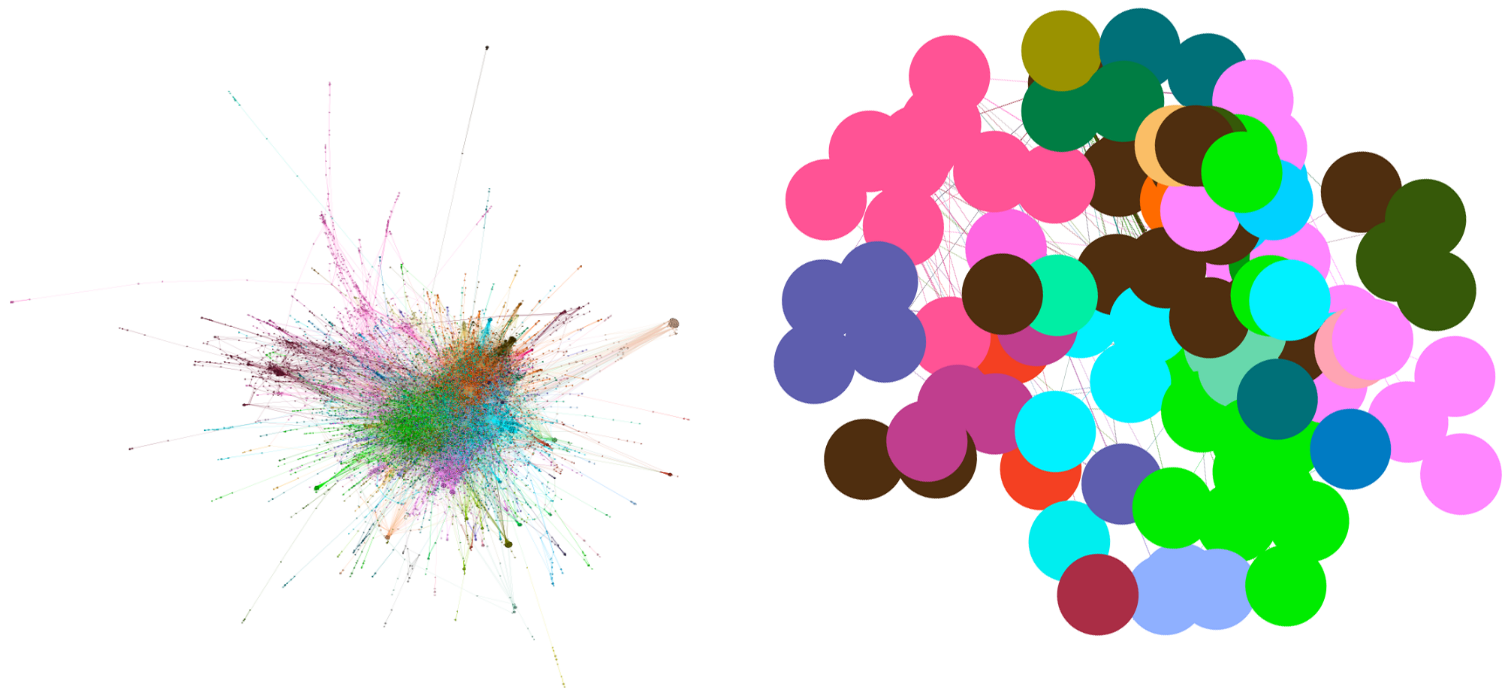
Figure 1: The entire #immigration retweet network[1] & the zoomed retweet network[2].



[1] In Figure 1, the large blue circle containing a few light green clusters (located on the left) represents liberal groups, and the red clusters (located on the right) indicate conservative groups.

[2] The zoomed retweet network consists of Twitter accounts whose degree centrality is more than 100 (*n* of nodes = 130 & *n* of edges = 393). Colors mean clusters calculated by the modularity.

Figure 2: The entire #immigration mention network & the zoomed retweet network[3].



3 The zoomed mention network consists of Twitter accounts whose degree centrality is more than 100 (*n* of nodes = 106 & *n* of edges = 266).

Among types of networks suggested by the Pew Research Center (2014), the retweet network can be described as a polarized network due to clear evidence of clustering based on political orientations, indicated by the moderate score > .6 and the presence of two large communities shaped by liberal and conservative clusters. Newman and Girvan (2004) and Garcia et al. (2015) argued that a network with modularity score more than 0.6 consists of divided clusters. The mention network can be categorized as community clusters rather than a polarized network, because multiple smaller clusters surround a few influential users with their cluster members (Figure 2).

Research question 2, “How are clusters in the a) retweet and b) mention networks divided from each other?,” examined the number of clusters and divisions of clusters, evidence of clustering based on political orientation from each other in the retweet and mention networks. The modularity score of 0.665 from 15 for the retweet network and the score of 0.720 from 47 clusters for the mention network showed clear divisions of clusters.

The author conducted a hand-coded content analysis to observe divisions of clusters in the retweet and mention networks. The author chose the 10 to 12 accounts that had the highest degree scores in each modularity cluster to figure out whether clusters are divided based on political orientation or other shared characteristics of the members in each cluster (*n* of Twitter accounts in the retweet network = 506, *n* of Twitter accounts in the mention network = 622). Because the modularity test results in a large number of clusters, the author chose to examine clusters that included at least one percent of the entire users (Guo, Rohde, & Wu, 2018).

Among 15 clusters in the retweet network, the author found five top clusters that included about 83.9% of Twitter accounts and showed political orientations (*n* = 29,282). Among 47 clusters in the mention network, the author found 12 clusters that contained about 30.7% of

Twitter accounts (*n* = 7,159) and showed political orientations. 5 clusters in the retweet network (*n* of Twitter accounts = 3,918) and 24 clusters in the mention network (*n* of Twitter accounts = 12,743) showed similarities among members, though they did not clearly show political orientations. Such a descriptive result indicated that 5 out of 15 clusters in the retweet network had political orientations, which accounted for more than 80 % of the Twitter accounts in the retweet network. In terms of the mention network, a quarter of clusters showed politically partisan clusters, and Twitter accounts in such clusters were about 30 % of the entire accounts.

After conducting manual content analysis, the author found that five clusters in the retweet network (5/15, *n* of Twitter accounts = 1,692, 4.8%) and eleven clusters in the mention network (11/47, *n* of Twitter accounts = 3,402, 14.6%) did not show similarities and had fewer than 30 members. For both reasons, these clusters were dropped from further analysis.

The author then examined politically opinionated clusters in the retweet network in depth. The author chose more than 60 accounts (the top 50 accounts that had the highest degree scores + 10 randomly selected accounts) in politically partisan clusters to figure out whether such clusters are divided based on political orientation (*n* of Twitter accounts in the retweet network = 455, *n* of Twitter accounts in the mention network = 720, Tables 1 & 2). In the retweet network, five clusters could be divided into two politically conservative or Republican clusters (*n* of accounts = 15,547, 45.6%) and three politically liberal or Democratic clusters (*n* of accounts = 13,715, 40.2%). Appendix A provides additional information about 5 clusters that were not included in the analysis. Among a total of 10 clusters, 5 clusters showed similarities such as nationality (U.K., Canada) and immigration lawyers, immigration workers like activists, news media and critics among members.

Table 1: Manually coding members in politically opinionated clusters in the retweet network[4].

Accounts	C1	C2	L1	L2	L3	Sum
Conservative-leaning or Republican	69	26	0	0	0	95
Liberal-leaning or Democratic	0	1	48	39	30	118
Neutral	44	33	95	39	31	242
Sum	113	60	143	78	61	455

Table 2: Manually coding members in politically opinionated clusters in the mention network.

Accounts	C1	C2	C3	C4	C5	L1	L2	L3	L4	L5	L6	L7	Sum
Conservative-leaning or Republican	30	21	30	27	18	3	0	1	1	3	1	1	136
Liberal-leaning or Democratic	1	0	1	0	0	18	20	25	16	15	17	17	130
Neutral	29	39	29	33	42	39	40	34	43	42	42	42	454
Sum	60	60	60	60	60	60	60	60	60	60	60	60	720

4 In Tables 1 & 2, ‘C’ means Conservative clusters, and ‘L’ means Liberal clusters. 2 conservative and 3 liberal clusters were found in the retweet network and 5 conservative and 7 liberal clusters were found in the mention network.

The author also investigated political clusters in the mention network. The author additionally conducted manual content analysis of political orientations for 60 Twitter accounts (the 50 top degree centrality scored + 10 randomly selected accounts) in each of the 47 clusters and examined similarities among members of each cluster. The author found five conservative-leaning clusters (*n* of Twitter accounts = 2,782, 11.9%) and seven liberal-leaning clusters (*n* of Twitter accounts = 4,377, 18.8%) based on the result of manual content analysis observing profiles of Twitter accounts. Twenty-four clusters showed similarities among members (Appendix B). Similarities among members in each cluster included neutral immigration lawyers, domestic and global news media, immigration workers from foreign countries like Canada, immigration activists, tech companies, and locally-based immigration workers or educators who worked for organizations only operated within a city (e.g., Seattle & Boston).

Thus, the author found divisions of clusters in the retweet and mention networks. Especially in the retweet network, the author could find political polarization created by conservative and liberal groups. Also, in the mention network, more clusters that shared similarities among members were detected, assuming that the mention network could be categorized as community clusters. While the modularity score of the mention network indicated a high level of clustering, characteristics other than political orientations (e.g., occupations, nationality, and news media) were found, thus the author categorized them as community clusters rather than polarized network. The author set additional research question to explore influential users in each cluster to understand characteristics of opinion leaders.

USERS IN THE RETWEET AND MENTION NETWORKS

Research question 3, “Who are influential users in the a) retweet and b) mention network?,” was examined by observing characteristics of users with high degree centrality scores.

The author focused on verified status and their occupations. The author and the second coder examined the top 50 accounts that had the highest degree scores in each partisan cluster to measure users' political orientations. The author also observed whether such users were verified or not.

Then, the author focused only on top 50 degree centrality accounts in politically partisan clusters in the retweet and mention networks to observe characteristics of influential users including their verified status and their occupations. The author did not examine randomly selected accounts because those accounts did not record high degree centrality scores (*n* of Twitter accounts in the retweet network = 404, *n* of Twitter accounts in the mention network = 600). Among 404 accounts in the retweet network, a total of 108 users were verified (108/404, 26.7%). This percentage is higher than the percentage of verified users in the retweet network (540/34,892, 1.6%) whose degree centrality scores were more than 2. Among 404 Twitter accounts, 149 accounts were categorized as ordinary citizens (149/404, 36.9%). A total of 255 Twitter accounts (255/404, 63.1%) were engaged in elite occupations, outnumbering ordinary citizens. Activists or social movement organizations ranked first as an elite occupation (*n* = 109/404, 27%). The next was news reporters or media organizations (*n* = 83/404, 20.5%), followed by lawyers (*n* = 20/404, 5%), politicians or governmental officials (*n* = 16/404, 4%), academic organizations and scholars (*n* = 13/404, 3.2%), authors (*n* = 9/404, 2.2%), and celebrities (*n* = 5/404, 1.2%). Bloggers were not found.

Among conservative clusters in the retweet network, @bfraser747, @SandraTXAS, @realDonaldTrump, @FAIRImmigration, @RealJamesWoods and @AnnCoulter were found as top 5 degree centrality scored Twitter accounts (*n* of Twitter accounts = 14,188). @bfraser747, which recorded the highest weighted degree centrality score (degree centrality = 8,143), is the

Twitter account of a conservative activist named Brian Fraser. His Twitter profile describes him as a "PROUD Supporter of #PresidentTrump fighting one tweet at a time #MAGA!! Retweeted by @realDonaldTrump #MAGA." This Twitter account mainly retweeted other conservative and President Trump's tweets, showing support for President Trump (*n* of tweets = more than 155,000, *n* of followees = more than 138,000, *n* of followers = more than 208,000). @SandraTXAS was the second highest weighted degree centrality scored Twitter account (degree centrality = 7,933). This Twitter profile provides the following description: "LifeLibertyPursuitOfHappiness VeteransLove Israel #Sharia is real #WarOnWomen. A Texan working to Keep Texas and the US Red." This Twitter account also retweeted other politically conservative tweets (*n* of tweets = more than 210,000, *n* of followees = more than 45,200, *n* of followers = more than 142,000). Terms like #MAGA (Make America Great Again, a slogan used for Donald Trump's 2016 Presidential campaign), "President Trump," and "US Red" in each profile indicate that both accounts were managed by politically conservative Twitter users. Both accounts were not officially verified. The author contacted two Twitter accounts and confirmed that both accounts were managed by ordinary citizens. They posted tweets frequently in a day, suggesting that they used automation machines simulating retweeting, mentioning and favoring activities (Murthy et al., 2016). Such frequent posting assumes that both users were bots, but they also posted their personal lives on their tweets, showing their identities.

@realDonaldTrump was the highest in-degree centrality scored Twitter account in two conservative clusters. @realDonaldTrump is owned by the 45th President of the US, Donald Trump (degree centrality = 4,068). @FAIRImmigration (an account run by the Federation for American Immigration Reform (FAIR), a non-partisan public organization aiming at reducing both legal and illegal immigration, degree centrality = 2,874), @RealJamesWoods (an account managed by James Woods, an American actor who has publicly voiced his conservative views, degree centrality = 2,706) and @AnnCoulter (an account run by Ann Coulter, a conservative political commentator, degree centrality = 2,318) were also detected as high degree centrality scored accounts in the main conservative cluster. In another conservative cluster (*n* of Twitter accounts = 1,359), a senior advisor for Immigration and Customs Enforcement (ICE, @JonFeere, degree centrality = 276), an author (@BreetMDecker, degree centrality = 245), and an executive director for the Center for Immigration Studies (@MarkSKrikorian, degree centrality = 146) were found.

Three liberal-leaning (or Democratic) clusters consisted of Twitter accounts showing favorable attitudes to US immigrants. In one liberal cluster, official Twitter accounts of immigration Law centers (@NILC_org, @immcouncil and @AILANational) and workers (@JuanSaaa and @WangCecillia) were gathered together. @NILC_org is owned by National Immigration Law Center. It is an officially verified and nationally run Twitter account that introduces the NILC organization's mission as "defending and advancing the rights and opportunities of low-income immigrants and their family members" (NILC, 2018). The second liberal-leaning cluster is a combination of media-related accounts (@amjoyshow, @AntonioArellano, and @LuiusKuryaki), activists (@marshallfitz, @CatPharm, and @smrtgrls), and scholars (@pwolgin, and @kalhan). The third liberal cluster mainly consisted of civic activist organizations (@votolatino, and @iAmericaorg) and ordinary citizens (@avilafavila, @amarvarma, and @JIStronger). These clusters are presented in Table 3. Twitter account @HillaryClinton was not detected in the retweet network, because tweets posted by Hillary Clinton did not include immigration issues, focusing more on women's right, LGBT and racial issues such as abolition of racial profiling by law enforcement (Lee & Xu, 2018).

Table 3: Noticeable Twitter accounts in the retweet network.

Political orientation	Cluster	Twitter account	Bio	Degree	Verified?
Conservative (anti-immigration)	C1 (*n* = 14,188)	@Bfraser747	PROUD Supporter of #PresidentTrumpfighting one tweet at a time #MAGA !!	8,143	No
		@SandraTXAS	Life Liberty Pursuit Of Happiness Veterans Israe l#Sharia is the real #WarOnWomen	7,933	No
		@realDonaldTrump	45th President of the United States of America	4,068	Yes
		@FAIRImmigration	Federation for American Immigration Reform (FAIR) fights for a stronger America with controlled borders, reduced immigration and better enforcement.	2,874	Yes
		@RealJamesWoods	American citizen. I judge every single discussion by one metric only: is it legal or is it a violation of the laws by which we all must live.	2,706	Yes
		@AnnCoulter	Author – follow me on #Facebook!	2,318	Yes
		@Lrihendry	God•Family•Country! Love Trump! #AmericaFirst	2,305	No
		@michealjohns	National Tea Party movement co-founder and leader. Former @WhiteHouse speechwriter and @Heritage policy analyst.	1,368	Yes
		@Fingersflying	Christian; Founder #CCOT	1,059	No
		@johncardillo	Weekdays 7-10AM ET, Salem's @880thebiz Miami/Ft. Lauderdale. Former #NYPD. Opinion is mine. RT äŠæ endorsement. Pro-#Trump, #NeverHillary	905	Yes
		@NewportLost	Be pro candidate not anti fellow citizen #Trump #Catholic Illegal is not a race it is a crime – I block satanists– pc kills #BostonStrong #RI	878	No
		@TrumpTheHill	Hispanic team of #Deplorable #TrumpTrain supporters. Push Those Podesta Emails! Pls Follow and help us #MAGA.	647	No
	C2 (*n* = 1,359)	@JonFeere	Senior Advisor, Immigration and Customs Enforcement (ICE) #Immigration All past tweets, reports, and op-eds may or may not be my personal views.	276	No
		@BrettMDecker	Frmr editor for Wall Street Journal & Wash. Times, NYT bestselling author, Asia books: Bowing to Beijing & Global Filipino, bank executive & Detroiter in exile.	245	No

Table 3 – Continued

Political orientation	Cluster	Twitter account	Bio	Degree	Verified?
		@MarkSKrikorian	Executive Director, Center for Immigration Studies. Author, "The New Case Against Immigration, Both Legal and Illegal" Either hawk of hawks or dove of doves	146	Yes
		@RightWingArt	your source for free images, graphics and resources for your use. You can also upload and share your own artwork with others. No DM. #TGDN	114	No
Liberal (pro-immigration)	L1 (*n* = 7,755)	@amjoyshow	@JoyAnnReid hosts 'AM JOY' every Saturday and Sunday, 10 am-12 pm ET on @msnbc. Follow the stimulating conversation on #AMJoy.	2,372	Yes
		@pwolgin	Managing Director, Immigration @amprog/@capaction. Ph.D. in History. Board Member @HIASrefugees. All views are my own.	2,371	Yes
		@AntonioArellano	Latino Voice in The Lone Star State. Communications director of @Jolt_Texas.	1,559	Yes
		@LuisKuryaki	Periodista independiente/Frelance Journalist. #Writer #Producer #Fixer	1,531	No
		@marshallfitz	Advocate for progressive immigration policies, equity, and justice. Sports junky, half-assed Buddhist, proud papa and spouse. Views all my own.	1,429	No
		@CatPharm	#Feminist #CivilRights #equality#socialjustice #FuckReligion#LGBTQFriend	1,235	No
		@igorvolsky	Deputy Director, Center for American Progress Action Fund. Director, @gunsdownamerica. Opinions, my own.	1,027	No
		@smrtgrls	Change The World By Being Yourself! Instagram: AmyPoehlerSmartGirls Facebook: Amy Poehler's Smart Girls Snapchat: APSmartGirls. #SmartGirlsAsk	840	Yes
		@kalhan	Prof @DrexelUniv • Fmr Intl hum rts chair, NYC Bar • Prev @NYULaw @WashULaw@FordhamLaw @ACLU @NewsHour • @BrownU @YaleLawSch alum • CLE native/partisan, runner	780	Yes
		@joseiswriting	Founder, @DefineAmerican. Author, "Dear America: Notes of an Undocumented Citizen": http://hc.com/dearamerica . Journalist. Filmmaker. Storyteller.	528	Yes

Table 3 - Continued

Political orientation	Cluster	Twitter account	Bio	Degree	Verified?
Liberal (pro-immigration)	L2 (*n* = 3,847)	@NILC_org	Defending and advancing the rights and opportunities of low-income immigrants and their family members.	1,842	Yes
		@JuanSaaa	Undocumented Immigrant. @AmericasVoice Comms. Manager. @HuffPost Columnist.	1,156	Yes
		@WangCecillia	Director, National ACLU Immigrants' Rights Project. Civil rights lawyer. Former public defender. Views expressed are my own.	916	Yes
		@FWD_us	Mobilizing tech to promote policies that keep the US competitive in a global economy, starting w/ fixing our broken immigration system	850	Yes
		@immcouncil	Through research, policy analysis, and litigation, we seek to shape a twenty-first century vision of the American immigrant experience.	809	Yes
		@AILANational	The American Immigration Lawyers Association (AILA) is a national association of 15,000 attorneys and law professors who practice and teach immigration law.	456	No
		@UNITEDWEDREAM	UWD is the first and largest immigrant youth-led organization in the nation. UwdA = United We Dream Action	397	Yes
	L3 (*n* = 2,133)	@votolatino	Voto Latino is a pioneering civic media organization that seeks to transform America by recognizing Latinos‰Ûª innate leadership.	263	Yes
		@avilafavila	(empty information on bio)	222	No
		@amarvarma	Possibilities are Endless –Life Coach & Spiritual / Relationship Advisor, Life Consultant & Unconscious Perceptions Enlightener @BarackObama is following me	100	No
		@iAmericaorg	iAmerica is for all American immigrant families, providing tools and support to get informed, inspire change and impact our future. #iAmerica #ImmigrationAction	76	No
		@JlStronger	#UniteBlue #AINF #ImmigrationReform #LatinosforLatinos #Obama #Hillary2016	62	No

The author also examined top 50 degree centrality accounts in politically partisan clusters in mention networks. Among 600 Twitter accounts in the mention network, 113 were conservative-leaning or Republican (18.8%), and 116 were liberal-leaning or Democratic (19.3%). 371 Twitter accounts (61.8%) were neutral or unclear in their political orientations. The total number of verified accounts was 204 (204/600, 34%). The total number of verified users in the mention network with degree centrality scores higher than 2 was 943 (943/23,304, 4%). Among 600 Twitter accounts that recorded top 50 degree centrality scores in each political cluster, a total of 270 ordinary public accounts were found (270/600, 45%). Among 330 elite Twitter accounts, journalists or news organizations (123/600, 20.3%) appeared most. The next highest is activists or social organizations (87/600, 14.5%), followed by politicians or government workers (57/600, 9.5%), academic organizations or scholars (n =32, 5.3%), lawyers (n = 23, 3.8%), authors (n = 16, 2.7%), and celebrities (n = 11, 1.8%). Elite accounts outnumbered ordinary citizens in both retweet and mention networks, but while the most frequently appearing occupations in the retweet network was activists or social movement organizations, journalists or news organizations appeared most in the mention network, which was ranked as the second in the retweet network.

Each partisan clusters in the mention network had notable Twitter accounts, indicating they were opinion leaders. In one conservative leaning cluster, @realDonaldTrump, @AZTRUMPTRAIN (an account managed by a huge President Trump supporter), @BreitbartNews (an account run by Breitbart, a far-right news site), @KellyannePools (an account run by Kellyanne Conway, a political consultant serving as Counselor to President Trump) and @michaeljohns (an account managed by Michael Johns, co-founder of National Tea Party Movement) were found. Another conservative cluster included @FoxNews (an account managed by Fox News), @JessicaV_CIS (an account managed by Director of Policy Studies at Center for Immigration Studies, a non-profit organizations and think tank favoring lower immigration numbers). A conservative media cluster was found (@seanhannity: an American conservative political talk show host on Fox News, @FoxBusiness, @DeirdreBolton: an account managed by a journalist working for Fox News, @AnnCoulter, and @LizMacDonaldFOX, an account managed by a journalist covering Fox Business news). Two clusters that consisted of Twitter accounts explicitly supporting President Trump (Cluster 1: @Trump_USA_, @ElizabethUSA, @pmbasse and Cluster 2: @LindaSuhler, @IndyK46220 and @Fingersflying) were detected.

In liberal leaning or pro-immigration clusters, @HillaryClinton, @SenSchumer (an account run by Chuck Schumer, a Democratic politician serving as a Senator from New York and Democratic minority leader of the Senate), @KamalaHarris (an account run by Kamala Harris, a Democratic Senator from California who is running for president), @NancyPelosi (an account run by Nancy Pelosi, a Democratic politician serving as the Minority Leader of the US House of Representatives) were gathered together in one liberal cluster. @ACLU (an account run by ACLU, The American Civil Liberties Union), @Das_Alina (an account managed by Law Professor Alina Das at New York University advocating immigrant rights) and @HMAesq (an officially verified account managed by Hassan Ahmad, an attorney supporting immigrants to the US) were members of another liberal clusters, being categorized as a cluster of immigration law workers. Other liberal cluster consisted of activists and media workers (@joseiswriting, @JoyAnnReid, @DefineAmerican, @amjoyshow, and @emerging US). @IssaRae (an account run by American actress Issa Rae), and @Michimmigrant (an account managed by Center of Michigan’s immigrants) were leaders of another liberal cluster that recorded higher degree centrality scores. Other three liberal clusters included activists (@Si_Jose, @pwolgin, and @exparisk), public Twitter accounts supporting the Democratic Party (@laloalcaraz and @co_rapunzel4), and activists and organizations (@MigrationPolicy and @pozoGoldstein).

In the mention network, top degree centrality scored Twitter accounts were owned by celebrities or politicians, or active Twitter users who supported them. This fact reflected on the public desire to create direct Twitter conversations with celebrities or important actors in US immigration policy (Table 4).

Table 4: Noticeable Twitter accounts in the mention network.

Political orientation	Cluster	Twitter accounts	Bio	Degree	Verified?
Conservative (anti-immigration)	C1 (*n* = 1,687)	@realDonaldTrump	45th President of the United States of America	6,719	Yes
		@POTUS	45th President of the United States of America, @realDonaldTrump.	4,591	Yes
		@AZTRUMPTRAIN	Wife, Mom, Pro-Life, Pro-Gun, Business Owner **I FOLLOW BACK, TRUMP SUPPORTERS ONLY. NO LISTS#Unite #MAGA #AmericaFirst#NeverHillary	4,071	No
		@BreitbartNews	News, commentary, and destruction of the political/ media establishment.	761	Yes
		@KellyannePolls	Mom. Patriot. Catholic. Counselor.	282	Yes
		@michaeljohns	National Tea Party movement co-founder and leader. Former @WhiteHousespeechwriter and @Heritage policy analyst. @UnivMiami grad	159	Yes
	C2 (*n* = 443)	@FoxNews	America's Strongest Primetime Lineup Anywhere! Follow America's #1 cable news network, delivering you breaking news, insightful analysis, and must-see videos.	539	Yes
		@JessicaV_CIS	Director of Policy Studies at Center for Immigration Studies.	185	No
		@JordanSekulow	attorney, radio show host	62	Yes
		@RepBrianBabin	Honored to serve citizens of #TX36 in U.S. Congress. Chairman of @HouseScience	26	Yes
		@PIRATE1775	Avid sports fan and political junkie. Catholic. Independent. Blocked by JulieMason,Donna Brazille. Joy Ann Reid	24	No
	C3 (*n* = 377)	@seanhannity	TV Host Fox News Channel 9 PM EST. Nationally Syndicated Radio Host 3-6 PM EST. http://Hannity.com Retweets, Follows NOT endorsements! Due to hackings, no DM's!	222	Yes

Table 4 – Continued

Political orientation	Cluster	Twitter accounts	Bio	Degree	Verified?
		@FoxBusiness	The official Twitter page of FOX Business Network: Capitalism lives here. Ask your cable provider for FOX Business in your neighborhood.	145	Yes
		@DeirdreBolton	Journo covering #Money Big&Small, Crypto&Paper @FoxBusiness@FoxNews; Host, "Women & Money". #markets #investing #tech #alts #fun.	122	Yes
		@AnnCoulter	Author - follow me on #Facebook! http://goo.gl/JvMjld Disregard my earlier claims that I'd never be on Facebook.	60	Yes
		@LizMacDonaldFOX	Watch Emac's reports on @FoxBusiness, @FoxNews, @ForbesonFox,	52	Yes
Conservative (anti-immigration)	C4 (*n* = 172)	@TeamTrump	Welcome To The Official #TeamTrump Account. Together, We WILL #MakeAmericaGreatAgain!	84	Yes
		@ElizabethUSA	I am American..Mexican descent..PROUD OF BEING AN AMERICAN! PROUD OF MY ROOTS! We need to UNITE IN MAKING AMERICA GREAT AGAIN! Army of God!	37	No
		@pmbasse	Conservative TEXAN 6th generation descendant of orig. 300 to Texas..Alamo Chapter DRT. Ranching, investments President Trump #MAGA Proud US Military Army brat	33	No
		@BIZPACReview	Conservative News Today. BizPac Review, news for conservatives.	29	No
	C5 (*n* = 103)	@LindaSuhler	Support Donald Trump for President! AMERICA FIRST Christian supports Family~Constitution~Capitalism~ 2A~NRA~Military~Police~Israel #AmericaFirst #TrumpPence16	31	No

Table 4- Continued

Political orientation	Cluster	Twitter accounts	Bio	Degree	Verified?
		@IndyK46220	Retweet doesn't necessarily indicate agreement, support, or validity of info. Use your own discretion. List = U get Blocked. Let truth & prevail! #MAGA	29	No
		@Fingersflying	Christian; Founder #CCOT Followers	25	No
		@Trump_USA_	#TrumpBroughtAmericanDream #TrumpHomelandCountry	20	No
Liberal (pro-immigration)	L1 (*n* = 1,863)	@joseiswriting	Founder/Editor of @EmergingUS; Founder/CEO of @DefineAmerican; producer of MTV's #WhitePeople and @DOCUMENTEDfilm. Undocumented, gay, Filipino, American.	939	Yes
		@JoyAnnReid	"Ignorance, allied with power, is the most ferocious enemy justice can have." - James Baldwin #AMJoy #reiders	583	Yes
		@DefineAmerican	Changing the conversation about immigrants, identity, and citizenship.	466	Yes
		@RaulAReyes	Attorney, http://NBCNews.com Contributor, CNN Opinion & Fox News Latino columnist. USA Today Board of Contributors.	424	No
		@BilldeBlasio	Mayor. Fighting for a better and fairer New York City, no matter how much money you make or where you live	336	Yes
		@amjoyshow	@JoyAnnReid hosts 'AM Joy' every Saturday and Sunday, 10 am-12 pm ET on @msnbc. Follow the stimulating conversation on #AMJoy.	205	Yes
		@emergingUS	#EmergingUS is a media startup that lives at the intersection of race, immigration and identity in a multicultural America.	185	No
	L2 (*n* = 852)	@IssaRae	Instagram.com/issarae	858	Yes
		@Michimmigrant	We are a legal resource & advocacy center for Michigan's immigrants. Member of @_MCIRR	841	No

Table 4 – Continued

Political orientation	Cluster	Twitter accounts	Bio	Degree	Verified?
Liberal (pro-immigration)	L3 (*n* = 606)	@Si_Jose	Pacifista Peace activist, vegetarian, Indigenista Thou shall not eat from the tree of knowledge No comeras del arbol del conocimiento. we want U dumb	316	Yes
		@chicanisima	Assoc Prof. of Journalism Columbia College Chicago; Chicanisima blog ChicagoNow.com; Founder Latina-Voices.com. Tweet on immigration, politics & Latino culture.	169	No
		@pwolgin	Managing Director, Immigration @amprog/@capaction. Ph.D. in History. Board Member @HIASrefugees. All views are my own.	80	Yes
		@expatrisk	Insuring the American Dream. We still believe that all men are created equal. Protecting the unalienable rights of life, liberty and the pursuit of happiness.	77	No
	L4 (*n* = 426)	@ACLU	The ACLU is a nonprofit, nonpartisan, legal and advocacy 501(c)(4) organization. Visit our site for more about us and our affiliated org, the ACLU Foundation.	418	Yes
		@Das_Alina	Associate Professor of Clinical Law & Co-Director, NYU Law School Immigrant Rights Clinic	46	No
		@HMAesq	#Immigration lawyer, #Polyglot, #Muslim.	29	Yes
		@juliesbooks	No Muslim Ban	28	No
	L5 (*n* = 296)	@HillaryClinton	2016 Democratic Nominee, SecState, Senator, hair icon. Mom, Wife, Grandma x2, lawyer, advocate, fan of walks in the woods & standing up for our democracy	2,397	Yes
		@SenSchumer	Official account of Senator Chuck Schumer - New York's Senator RT≠endorsement	598	Yes
		@KamalaHarris	U.S. Senator for California. Former CA Attorney General. Fighting for justice and giving voice to the voiceless. Wife, Momala, Sister, Auntie. Aspiring chef.	106	Yes

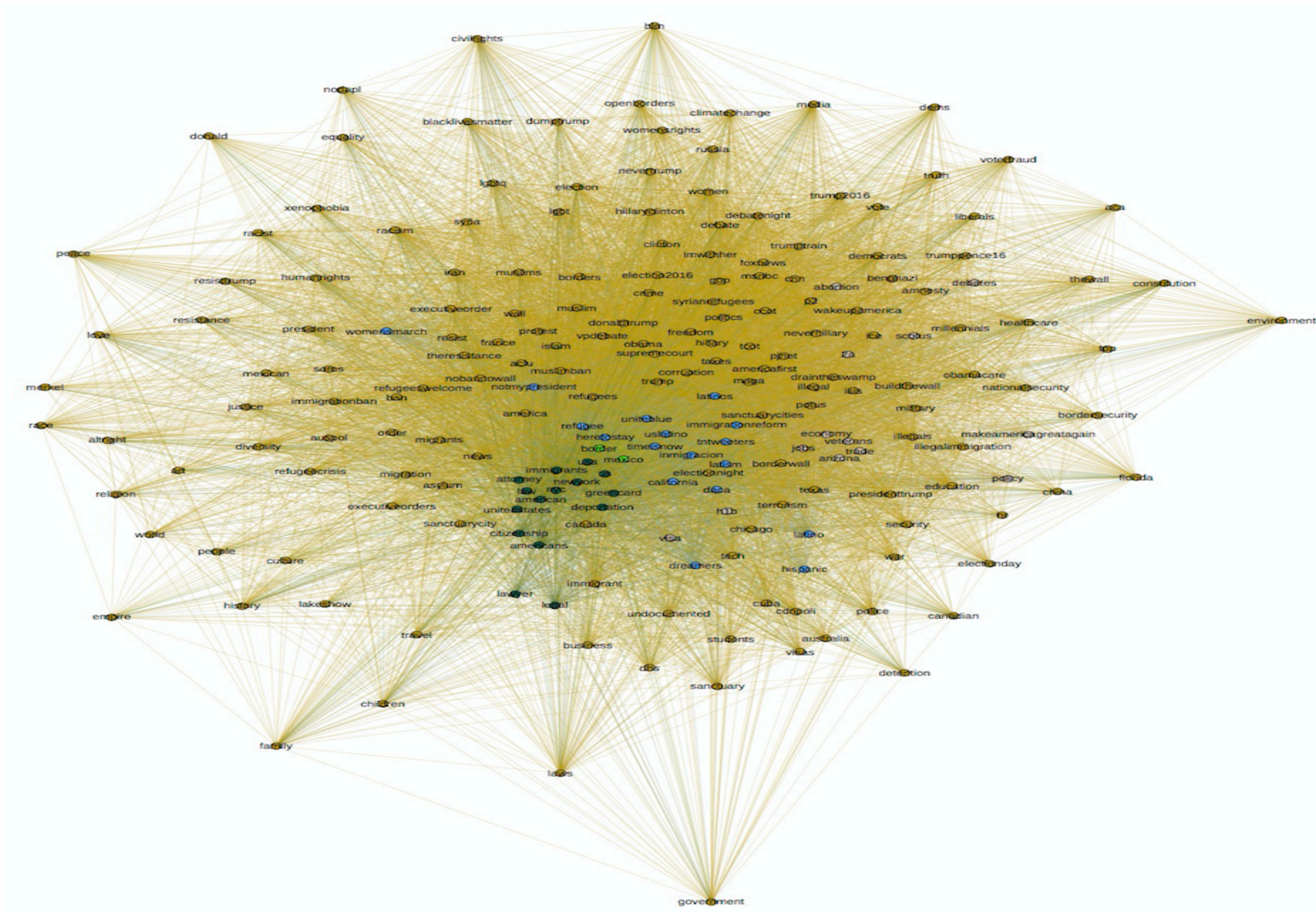
Table 4 - Continued

Political orientation	Cluster	Twitter accounts	Bio	Degree	Verified?
		@NancyPelosi	Democratic Leader, focused on strengthening America's middle class and creating jobs; mother, grandmother	74	Yes
Liberal (pro-immigration)	L6 (*n* = 203)	@laloalcaraz	Border in the court! Objections overruled. Cartoonista/ Writer/ La Cucaracha/ Bordertown/ TV/ Film/ Pixar/ Comics/ Radio/	135	No
		@GottaLaff	Regular on Nicole Sandler radio show. Posting at Laffy's Place http://nicolesandler.com/laffys-place/, Hooked on humor, Progressive. #NeverNormalize	118	No
		@georgelopez	Life is just a party and parties weren't meant to last	116	Yes
	L7 (*n* = 131)	@MigrationPolicy	The Migration Policy Institute is the premier non-partisan, independent think tank dedicated to analysis of U.S. and global immigration. RTs not endorsements.	120	Yes
		@pozogoldstein	Immigration Law & Criminal Defense. Former U.S. #Immigration Prosecutors & Former Judge #greencard #visa #advocate	118	No
		@ElGerryChicago	Fauno del Peloponeso, más o menos. Basado en hechos reales.	118	No

Research question 4, "Does a hashtag network created by hashtag co-occurrences with #immigration show divisions of clusters?", examines hashtags networks to understand whether hashtags with similar political orientations are coalesced together, shaping separate groups to represent divisions. A total 31,484 hashtags appeared in the US #immigration network, creating 200,616 edges. The author did not include #immigration for the analysis because it was the main hashtag co-occurred with other hashtags. The most hashtags used with #immigration were #trump (n = 5,105), followed by #refugees (n = 1,949), #usa (n = 1,656), #maga (n = 1,603) and #canada (n = 1,532). Among them, #refugees could represent Syrian refugees, describing public interest in an executive order by President Trump to establish a ban on accepting them. #trump and #maga directly showed a support for President Trump who had been hostile to immigrants, especially during the presidential campaign period. #usa was a hashtag that represented Twitter users' nationality during the 2016 Presidential campaign, and it was closely related to 'America' in #maga. #canada was a hashtag that was used in tweets to represent online 'move to Canada' movement when President Trump was just elected. While #refugees and #usa could be used as neutral hashtags, #maga (anti-immigration) was politically partisan hashtags used with #immigration. #canada was used to implicate Twitter users' negative sentiments to President Trump (e.g., Canada's immigrations site is down. #immigration #movetocanada & It's time to move to Canada. #USElection2016).

Among 31,484 nodes, a total 1,118 clusters were found based on the modularity function in Gephi. The modularity score of the entire hashtag network was 0.619, after deleting all nodes with a single connection. The author also followed Borgatti, Everett, and Johnson (2013)'s instruction on reducing the large network into a reasonable size for analysis. The author extracted the pairs of hashtags that co-occurred at least 200 times in the #immigration issue network (the co-occurrence degree ≥ 200), based on the suggestion by Borgatti, Everett and Johnson (2013). The #immigration network was then visualized in Figure 3, which contains 5 clusters with 212 co-occurrence nodes and 10,314 edges. The modularity score of hashtag network was 0.596, indicating a moderate degree of divisions among clusters.

Figure 3: Hashtag network based on #immigration



Among a total of 212 hashtags, the main cluster had about 80% of hashtags (n = 170, 80.1%), including politically opinionated hashtags such as #trump, #refugees, #maga, #muslimban (n = 1,201), #america (n =1,115), #nobannowall (n = 713), #obama (n = 998), #buildthewall (n = 713) and #imwithher (n = 497). Such evidence indicated a combination of politically liberal (#nobannowall, #obama and #imwithher) and conservative (#trump, #maga, #muslimban, and #buildthewall) hashtags to shape one cluster. Among 170 hashtags, 30 (17.6%) hashtags were conservative-leaning or Republican, and 23 (13.6%) hashtags were liberal-leaning or Democratic. On the other hand, 117 (68.8%) hashtags were politically neutral or unidentified in political partisanship. Both politically partisan (liberal and conservative) hashtags appeared to represent Twitter users' political orientations and their support for or opposition to US immigration issues.

However, even though numbers of hashtags in each cluster were far smaller than the main cluster, each cluster has its own themes. One cluster consisted of #usa, #law (n = 804), #deportation (n = 575), #nyc (n = 515), #business (n = 445), #american (n = 359), #greencard (n = 343) and #attorney (n = 243). Such gathering of hashtags could be interpreted as immigrants' interest to stay in the US and legally get citizenships (Total number of hashtags = 15, 7.1%).

The liberal cluster (Total number of appearances = 1,374, 5.2%) included #daca (n = 710), #immigrationreform (n = 696), #latism (n = 507), #notmypresident (n = 480), #tntweeters (n = 470), #california (n = 455), #uslatino (n = 439), #heretostay (n = 413) and #uniteblue (n = 285). #tntweeters was a hashtag initiated by an online activist group to retweet daily tweets to Republican members of Congress who did not sign a petition filed by Democrats supporting the immigration reform bill (HR 15, Border Security, Economic Opportunity, and Immigration Modernization Act) at 2014. (Reynolds, 2014). #twtweeters seemed to reappear during the 2016 presidential election campaign period. #notmypresident and #uniteblue were politically opinionated hashtags showing liberal ideas of Twitter users who post such hashtags (Total number of hashtags = 17, 8.1%). The themes of other 2 hashtag clusters included (1) a group of #mexico (n = 915) and #border (n = 602, Total number of hashtags = 2, 1.0%) and (2) a group of #jobs (n = 984), #economy (n = 858), #visa (n = 832), #trade (n = 450) and #policy (n = 429, Total number of hashtags = 13, 6.1%, Table 5). A hashtag cluster with #mexico and #border showed that posters express their interest in the borders between US and Mexico, being interpreted as (1) favoring a border wall or (2) focusing on more humanitarian immigration policies. A cluster with #jobs, #economy, #visa, #trade, and #policy indicated posters' interest in the job status of immigrants to the US.

Table 5: Hashtag clusters.

Cluster	Hashtags	Degree	Cluster	Hashtags	Degree
1	#trump	5105	2	#usa	1657
	#refugees	1949		#immigrants	1603
	#maga	1637		#us	1025
	#canada	1532		#law	804
	#news	1497		#deportation	575
	#muslimban	1201		#nyc	515
	#donaldtrump	1163		#legal	454
	#america	1115		#citizenship	426
	#obama	998		#american	359
	#migrants	961		#greencard	343
	#islam	871		#lawyer	332
	#muslim	847	3	#daca	710
	#election2016	822		#refugee	705
	#politics	804		#immigrationreform	696
	#tcot	789		#latism	507
	#buildthewall	776		#notmypresident	480
	#hillary	741		#tntweeters	470
	#illegal	715		#california	455
	#nobannowall	713		#uslatino	439
	#muslims	644		#heretostay	413
	#racism	632		#latinos	389
	#education	623		#latino	352
	#debate	616		#dreamers	340
	#terrorism	614		#womensmarch	319
	#obamacare	593		#uniteblue	285
	#resist	572		#timeisnow	278
	#ban	569	4	#jobs	984
	#potus	568		#economy	858
	#gop	565		#visa	832
	#healthcare	565		#trade	450
	#debatenight	556		#policy	426
	#wall	543		#arizona	297
	#migration	542		#veterans	277
	#diversity	539	5	#mexico	915
	#immigrant	531		#border	602

Research question 5, “Are the structures of the discussion group on the #immigration a) retweet network and b) mention network concentrated on a few individuals, based on individual in-degree centrality scores?,” examined the distribution of Twitter accounts that were frequently retweeted and mentioned by others. Research question 6, “Are the structures of the discussion group on the #immigration a) retweet network and b) mention network concentrated on a few individuals, based on the number of tweets?,” examined the distribution of the number of tweets posted by individual users in the issue retweet and mention networks. Gini coefficients were used to measure distributions. A value of zero (0) indicates perfect equality, meaning that every participant in each network had an equal in-degree centrality score, and the network structure was not led by a few individuals. A value of one (1) indicates perfect inequality, meaning that a few individuals recorded higher in-degree centrality scores than the rest of members in networks.

In answering Research question 5, the result of calculating Gini coefficients through R shows that a few individuals attained higher in-degree centrality scores than the rest of the members in the retweet and mention networks. The Gini coefficient of the retweet network was 0.981, and that of the mention network was 0.954. Both Lorenz curves covered a full half of the space created by the x- and y- axis, indicating high Gini coefficients (Figures 4 and 5).

Figure 4: Lorenz curve measuring individual in-degree centralities of the US #immigration retweet network.

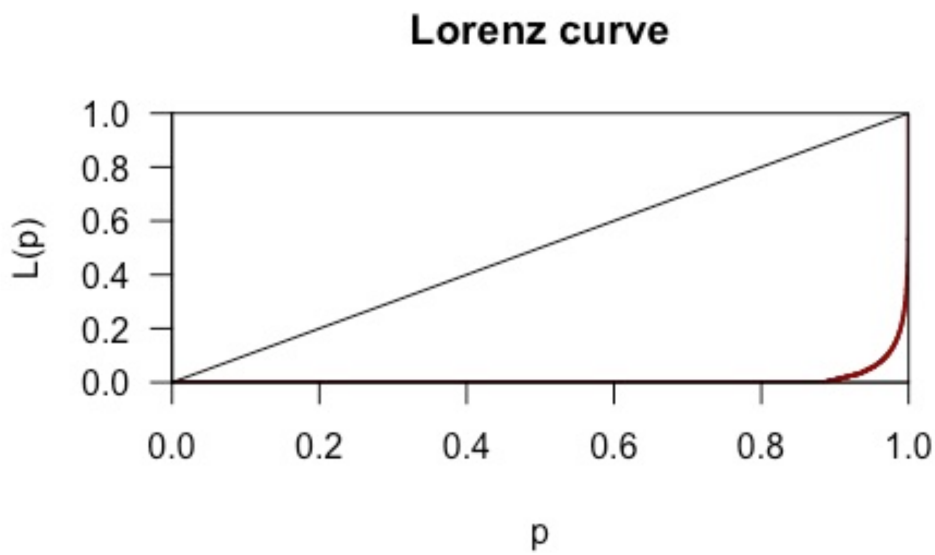
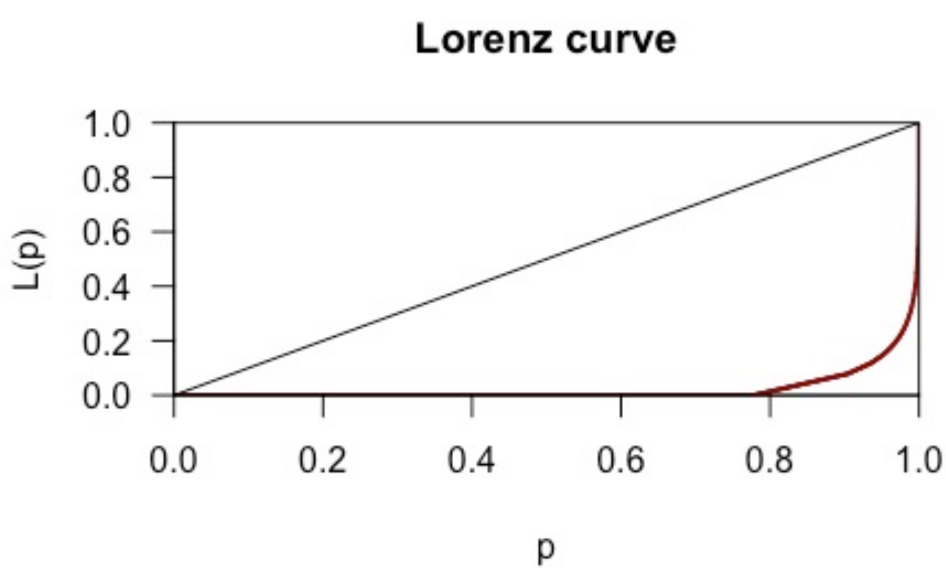


Figure 5: Lorenz curve measuring individual in-degree centralities of the US #immigration mention network.



In terms of descriptive analysis, the means of in-degree centrality were 1.46 (SD = 43.74) for the retweet network and 1.60 (SD = 45.20) in the mention network. The highest in-degree centrality scores were 8,131 (scored by @bfraser747) and 6,719 (scored by @realDonaldTrump). About 12% (14,551/117,040) of Twitter accounts in the retweet network and about 27% (13,625/50,395) of those in the mention network recorded in-degree centrality scores higher than 1.

The result for research question 6 was different from the result for research question 5, showing that both networks recorded Gini coefficients lower than 0.5. The Gini coefficient of the retweet network was 0.426, and that of the mention network was 0.441. Because Gini coefficient scores closer to 0 indicate a perfect equality in the distribution of tweets among Twitter accounts in each network, the author could assume that participation in posting tweets with #immigration was not limited to a few individuals. Spaces in the Lorenz curves measuring the number of tweets posted by individual Twitter accounts were smaller than the ones measuring in-degree centralities in the retweet and mention networks (Figures 6 and 7).

Figure 6: Lorenz curve measuring the number of tweets individual Twitter users posted on the US #immigration retweet network.

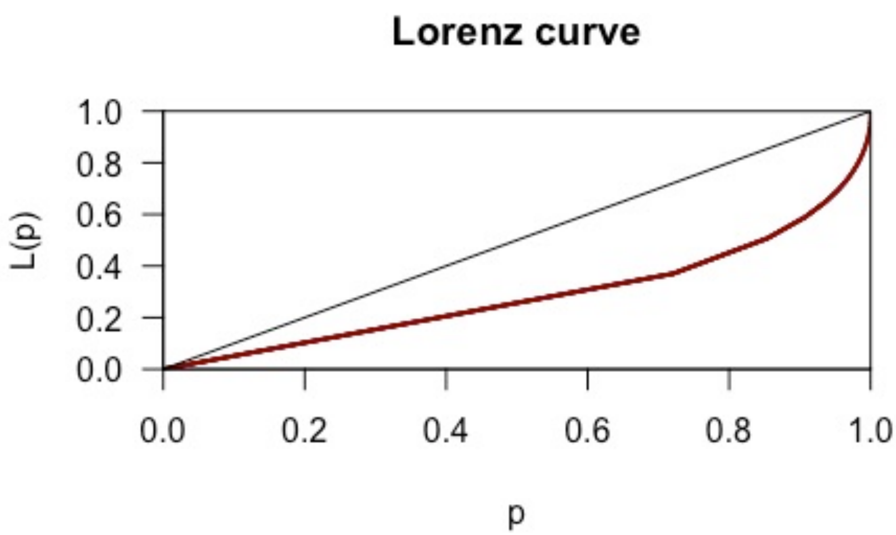
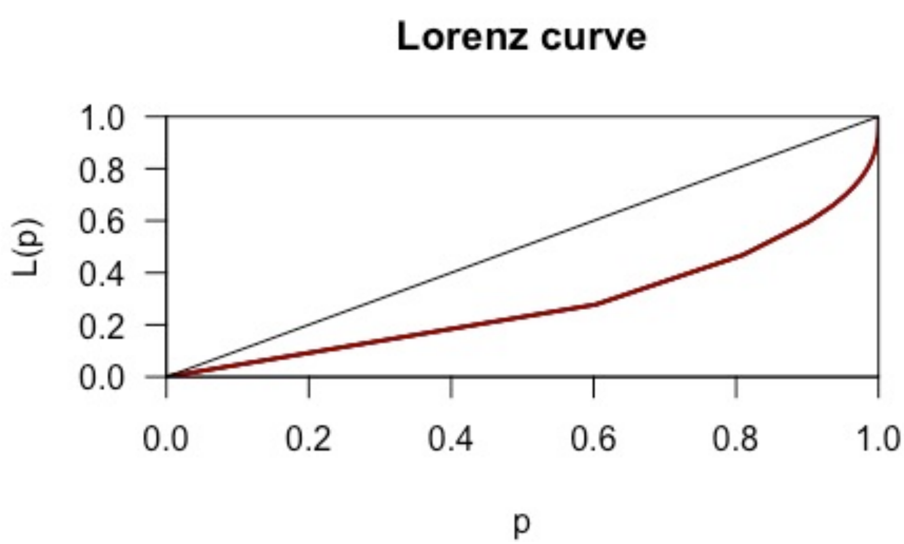


Figure 7: Lorenz curve measuring the number of tweets individual Twitter users posted on the US #immigration mention network.



The means of in-degree centrality were 1.95 (*SD* = 4.92) in the retweet network and 2.17 (*SD* = 5.97) in the mention network. Twitter accounts that posted the largest number of tweets were @CathieMarie2014 (a Twitter account owned by an ordinary female user who mainly retweeted President Trump's tweets, *n* = 587) in the retweet network, and @WWICSReviews (a Twitter account owned by an Indian immigration consultant group working for Indians who wish to migrate to the US, *n* = 387). Both accounts were not officially verified. Most Twitter accounts in each network posted a tweet more than one time. 98.6% (115,413/117,040) of Twitter accounts in the retweet network and 99.6% (50,206/50,395) of the ones in the mention network posted more than one tweet in each network (Table 6).

These findings indicated that while the distributions of in-degree centrality scores were skewed by a few influential Twitter users, most individual Twitter accounts posted tweets more than one time. They supported evidence of a few influential users in both retweet and mention networks, even though those users did not post tweets frequently. For example, while Twitter account managed by President Trump (@realDonaldTrump) scored 4,068 in-degree centrality score in the retweet network, this account did not post retweets from others in the retweet network. Also, this account scored 6,719 in-degree centrality score in the mention network, but it did not mention other Twitter accounts.

Other centrality scores, including out-degree, betweenness, and eigenvector centrality scores were also considered in the retweet and mention networks. Means and standard deviations of different centrality scores in each network are provided (Table 6). Noticeable differences between in-degree and out-degree centrality scores indicated the prestigious (a node with lots of in-degree centrality due to its popularity) and socialite (a node with lots of out-degree centrality) in the network analysis (Tables 7 & 8). Most Twitter accounts that scored top 20 out-degree centrality scores were owned by ordinary citizens (18 among 20 for the retweet network & 12 among 20 for the mention network). None of top 20 out-degree centrality scored Twitter accounts were officially verified. Most Twitter users in each network has one out-degree centrality, which means that most users 'retweet' or 'mention' other popular actors in the network only once. Descriptive results of top centrality scored users indicated active participations in Twitter discussion by activists or ordinary citizens (Tables 9 & 10).

Some Twitter accounts, including @realDonaldTrump and @POTUS owned by the President Trump and national organizations like @NILC_org and @FAIRImmigration were recorded as high betweenness and eigenvector centrality users due to their popularity and their roles of policy makers. Twitter accounts owned by activists or social movement organizations occupied the most positions among top 20 betweenness centrality scored accounts, especially for the retweet network. Officially verified Twitter accounts were also found among top 20 betweenness and eigenvector centrality scored accounts.

Table 6: Means and standard deviations of centrality scores in the issue networks.

	Retweet network		Mention network	
	Mean	SD	Mean	SD
Out-degree centrality	1.95	4.92	2.17	5.97
Betweenness centrality	2,793.75	125,753.67	429.09	14,626.32
Closeness centrality	.000017	.00413	.000020	.00445

Table 7: The top 20 centrality Twitter users in the retweet network.

	Out-degree centrality			Betweenness centrality			Eigenvector centrality		
Ranking	Account	Score	Occupations[5]	Account	Score	Occupations	Account	Score	Occupations
1	@WWICSReviews	587	8	@SandraTXAS	20401480.96	9	@bfraser747	1	9
2	@VirtualAsstMom	343	9	**@kalhan**	**12167897.29**	**1**	@SandraTXAS	0.977683	9
3	@ImmoralReport	285	9	@topiclyimnews	11796068.52	9	**@realDonaldTrump**	**0.490443**	**2**
4	@POLSNJ	283	9	@TrumpReady	11764925.20	9	@ResistTyranny	0.362676	9
5	@POLSNewark	282	9	@MaryPatriotNews	11756879.27	9	**@FAIRImmigration**	**0.343993**	**8**
6	@ImmRefNJ	282	9	@michaelkeyes	10347009.43	9	**@RealJamesWoods**	**0.324568**	**6**
7	@GjeanJames	257	9	@BeladonnaRogers	10175055.83	3	**@pwolgin**	**0.294955**	**1**
8	@POLSDenver	211	9	@bfraser747	10148757.39	9	@Lrihendry	0.288108	9
9	@ImmRefColorado	211	9	**@FWD_us**	**9447590.88**	**8**	**@amjoyshow**	**0.285632**	**4**
10	@POLSBoulder	211	9	@ResistTyranny	7202441.71	9	**@AnnCoulter**	**0.277096**	**4**
11	@chicoscperez	181	9	**@JuanSaaa**	**6851118.37**	**4**	**@NILC_org**	**0.238120**	**8**
12	@POLSLosAngeles	173	9	**@pwolgin**	**5991848.27**	**1**	**@AntonioArellano**	**0.187990**	**4**
13	@jbreisblatt	172	3	**@NILC_org**	**5796019.66**	**8**	@LuisKuryaki	0.183310	4
14	@routeofthesun	171	9	@numquam_desiste	5242297.78	9	@marshallfitz	0.173185	3
15	@polssf	170	9	@immcouncil	5234438.10	8	**@michaeljohns**	**0.165795**	**2**

[5] Occupations: (1) academic workers, (2) politicians, (3) lawyers, (4) journalists & news organizations, (5) authors, (6) celebrities, (7) bloggers, (8) activists, NGOs, etc., and (9) ordinary citizens & Bolded: verified users

16	@NelsyUmanzor	170	9	@crimmigration	4834660.67	1	@SpecialKMB1969	0.162321	9
17	@ImmRefCA	168	9	**@UNITEDWEDREAM**	**3716539.38**	**8**	@CatPharm	0.147835	9
18	@POLSSanDiego	168	9	**@NIJC**	**3332650.70**	**8**	**@BostonGlobe**	**0.147514**	**4**
19	@POLSBerkeley	168	9	@CitiesMigration	3194174.52	8	**@JuanSaaa**	**0.146802**	**4**
20	@POLSSanJose	168	9	@pnmcdaniel	3015728.62	1	@ConstanceQueen8	0.142193	9

Table 8: The top 20 centrality Twitter users in the mention network.

	Out-degree centrality			Betweenness centrality			Eigenvector centrality		
Ranking	Account	Score	Occupations	Account	Score	Occupations	Account	Score	Occupations
1	@CathieMarie2014	387	9	**@joseiswriting**	**1839233.101**	**4**	**@realDonaldTrump**	**1**	**2**
2	@bdevil89	358	9	@immcouncil	1123133.678	8	**@POTUS**	**0.677548**	**2**
3	@Si_Jose	346	8	@AfroLatinoAssoc	959119.771	8	@AZTRUMPTRAIN	0.596152	9
4	@MJASpeakers	334	8	**@pwolgin**	**775529.219**	**1**	**@HillaryClinton**	**0.354281**	**2**
5	@WWICSReviews	314	8	@jbreisblatt	654266.354	3	**@thetimes**	**0.153346**	**4**
6	@RNunezLawrence	236	1	**@FWD_us**	**613361.405**	**8**	**@DHSgov**	**0.146227**	**2**
7	@HR_PAC	214	8	**@NIJC**	**533232.589**	**8**	**@joseiswriting**	**0.135714**	**4**
8	@Shenner649	213	9	**@MarielenaNILC**	**529195.789**	**8**	**@IssaRae**	**0.125751**	**6**
9	@MyAmman	211	9	**@ACLU**	**524637.344**	**8**	@Michimmigrant	0.123271	8
10	@chicanisima	192	1	@TomJawetz	519138.651	8	**@insecurehbo**	**0.122382**	**4**
11	@NYC_Immigration	186	8	**@CAPAction**	**486545.004**	**4**	**@BreitbartNews**	**0.111972**	**4**
12	@lawyers_au	181	9	**@thenyic**	**473082.484**	**8**	**@timkaine**	**0.108899**	**2**
13	@DallasMetro360	178	4	@RaulAReyes	448484.654	3	**@JoyAnnReid**	**0.089869**	**4**
14	@FilipinoAmazing	175	8	**@NILC_org**	**444539.299**	**8**	**@SenSchumer**	**0.088071**	**2**
15	@AndyRodriguez	170	9	**@anoorani**	**421229.891**	**5**	@CustomsBorder	0.081717	9
16	@AfroLatinoAssoc	159	8	**@JuanSaaa**	**419006.299**	**4**	**@bpolitics**	**0.080689**	**4**
17	@expatrisk	156	9	**@DefineAmerican**	**412335.881**	**8**	**@FoxNews**	**0.079332**	**4**
18	@DulcimerGreenmn	138	9	**@MigrationPolicy**	**405416.379**	**8**	**@nytimes**	**0.077175**	**4**
19	@ACT_Migration	132	9	**@JoyAnnReid**	**403939.698**	**4**	**@DefineAmerican**	**0.067042**	**8**
20	@SHRMRoy	131	9	@Das_Alina	301181.959	1	@RaulAReyes	0.063022	3

SUMMARY & DISCUSSION

Research question 1 explored the visual representation of the retweet and mention networks, and research question 2 inquired divisions of clusters in each network. Visually, the retweet network could be categorized as a polarized crowd due to the presence of two political gatherings with few cross-connections to others and the mention network could be classified into community clusters due to evidence of multiple clusters shaped by similarities among members in clusters. While the modularity score of both retweet and mention networks indicated a high level of clustering, more similar characteristics other than political orientations such as occupations, nationality, and groups of news media were detected in the mention network.

Research question 3 examined characteristics of influential users including their verified status and their occupations. After conducting manual content analysis for top 50 degree centrality accounts in politically partisan clusters, the author could find that the percentage of verified users were 26.7% for the retweet network, and 34% for the mention network, surpassing the percentage of verified users in the entire Twittersphere. Moreover, 63.1% for the retweet network and 55% for the mention network were engaged in elite occupations outnumbering ordinary citizens. In the retweet network, activists and social movement organizations were found most, and in the mention network, journalists and news organizations appeared most.

Research question 4 examined hashtags networks produced by co-occurrences with #immigration and other immigration-related hashtags. While one main cluster shaped by a combination of politically liberal and conservative hashtags was found, additional four clusters were detected whose similarities were (1) immigrants' interest to stay in the US, and legally get a citizenship, (2) liberal publics, (3) protesters' interest in the borders between US and Mexico (a) favoring a border wall or (b) focusing on more humanitarian immigration policies, and (4) hashtag posters' interest in the employment of US immigrants being represented as #jobs, #economy, #visa, #trade, and #policy.

Research question 5 examined the distribution of in-degree centrality and Research question 6 inquired the distribution of the number of tweets in the issue retweet and mention networks. While a few individuals recorded higher in-degree centrality scores than the rest of the members, participation in posting tweets with #immigration was not limited to a few individuals in the retweet and mention networks.

Chapter 5: Hierarchical Linear Regression Analyses

Chapter 5 investigates the contribution of several contextual components as well as Twitter affordances in explaining opinion leadership in the retweet and mention networks through conducting hierarchical linear regression analyses on the entire retweet and mention networks. Factors examined included Twitter affordances (the average numbers of mentions and hashtags), contextual factors (elite status, verified status, number of followers, number of followees and total number of tweets), and issue involvement on opinion leadership, measured by in-degree centrality. Then the author randomly selected 1,116 tweets from the retweet network to examine the influence of content (disseminating information, offering opinions, and calling for specific actions), contextual factors (tweets posted by verified users and elite users), and Twitter affordances (number of hashtags and mentions embedded in tweets) on the frequency of being retweeted, another indicator of influence. For the contextual variable of elite status, the author investigated Twitter users' specific occupations. Academics, politicians, lawyers, journalists, activists, authors, publishers, and celebrities were designated as "elite," and ordinary users as "public."

RETWEET NETWORK: DESCRIPTIVE ANALYSIS AND RESULTS

The entire number of users in the retweet network was 117,040. Among them, 1,821 users were officially verified (1.6%). Also, 13,021 users had knowledge-intensive (elite) occupations (11.1%). The author additionally measured the frequency of elite occupations and found that some users listed more than two elite occupations on their bios. Among a total of 13,021 users, the most frequently appeared occupation was authors and writers (*n* = 4,559). The second one was journalists and news media organizations (*n* = 3,218), followed by academic workers (*n* = 2,358), activists and social organizations (*n* = 2,224), lawyers (*n* = 1,290), bloggers (*n* = 692), celebrities (*n* = 342), and politicians and government workers (*n* = 311). The average number of followers was 2,834.99 (*SD* = 35,141.23) and the median score of followers was 396. The average number of followees was 1,433.57 (*SD* = 5,293.31) and the median was 537. The average number of tweets users posted, defined as general Twitter activity in this study, was 22,066.98 (*SD* = 48,714.41) and the median was 6,566. These large differences between mean and median scores suggest that opinion leaders had many more followers and followees, and they were more active in posting tweets than ordinary individuals. The average number of tweets users posted with #immigration (defined as issue involvement in this study) was 2.37 (*SD* = 21.18). The average number of mentions users embedded in their tweets was 0.95 (*SD* = 0.84), and the average number of hashtags users used in their tweets was 2.87 (*SD* = 2.27). The mean of in-degree centrality, the measure of opinion leadership in this study, was 1.10 (*SD* = 56.95). The mean of square-rooted in-degree centrality score, which was converted from in-degree centrality scores to reduce skewedness, was 0.10 (*SD* = 1.05).

Bivariate correlation tests were conducted before hierarchical linear regression analyses to examine relationships among variables. Bivariate correlation of .70 refers to a higher chance of multicollinearity (Pallant, 2013). The correlations of each variable in the retweet network were all less than .70 (Table 9). In addition, the Variance Inflation Factor (VIF) scores for independent variables were measures to test multicollinearity in hierarchical linear regression analyses. No VIF scores were above 10.0, suggesting that the hierarchical linear regression model for the retweet network was not problematic in terms of multicollinearity (Myers, 1990). Basically, Hair et al. (1995) suggested that a VIF score less than 10 indicated inconsequential collinearity.

Among variables in the correlation table, some significant relationships were detected. The officially verified status and elite occupations were positively correlated ($r = .347$, $p < .01$). In addition, the more likely Twitter accounts had a high number of followers, the more likely such accounts to be verified ($r = .253$, $p < .01$). The more likely Twitter accounts to have a large number of followees, the more likely such accounts to be active on Twitter by posting a large number of tweets ($r = .253$, $p < .01$). A mutual significant correlation between the number of followers and the number of followees was also found ($r = .228$, $p < .01$).

The author conducted hierarchical linear regression analysis to examine the influences of Twitter affordances (the average numbers of mentions and hashtags), contextual factors (elite status, verified status, number of followers, numbers of followees and total number of tweets), and issue involvement on opinion leadership. Research question 7a and 8a examined the influence of Twitter affordances on opinion leadership in the retweet network. Hypothesis 1a, 2a, 3a, and 4a, and Research question 9a investigated the predictive powers of contextual factors on the opinion leadership in the retweet network. Hypotheses 5a tested the influence of issue involvement on the opinion leadership in the retweet network.

The results of hierarchical linear regression analysis on the retweet network indicated that the numbers of followers and followees, verified status, elite status, and the degree of issue involvement were positively associated with opinion leadership, while general Twitter activities negatively predicted opinion leadership (Total R-squared = .104). Specifically, in the second block which measures the statistical association between contextual factors and opinion leadership, the number of followers (β = .05, $p <$ 0.001), the number of followees (β = .06, $p < 0.001$), verified status (β = .07, $p < 0.001$), and elite status (β = .03, $p < 0.01$) were significant predictors (R-squared = .059). Individual issue involvement (β = .20, $p < 0.001$) could positively predict opinion leadership (R-squared = .044). On the other hand, general Twitter activity was negatively associated with opinion leadership (β = -.14, $p < 0.001$, Table 10). Thus, hypotheses 2a, 3a, and 4a were supported, while hypothesis 1a was rejected. In terms of RQ9a, a positive relationship between elite occupations of Twitter accounts and opinion leadership was found. Twitter communication affordances in the first block were not associated with opinion leadership.

The more Twitter users were followed by others, the more likely they were to be opinion leaders. Also, the more Twitter users followed others, the more likely they were to be opinion leaders. Such results indicated that mutual Twitter interactions initiated by being followed by others and following others could be determinant factors for gaining popularity in the issue network. Such users had more chances to be detected by other users due to the large amount of followers and friends they have on Twitter. Also, users who were officially verified by Twitter and had knowledge-intensive occupations were more likely to be retweeted by other users. Twitter users could believe that such users were credible information resources based on observing their Twitter profiles. Lastly, users who showed more interest in the specific issue—in this case, those who showed interest in US immigration policy by frequently posting tweets with #immigration—were more likely to be opinion leaders. The positive relationship between individual issue involvement and opinion leadership emphasized the importance of individual contributions by posting relevant hashtags (#immigration) to the Twitter retweet network, which can expand issue networks by attracting other users to participate in Twitter conservations. On the other hand, general Twitter activity, measured as number of tweets, was negatively associated with opinion leadership, indicating that users who only focused on the main issue in the network could earn more popularity.

Table 9: Bivariate tailed correlation table (Retweet network, n = 117,040).

	1	2	3	4	5	6	7	8
1. Followers								
2. Followees	.228**							
3. Activeness	.106**	.253**						
4. Verified	.253**	.037**	.035**					
5. Elite jobs	.097**	.039**	.012**	.347**				
6. Issue involvement	.004	.015**	.041**	.007*	.004			
7. Average mentions	.002	.006*	-.001	.003	.001	.001		
8. Average hashtags	-.006*	.000	-.004	.000	.006*	.001	-.226**	
9. Opinion leadership	.072**	.081**	.044**	.092**	.056**	.202**	.010	.002

*** $p < .001$, ** $p < .01$, * $p < .05$

Table 10: Hierarchical linear regression analysis predicting opinion leadership in the retweet network.

Variable	Model 1	Model 2	Model 3
	ß	*ß*	*ß*
Twitter communication affordances			
Average use of mentions	.00	.00	.00
Average use of hashtags	.01	.01	.01
Contextual factors of Twitter users			
General Twitter activities		-.22***	-.14***
Total number of followers		.06***	.05***
Total number of followees		.07***	.06***
Verified status		.07***	.07***
Knowledge-intensive occupation (elite jobs)		.03**	.03**
Individual issue involvement			
Issue involvement			.20***
R^2	.001	.060***	.104***

*** $p < .001$, ** $p < .01$, * $p < .05$. n = 117,040.

MENTION NETWORK: DESCRIPTIVE ANALYSIS & RESULTS

A total of 50,395 users were found on the mention network. 1,206 users were officially verified (2.4%), and 6,840 users were designated as elite (13.5%). The author also measured the frequency of elite occupations. Like the retweet network, the most frequently appearing occupation was authors and writers (*n* = 2,245). The second one was journalists and news media organizations (*n* = 1,719), followed by activists and social organizations (*n* = 1,211), academic workers (*n* = 1,038), lawyers (*n* = 724), bloggers (*n* = 323), politicians (*n* = 196), and celebrities (*n* = 88). The average number of followers was 4,020.52 (*SD* = 61,637.846) and the median was 475. The average number of followees was 1,580.53 (*SD* = 5,889.82) and the median number was 593. The average number of tweets users posted was 24,757.10 (*SD* = 54,997.70) and the median was 7,189. Differences between mean and median scores indicated skewedness based on opinion leaders having more followers and followees and being more active on Twitter than ordinary Twitter users. The average number of tweets users posted with #immigration was 3.71 (*SD* = 32.26). The average number of mentions users posted was 0.94 (*SD* = 0.77), indicating that users in the mention network "mentioned" other users less than one time, and the average number of hashtags users embedded in their tweets was 2.88 (*SD* = 2.12). The mean of in-degree centrality for users in the mention network, the measure of opinion leadership, was 0.60 (*SD* = 21.13) and the mean of square-rooted in-degree centrality, a score to avoid skewedness, was 0.12 (*SD* = 0.76).

The mean, median and standard deviation scores among the retweet and mention networks were compared. The mention network had higher percentages of users with officially verified users (2.4%) and elite occupations (13.5%) than the retweet network (verified users: 1.6% & elite occupations: 11.1%). The average numbers of followers (4,020.52), followees (1,580.53) and tweets (24,757.10) per individual users in the mention network were also higher than the numbers in the retweet network (the average number of followers: 2,834.99, the average number of followees: 1,433.57, & the average number of tweets: 22,066.98). The medians of followers (475), followees (593), and tweets (7,189) per users in the mention network were also higher than medians in the retweet network (followers: 396, followees: 537, & tweets: 6,566). The average number of tweets users posted with #immigration in the mention network (n = 3.71) was also higher than the number in the retweet network (n = 2.87). The average numbers of mentions (retweet network: 0.95 & mention network: 0.94) and hashtags (retweet network: 2.87 & mention network: 2.88) posted by users were similar in both networks. The average of in-degree centrality scores in the retweet network (1.10) was higher than the average in the mention network (0.60). However, the square-rooted in-degree centrality scores were in contrast (retweet network: 0.10 & mention network: 0.12). The higher score of average square-rooted in-degree centrality for the mention network suggested that the proportion of users who scored zero in-degree centrality was larger in the retweet network (n of Twitter users who scored more than 1 in-degree centrality score = 4,240 & 112,800/117,040, 96.4%) than in the mention network (n of Twitter users who scored more than 1 in-degree centrality = 2,631 & 47,764/50,395, 94.8%).

The author conducted correlation tests among variables used in hierarchical linear regression analysis. The result showed no multicollinearity in the mention network, by measuring bivariate correlations among each variable and VIF scores of independent variable in hierarchical linear regression analysis (Table 11). Among variables in the correlation table, some significant relationships were also found. The more likely Twitter accounts had a large number of followers, the more likely such accounts to be verified ($r = .202$, $p < .01$). The more likely Twitter accounts to have a large number of followees, the more likely such accounts to be active on Twitter by posting a number of tweets ($r = .252$, $p < .01$). The mutual significant correlation between the number of followers and the number of followees was also found ($r = .171$, $p < .01$). Unlike the retweet network, no significant relationship was found between Twitter accounts with verified status and elute occupations ($r = .018$, $p > .05$). The overall results between retweet and mention networks were similar, especially in terms of having a large number of followers and being officially verified.

The author additionally conducted hierarchical linear regression analysis to examine the influences of Twitter affordances (the average numbers of mentions and hashtags), contextual factors (elite status, verified status, number of followers, number of followees and total number of tweets), and issue involvement on opinion leadership in the mention network. Research question 7b and 8b inquired the influence of Twitter affordance on the opinion leadership. Hypothesis 1b, 2b, 3b, and 4b, and Research question 9b tested the predictive powers of contextual factors on the opinion leadership. Hypotheses 5b tested the influence of issue involvement on the opinion leadership in the mention network. The results of hierarchical linear regression analysis on the mention network indicated that the number of followers, verified status, elite status, and issue involvement positively predicted in-degree centrality (Total R-squared = .057). In the second block measuring the contribution of contextual factors, the number of followers (β = .09, $p < 0.001$), verified status (β = .18, $p < 0.001$), elite status (β = .08, $p < 0.05$) were significantly associated with opinion leadership (R-squared = .047). In the third block, individual issue involvement (β = .19, $p < 0.001$) was also a significant predictor of opinion leadership (R-squared = .009, Table 12).

Thus, hypotheses 2b and 4b were supported, while hypotheses 1b and 3b were rejected. In terms of RQ 7b and 8b, Twitter communication affordances were not associated with opinion leadership in the mention network. There was a positive relationship between the number of followers and opinion leadership, indicating that a larger number of followers provided more chances for Twitter users to be detected and mentioned by others. Also, verified status and knowledge-intensive occupations were related to opinion leadership. Lastly, Twitter users who were more involved in the main issue were likely to be mentioned by others.

Research question 10 asked the strongest predictor of opinion leaders in two networks. In both networks, individual issue involvement was the strongest predictor, emphasizing the importance of individual contribution by using relevant hashtag. The author found that (1) elite status, verified status, the number of followers, and individual issue involvement were common predictors of opinion leadership in each network; (2) general Twitter activities were negatively associated with opinion leadership in the retweet network, while they did not predict opinion leadership in the mention network.

Table 11: Bivariate tailed correlation table (Mention network, n = 50,395).

	1	2	3	4	5	6	7	8
1. Followers								
2. Followees	.171**							
3. Activeness	.101**	.252**						
4. Verified	.202**	.034**	.030**					
5. Elite jobs	.085**	.027**	-.005	.018				
6. Issue involvement	.003	.015**	.045**	.099	.003			
7. Average mentions	.002	.006	-.001	.099*	.004	.003		
8. Average hashtags	.001	.002	-.001	.117*	.013**	.000	-.225**	
9. Opinion leadership	.129**	.063**	.031**	.219**	.137**	.085**	.005	.006

*** $p < .001$, ** $p < .01$, * $p < .05$

Table 12: Hierarchical linear regression analysis predicting opinion leadership in the mention network.

Variable	Model 1	Model 2	Model 3
	ß	*ß*	*ß*
Twitter communication affordances			
Average use of mentions	.08	.08	.06
Average use of hashtags	.07	.07	.05
Contextual factors of Twitter users			
General Twitter activities		.08	.05
Total number of followers		.09***	.09***
Total number of followees		.04	.04
Verified status		.18***	.18***
Knowledge-intensive occupation (elite jobs)		.09**	.08*
Individual issue involvement			
Issue involvement			.19***
R^2	.001	.048***	.057***

*** $p < .001$, ** $p < .01$, * $p < .05$. n = 50,395.

CONTENT FACTORS PREDICTING THE FREQUENCY OF BEING RETWEETED

From the entire retweet network (n = 227,962), the author randomly selected 1,116 tweets for additional hierarchical linear regression analysis to examine the influence of content factors on tweets (distributing information, offering personal information and calling for specific actions), users' contextual factors (verified status and knowledge-intensive occupations), and Twitter affordances on the frequency of being retweeted. This modeling serves as a proxy to measure the degree of influence for tweets.

The author and the second coder manually coded characteristics of tweets as well as Twitter users' occupations. In terms of content factors, the coders found that most of retweets were intended to distribute factual information (n = 887, 79.4%). Retweets for the purpose of offering personal information comprised 15.1% (n = 169) of the samples, and only 19 retweets included calls for specific actions, like petitions and offline protests (1.7%). Tweets which did not have any additional information (e.g., hashtags only, hyperlinks only, and images only) accounted for 3.7% of the sample (n = 41).

Among these 1,116 tweets, about 30% (n = 334) tweets were posted by officially verified users. Also, about 40% (n = 438) were posted by users with knowledge-intensive occupations. Multiple choices were allowed based on users' bios because some users mentioned more than two elite occupations. Knowledge-intensive occupations were operationally divided into the following categories: educators, politicians, lawyers, journalists, activists, authors (and publishers), celebrities, bloggers, and organizations. Among 438 tweets posted by knowledge-intensive users, activists (n = 114, 23.0%), organizations (n = 108, 21.9%), and journalists (n = 104, 21.1%) appeared most.

Politicians (n = 49, 10.0%), authors (n = 39, 7.9%), lawyers (n = 32, 6.5%), celebrities (n = 25, 5.0%) and professors and educators (n = 20, 4.0%) followed.

The author conducted descriptive analyses on the randomly selected tweets. The average number of mentions per tweet was 1.96 (SD = 2.36), and the average number of hashtags was 5.45 (SD = 4.31). The average frequency of tweets being retweeted was 805.68 (SD = 1262.50). The correlations of each variable were presented (Table 15). The author conducted multicollinearity tests while conducting a hierarchical linear regression analysis to measure predictors of the number of being retweeted. The author could find that VIF scores of all predictors were under 10 (Hair et al., 1995). A strong association between tweets written by verified users and elite users was detected ($r = .698$, $p < .001$). The average numbers of mentions and hashtags were also significantly correlated ($r = .624$, $p < .001$), suggesting both Twitter communication affordances could be mutually utilized to enlarge Twitter conversations. A negative relationship between tweets to distribute information and offer personal information was also detected ($r = -.631$, $p < .001$), indicating the contradictory purposes of those two purposes (spreading factual messages vs informing personal ideas) (Table 13).

The author conducted a hierarchical linear regression analysis to examine the influence of Twitter affordances (number of hashtags and mentions embedded in tweets), contextual (tweets posted by verified users and elite users), and content (disseminating information, offering opinions, and calling for specific actions) factors on the frequency of being retweeted, another indicator of influence. Research questions 11 and 12 examined the relationship between Twitter communication affordances (average number of mentions and hashtags in a tweet) and number of retweets, respectively. Research questions 13 and 14 examined the relationship between contextual factors of tweets (tweets posted by verified and elite-status users) and the frequency of being retweeted. Research questions 15, 16, and 17 examined the influence of content factors (distributing information, offering personal information, and calling for specific actions) on the frequency of being retweeted.

The results indicated that the average number of mentions and hashtags and tweets posted by officially verified users significantly predicted the frequency of being retweeted (Total R-squared = .173) (Table 14). After measuring the influence of all blocks, all Twitter communication affordance variables in the first block were significantly associated with the frequency of being retweeted. The average number of mentions (β = .27, $p < .001$) and the average number of hashtags (β = .12, $p < .001$) were positively associated with the frequency of being retweeted (R-squared = .138). In addition, tweets posted by verified users in the second block significantly predicted the frequency of being retweeted (β = .14, $p < .01$, R-squared = .031). Among content factors in the third block, the tweets offering personal information (β = .11, p = .071) marginally predicted the frequency of being retweeted, while other two factors were not statistically associated (R-squared = .004).

Table 13: Bivariate tailed correlation table (n = 1,116).

	1	2	3	4	5	6	7
1. Tweets written by verified users							
2. Tweets written by 'elite' users	.698**						
3. Tweets to distribute information	-.031	-.001					
4. Tweets to offer personal information	.084**	.039	-.631**				
5. Tweets to call for specific actions	-.010	.036	-.259	-.056			
6. Average mentions in each tweet	.034	.071*	-.058	.069*	-.024		
7. Average hashtags in each tweet	-.009	.007	-.050	.053	-.036	.624**	
8. Total number of being retweeted	.178**	.167**	-.046	.081*	-.024	.309**	.354**

*** $p < .001$, ** $p < .01$, * $p < .05$

Table 14: Hierarchical linear regression analysis predicting the frequency of being retweeted.

Variable	Model 1	Model 2	Model 3
	ß	*ß*	*ß*
Twitter communication affordances			
Average use of mentions	.27***	.27***	.27***
Average use of hashtags	.14***	.13***	.12***
Contextual factors of Twitter users			
Tweets posted by verified users		.15**	.14**
Tweets posted by elite users		.04	.04
Content factors of tweets			
Distributing information			.07
Offering personal information			.11 (p = .071)
Calling for specific actions			.02
R^2	.138***	.169***	.173***

*** $p < .001$, ** $p < .01$, * $p < .05$. n = 1,116.

SUMMARY & DISCUSSION

In sum, the author found that Twitter communication affordances and tweets offering personal opinions were positively associated with the frequency of being retweeted. This result indicated that if Twitter users utilized Twitter affordance tools to enlarge conversations by mentioning others and embedding more hashtags in tweets, such tweets were highly retweeted. While no statistical relationship was found between tweets posted by knowledge-intensive Twitter users and the frequency of being retweeted, tweets posted by officially verified users were retweeted more than others posted by non-verified users. Twitter users can retweet specific tweets posted by credible sources. Also, this finding also suggests that users may consider verified users to be more credible sources of information than users with elite occupations; thus, verified users were more likely to be opinion leaders. Only tweets which offered personal information significantly predicted the number retweets. Such tweets might voice opinions regarding specific issues, that is, US immigration policy, either supporting or opposing stricter regulations. US immigration policy is one of the most polarized issues among the public (Johnston, Newman, & Velez, 2015; Pew Research Center, 2016). Thus, Twitter users retweeted other tweets which aligned with the ideas they endorsed; they also retweeted tweets stating opinions that they opposed in order to refute those opinions.

Chapter 6: Longitudinal agenda-setting effects in #immigration network

Chapter 6 identifies origins and multiple directions of agenda-setting effects in the retweet and mention networks. The author conducted Granger causality tests to measure longitudinal agenda-setting effects of news media, opinion leaders, and the public. For the first-level agenda-setting studies, three different forms of network were created: (1) the entire network consisting of all tweets with #immigration over the four-month period (n = 397,655), (2) the retweet network (n = 227,962), and (3) the mention network (n = 109,412). The news media group was calculated by the sum of news articles covering US immigration policy in traditional news media outlets, including *New York Times, Washington Post, USA Today*, ABC, CBS, CNN, FOX and NBC (n = 4,981). Based on the criteria for opinion leadership, which were operationally defined by the author as verified Twitter accounts and top 10% of weighted in-degree centrality scores, the author extracted tweets in which opinion leaders were retweeted or mentioned by other users. Descriptive analyses of the number of tweets for the entire, retweet and mention networks were provided (Table 15).

The author tested first- and second- level agenda-setting effects. The author investigated first level agenda-setting by examining longitudinal differences in volumes of news articles and tweets posted by opinion leaders and the public. The author additionally classified entire Twitter networks into several groups (conservative opinion leaders and public & liberal opinion leaders and the public) based on their Twitter bios and conducted second level agenda-setting tests. Research question 18, "What is the causal relationship among news media, opinion leaders and the public in terms of issue salience in US immigration issue networks?," examined the first-level agenda-setting in three networks (the entire, retweet and mention groups). Research question 19, "What is the causal relationship among news media, opinion leaders and the public in terms of affective attributes in US immigration issue networks?," measured the transfer of salience of affective attributes among three networks. The affective attributes were used to categorize Twitter users into Republican and Democratic groups based on political orientations mentioned on their bios. Hypothesis 6, "News media are more likely to set the issue agenda of opinion leaders on the #immigration issue network on Twitter in the a) retweet network & b) mention network," posited that news media are more likely to set the issue agenda of opinion leaders and the public on the #immigration issue network on Twitter. The study tested three rival hypotheses examining whether the news media, opinion leaders or the public set the agenda. Hypothesis 7, "Opinion leaders are more likely to set the issue agenda of the public on the #immigration issue network on Twitter in the a) retweet network & b) mention network," assumed that opinion leaders influence of the agenda of the news media and the public. Hypothesis 8, "The public is more likely to set the issue agenda of the news on the #immigration issue network on Twitter in the a) retweet network & b) mention network," assumed that the public is more likely to set the issue agenda of news media and opinion leaders on the #immigration issue network, testing reversed agenda-setting effects. The results of this chapter showed diversified information flows initiated by each group, which can be explained as a combination of top-down and bottom-up agenda-setting processes.

Table 15: The number of tweets on #immigration issue networks (First-level agenda-setting).

	Tweets including verified users	Tweets including opinion leaders	Tweets posted by the public
Entire Network	9,502	144,475	252,980
Retweet Network	3,225	21,060	206,902
Mention Network	2,905	11,345	98,067

PROCESSES

Before measuring Granger causality, the author verified that several conditions were satisfied. First of all, Augmented Dickey-Fuller tests were conducted to confirm whether time-series variables have stationarity, meaning that statistical properties like mean and variances are all constant for each group over time. For Augmented Dickey-Fuller tests, the null hypothesis tests whether a unit root, a feature of some stochastic process resulting in non-stationarity of time-series variables, exists in the time-series analysis. The alternative hypothesis tests that all time-series variables are maintaining the stationarity among them, satisfying statistical validity of time-series analyses. Time-series models should reject the null hypotheses in Augmented Dickey-Fuller tests. The results of three Augmented Dickey-Fuller tests indicated that all time-series groups (the entire network, retweet network and mention network) maintained stationarity by recording p-values lower than 0.05, supporting alternative hypotheses (Table 16).

Later, the author selected the most appropriate time lags for each of the three networks based on Akaike's information criterion (AIC). The author measured Akaike's information criterion (AIC) before conducting Granger causality tests, and it turned out that the appropriate lags of agenda-setting effects for each of the three networks were different. First of all, the author assumed that agenda-setting effects between traditional news media and Twitter would take less than one week. Roberts et al. (2002) argued that it took seven days to transfer the issue agenda from traditional news outlets to online discussion boards. However, since the time of their study, the time lag between traditional news outlets and Twitter has been significantly reduced to one day (Groshek

& Groshek, 2013). Still, there is no conventional standard for confirming time lag, so that, most longitudinal analysis studies have relied on statistical criteria like the lowest AIC values to determine the best time lag (Becketti, 2013). Considering the large amount of information transfer and rapid communications on Twitter, the author set seven days as the longest lag for the agenda-setting effects to find the lowest AIC values. After measuring AIC values, the author found that the best time lag varied: five days for the entire #immigration network, five days for the retweet network, and four days for the mention network, based on the lowest AIC scores respectively (Table 17).

After confirming the best time lag for each network, the author measured autocorrelations for each of the three groups. The author conducted Portmanteau tests to confirm that there were no autocorrelations and that residuals were independent from each time series variable. The results of these three Portmanteau tests (entire network, retweet network, and mention network) all supported null hypotheses, rejecting the possibility of autocorrelations (Table 18).

Table 16: Augmented Dickey-Fuller tests on #immigration issue networks.

	Group	ADF test statistics
Entire Network	News media	-4.6629***
	Opinion leaders	-5.5311***
	The Public	-4.7429***
Retweet Network	News media	-4.6629***
	Opinion leaders	-7.7401***
	The Public	-5.0440***
Mention Network	News media	-4.6629***
	Opinion leaders	-6.9750***
	The Public	-5.7523***

*** $p < .001$, ** $p < .01$, * $p < .05$

Table 17: Akaike's Information Criteria for each time lag in the first-level agenda-setting effect.

	Time lag (days)						
	1	2	3	4	5	6	7
Entire Network	32.10	32.00	31.92	31.92	**31.76**	31.79	31.88
Retweet Network	27.84	27.65	27.39	27.31	**27.28**	27.37	27.42
Mention Network	25.92	25.85	25.71	**25.67**	25.71	25.78	25.75

Table 18: Portmanteau tests on #immigration issue networks.

	Degree of Freedom	Chi-Squared values	Probability (p-value)
Entire Network	99	94.11	0.6201
Retweet Network	99	78.77	0.9333
Mention Network	108	100.66	0.6792

*** $p < .001$, ** $p < .01$, * $p < .05$

GRANGER CAUSALITY TEST OF THE FIRST-LEVEL AGENDA-SETTING EFFECTS

The author drew a total of nine line graphs (the entire, retweet, and mention networks; Republican entire, retweet, and mention networks; and Democratic entire, retweet, and mention networks). These graphs describe longitudinal changes in the number of news articles and tweets to visualize impulses caused by relevant events and to enable comparisons across the three groups. Figures 8, 9, and 10 show longitudinal changes in news and tweets posted by opinion leaders and the public over the four-month period. There were three discernible surges in news and tweets: the week of October 15 to 22, 2016 (the early voting period for the 2016 presidential election and the third presidential debate, which was held on October 19, 2016), the week of January 7 and 14, 2017 (President Donald Trump's immigration meeting with members of Congress on January 9, 2017), and the week of January 21 and 28, 2017 (President Donald Trump's executive order to bar entry to the US for people from Iraq, Iran, Libya, Somalia, Sudan, Syria and Yemen for 90 days).

After determining the best time lags, the author conducted Wald tests, which measured Granger causality among more than two time-series variables. Research question 18 examined the first level-agenda setting effects of three types of networks (the entire, retweet, and mention networks). Specifically, Hypothesis 6 assumed a top-down process of agenda-setting, in which the news media sets the issue agenda of opinion leaders and the public on Twitter. Hypothesis 7 posited that opinion leaders could set the agenda in both top-down (to the public) and reversed (to news media) directions. Hypothesis 8 tested the reversed agenda-setting effects initiated by the public, analyzing how the public sets the issue agenda of news media and opinion leaders. The author tested three alternative hypotheses because it can be interpreted differently in a total of 54 time-series relationships (first- and second-level), indicating that while one hypothesis can be rejected in one case, it can be supported in a different case.

As indicated in Table 19, in the entire network, the news media did not significantly Granger-cause agendas among opinion leaders or the public. In the retweet network, the media did not Granger-cause any significant effects to opinion leaders and the public. Only one marginally significant direction from news media to the public was found on the mention network ($\chi 2 = 2.07$, $df = 4$, $p < .08$), while news media did not significantly Granger-cause the agenda of opinion leaders. Based on this finding, it turned out that news media slightly set the agenda of the public in the mention network, but no significant relationships were found in other forms of #immigration issue networks. The author found that there is a little indication of traditional agenda-setting effects.

In the entire network, opinion leaders Granger-caused the agenda of news media ($\chi 2 = 2.86$, $df = 5$, $p < .01$), while they did not Granger-cause the agenda of the public. In the retweet network, opinion leaders Granger-caused the agenda of the public ($\chi 2 = 3.04$, $df = 5$, $p < .01$), but they did not Granger-cause the agenda of the news media. In the mention network, opinion leaders Granger-caused the agenda of the public ($\chi 2 = 2.07$, $df = 4$, $p < .08$), but they did not Granger-cause the agenda of the news media. Thus, the role of opinion leaders is complex in each network: (1) reversed agenda-setting effects initiated by opinion leaders occurred throughout the entire network, and (2) opinion leaders set the agenda of the public in both retweet and mention networks.

In the entire #immigration networks, Granger causality analysis revealed that the public had significant agenda-setting effects on both news media ($\chi 2 = 4.19$, $df = 5$, $p < .001$), and opinion leader ($\chi 2 = 2.28$, $df = 5$, $p < .05$) agendas. This is a reverse agenda-setting process, indicating that the public initiated the agenda-setting, opinion leaders perceived it, and finally, the agenda of news media was influenced by opinion leaders. This reversed relationship can be interpreted as opinion leaders playing a mediating role between news media and the public.

In the retweet network, the public Granger-caused the agenda of both news media ($\chi 2 = 5.01$, $df = 5$, $p < .001$) and opinion leaders ($\chi 2 = 4.21$, $df = 5$, $p < .001$). This is a circular agenda-setting process in which opinion leaders set the agenda of the public, and the public, in turn, influenced news media. Mutual agenda-setting effects were found between Twitter opinion leaders and ordinary Twitter users.

In the mention network, the public also marginally Granger-caused the agenda of opinion leaders ($\chi 2 = 1.95$, $df = 4$, $p < .09$), while it did not Granger-cause the agenda of news media. The public can directly set the agenda of the news media, and its agenda-setting effects on opinion leaders were less significant than its agenda-setting effects on the news media, based on differences in strong $\chi 2$ scores for longitudinal agenda-setting. In the mention network, the news media could set the agenda of the public directly without opinion leaders. The public was influenced by both news media and opinion leaders, but mutual agenda-setting effects were also found between opinion leaders and the public. Figures 9 and 10 show longitudinal flows of retweets and tweets with mentions over the four-month periods.

The results of the first-level agenda-setting tests conducted by Wald tests on Granger causality comparing differences in issue salience, the transfer of volume of news coverage and tweets offered mixed results. In terms of the first-level agenda-setting effects, top-down and bottom-up relationships were both found, and to some degree, opinion leaders mediated the agenda-setting effects from news media to the public and they mutually set the agenda with the public.

A total of 9 first-level agenda-setting effects among 18 possible relationships were found in the entire, retweet, and mention networks. Among six possible causality tests, the news media was partly successful at setting the agenda of the public in the mention network ($\chi 2 = 2.07$, $df = 4$, $p < .08$), while rejecting statistically significant relationships in the other five networks. Opinion leaders set the agenda in three of the six possible relationships, including the agenda of the news media in the entire network and the agenda of the public in the retweet and mention networks. The public set the agenda in five out of six networks; the only exception was the agenda of news media in the retweet network. In the entire network, news media and the public could mutually set the agenda for each other. Also, opinion leaders and the public mutually affect the transfer of salience in the retweet network. The public could set the agenda of opinion leaders in all three relationships.

Figure 8: Total number of news and tweets posted by opinion leaders and the public.

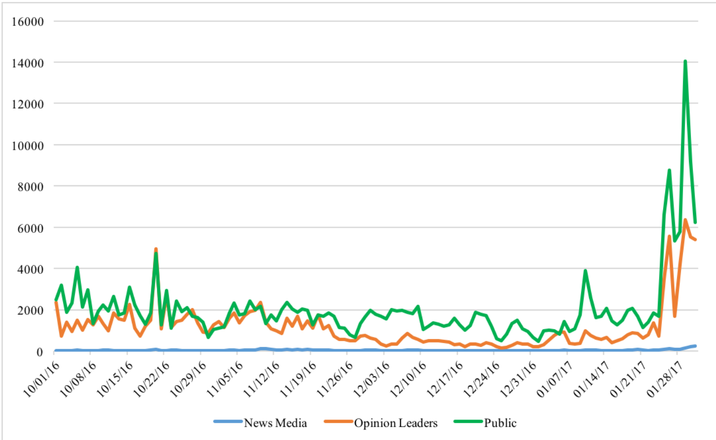


Figure 9: Total retweet network.

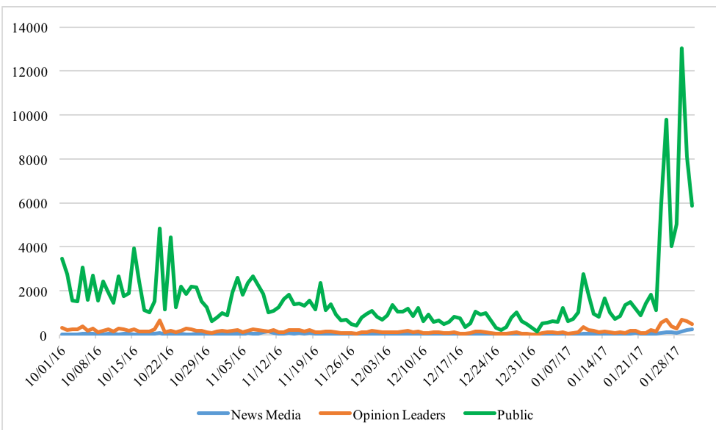


Figure 10: Total mention network.

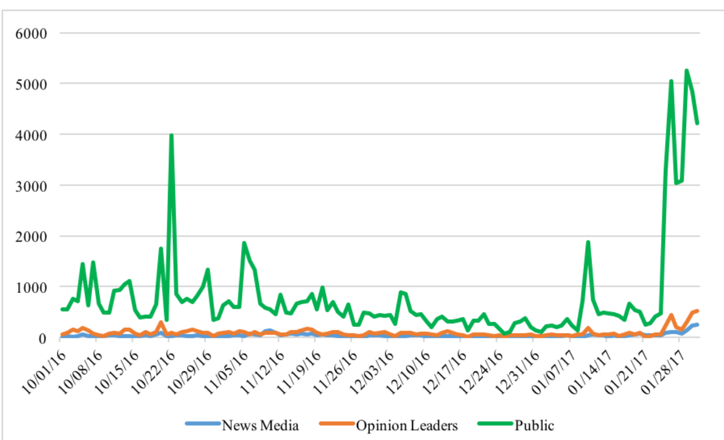


Table 19: Granger causality tests on #immigration issue networks (first-level).

	Directions (From -> To)	Degree of Freedom	Chi-Squared values
Entire Network	News media -> Opinion leaders	5	0.4752
	News media -> The public	5	1.2426
	Opinion leaders -> News media	5	2.8632**
	Opinion leaders -> The public	5	0.9286
	The public -> News media	5	4.1871***
	The public -> Opinion leaders	5	2.2819*
Retweet Network	News media -> Opinion leaders	5	0.3897
	News media -> The public	5	1.1651
	Opinion leaders -> News media	5	0.3424
	Opinion leaders -> The public	5	3.0427**
	The public -> News media	5	5.0059***
	The public -> Opinion leaders	5	4.2146***
Mention Network	News media -> Opinion leaders	4	0.3334
	News media -> The public	4	2.074 ($p < .08$)
	Opinion leaders -> News media	4	0.770
	Opinion leaders -> The public	4	2.068 ($p < .08$)
	The public -> News media	4	1.453
	The public -> Opinion leaders	4	1.946 ($p < .09$)

*** $p < .001$, ** $p < .01$, * $p < .05$, (.) $p < .10$

OVERVIEW OF THE SECOND-LEVEL AGENDA-SETTING EFFECTS

The author conducted additional Granger causality tests to further examine second-level agenda-setting in each political ideology group. Second-level agenda-setting studies examine the transfer of affective attributes within the immigration issue. Based on the fact that Republicans and Democrats have highly clustered perceptions of US immigration policy, the author assumed differences in agenda-setting effects within each political group. The author classified "pro-immigration" (Democratic and liberal users) and "anti-immigration" (Republican and conservative users) by using Python scripts based on politically opinionated keywords (e.g., Iamwithher and UniteBlue for Democratic and liberal users, and TCOT (Top Conservative users on Twitter) and MAGA for Republican and conservative users) (Appendix C). The author created six additional groups, including the entire Republican network (n = 121,262), the Republican retweet network (n = 94,885), the Republican mention network (N = 11,661), the entire Democratic network (n = 31,395), the Democratic retweet network (n = 30,014), and the Democratic mention network (n = 13,612). The author further divided Twitter groups based on tweets posted by opinion leaders (those with verified status who are in the top 10% of in-degree centrality scores) and the public (Table 20).

The author conducted Augmented Dickey-Fuller tests to confirm stationarity within Democratic and Republican groups. Results of ADF tests indicate that all time-series variables in both Republican and Democratic groups maintained stationarity (Table 21).

Later, the author selected the best time lag for news media, Twitter opinion leaders, and public groups based on Akaike's information criterion (AIC). AIC tests indicated that the best time lag for "anti-immigration" networks were five days for the entire Republican network, two days for the Republican retweet network, and three days for the Republican mention network (Table 22).

The most appropriate time lag for "pro-immigration" networks were three days for the entire Democratic network, five days for the Democratic retweet network, and one day for the Democratic mention network (Table 23). Same time lag could not be applied to all six networks because of the problem of autocorrelation. For example, if the author arbitrarily set a lag as one day based on the finding suggested by Groshek and Groshek (2013), three autocorrelations were detected out of a total of six models.

Lastly, the author conducted Portmanteau tests to examine autocorrelations among variables on Republican and Democratic groups. While the results of Portmanteau tests on Republican retweet and mention networks were closer to the significant level (0.05), all groups passed Portmanteau tests, leading the author to conclude that there were no autocorrelations among time-series variables (Table 24 & 25).

Table 20: Number of tweets on the second-level agenda-setting effects.

	Republican group		Democratic group	
	Tweets posted by opinion leaders	Tweets posted by the public	Tweets posted by opinion leaders	Tweets posted by the public
Entire Network	44,062	77,001	11,574	19,787
Retweet Network	8,374	86,506	2,965	27.047
Mention Network	470	11,131	123	11,660

Table 21: Augmented Dickey-Fuller tests on the second-level agenda-setting effects.

		Republican group	Democratic group
		ADF test statistics	ADF test statistics
Entire Network	Opinion leaders	-5.29***	-7.48***
	The Public	-4.97***	-6.30***
Retweet Network	Opinion leaders	-7.03***	-8.72***
	The Public	-5.96***	-7.26***
Mention Network	Opinion leaders	-8.26***	-9.33***
	The Public	-7.09***	-5.66***

*** $p < .001$, ** $p < .01$, * $p < .05$

Table 22: Akaike's Information Criterion for each time lag in the second-level agenda-setting effects (Republican).

	Time lag (days)						
	1	2	3	4	5	6	7
Entire Network	28.61	28.43	28.52	28.40	**28.37**	28.40	28.38
Retweet Network	25.53	**25.29**	25.34	25.30	25.31	25.39	25.38
Mention Network	19.05	19.08	**19.04**	19.12	19.17	19.25	19.17

Table 23: Akaike's Information Criterion for each time lag in the second-level agenda-setting effects (Democratic).

	Time lag (days)						
	1	2	3	4	5	6	7
Entire Network	24.43	24.47	**24.24**	24.29	24.38	24.48	24.53
Retweet Network	22.12	21.97	21.92	21.89	**21.87**	21.88	21.90
Mention Network	**19.69**	19.77	19.74	19.79	19.88	19.89	19.96

Table 24: Portmanteau tests on second-level agenda-setting effects (Republican).

	Degree of Freedom	Chi-Squared values	Probability (p-value)
Entire Network	99	100.24	0.446
Retweet Network	126	148.90	0.089
Mention Network	117	141.76	0.069

*** $p < .001$, ** $p < .01$, * $p < .05$

Table 25: Portmanteau tests on second-level agenda-setting effects (Democratic).

	Degree of Freedom	Chi-Squared values	Probability (p-value)
Entire Network	117	81.27	0.951
Retweet Network	99	101.07	0.423
Mention Network	135	104.49	0.976

*** $p < .001$, ** $p < .01$, * $p < .05$

GRANGER CAUSALITY TESTS OF THE SECOND-LEVEL AGENDA-SETTING EFFECTS

Research question 19 inquired the second level-agenda setting effects, measuring the transfer of salience of affective attributes among three groups. The author conducted Wald tests on six groups (entire Republican network, Republican retweet and mention networks, entire Democratic network, Democratic retweet and mention networks. Figures 11, 12, 13, 14, 15, & 16). In both the entire networks, the news media did not significantly Granger-cause the agenda of opinion leaders or the public. The news media Granger-caused the agenda of the public in the Republican retweet network ($\chi 2$ = 5.08, df = 2, $p < .01$), but it did not initiate any Granger causality effects on opinion leaders in the Republican retweet network; it also did not initiate these effects among opinion leaders or the public in the Democratic retweet network. In the Democratic mention network, news media Granger-caused the agenda of opinion leaders ($\chi 2$ = 3.38, df = 1, $p < .05$) and the public ($\chi 2$ = 4.53, df = 1, $p < .05$).

In terms of the second-level agenda-setting effects of opinion leaders, they Granger-caused the agenda of the public in the entire Republican network ($\chi 2$ = 4.30, df = 5, $p < .01$) and Democratic network ($\chi 2$ = 2.24, df = 3, $p < .08$), while they did not Granger-cause the agenda of news media in either of the entire networks. Opinion leaders Granger-caused the agenda of the public ($\chi 2$ = 2.42, df = 2, $p < .05$) in the Republican retweet network, while they did not Granger-cause the agenda of the public in Democratic retweet and did not Granger-cause the agenda of the news media in both Republican and Democratic retweet networks. In the mention network, only opinion leaders in the Republican retweet network marginally Granger-caused the agenda of the public ($\chi 2$ = 2.30, df = 3, p < .08).

The public Granger-caused the agenda of opinion leaders in the entire Republican retweet network ($\chi 2$ = 4.19, df = 5, p < .001). Both opinion leaders and the public Granger-caused mutual agendas in the entire Republican network. The public also Granger-caused the agenda of opinion leaders in the Democratic retweet network ($\chi 2$ = 2.46, df = 5, p < .05). The public did not Granger-cause any agenda of news media in six networks **(**Table 26 & 27).

In answering research question 19, nine significant relationships were found in the second-level agenda-setting tests among 36 possible Granger causality effects. Among 12 possible effects, news media set three agendas. The news media could set the agenda of opinion leaders and the public in the Democratic mention network. The news media was also successful at setting the agenda of the public in the Republican retweet network. Among 12 possible effects initiated by opinion leaders, four significant top-down agenda-setting effects were detected. None of bottom-up agenda-setting processes initiated by opinion leaders was found. Opinion leaders set the agenda of the public in all Republican (entire, retweet and mention) networks, showing a top-down agenda-setting process from opinion leaders to the public. They could also set the agenda of the public in the entire Democratic network. The public was successful at setting agendas in two of 12 possible relationships. The public could set the agenda of opinion leaders in the entire Republican network and in the Democratic retweet network.

Figure 11: Entire Republican network.

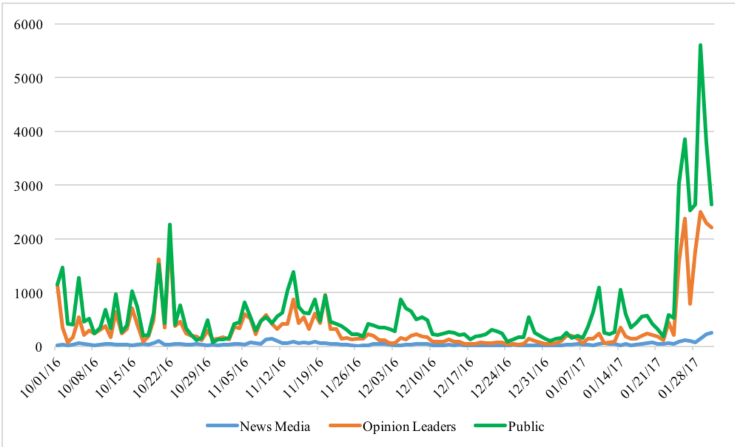


Figure 12: Republican retweet network.

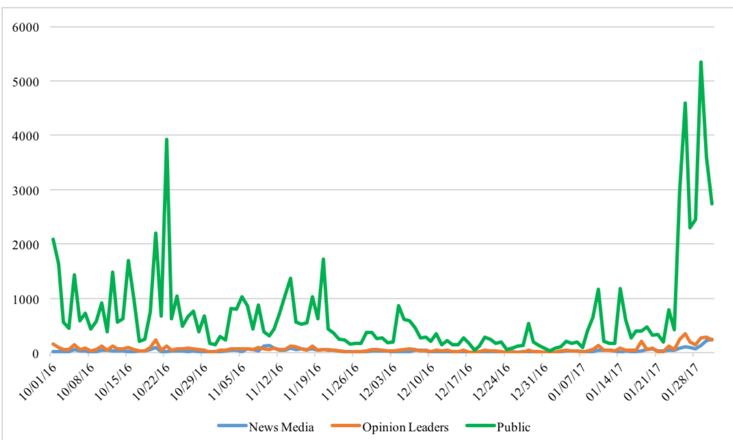


Figure 13: Republican mention network.

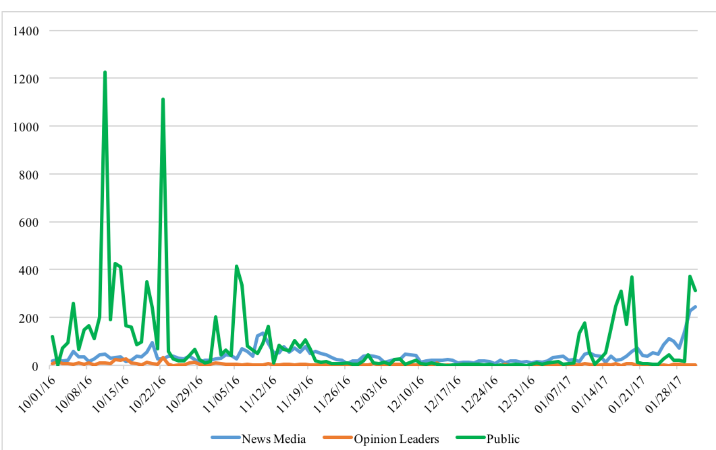


Figure 14: Entire Democratic network.

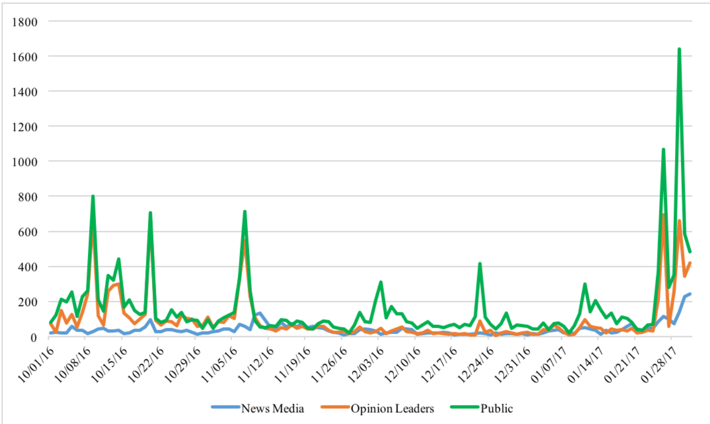


Figure 15: Democratic retweet network.

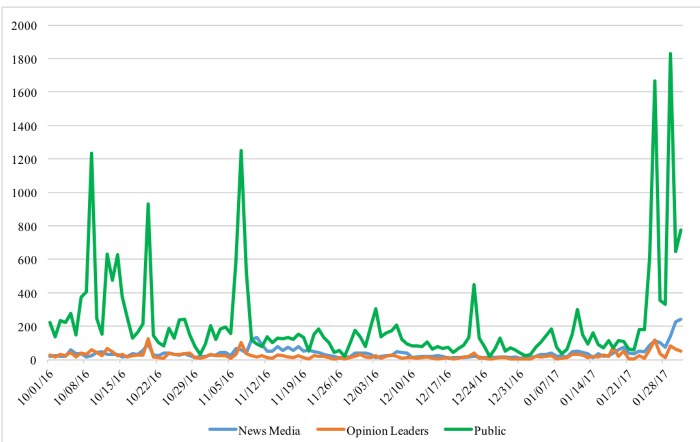


Figure 16: Democratic mention network.

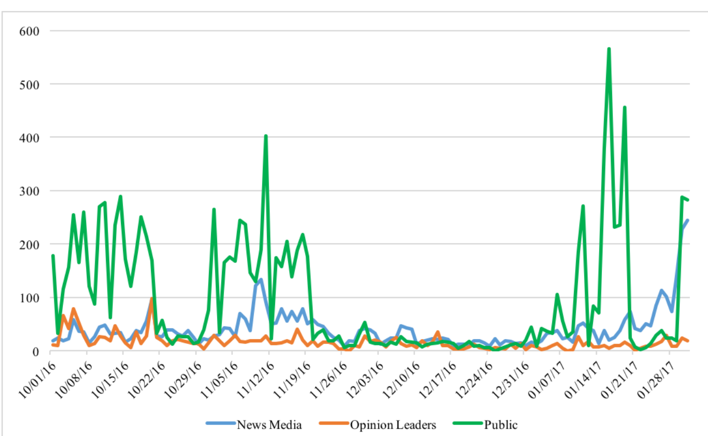


Table 26: Granger causality tests on Republican #immigration issue networks (second-level).

	Direction (From -> To)	Degree of Freedom	Chi-Squared value
Entire Network	News media -> Opinion leaders	5	0.960
	News media -> The public	5	1.283
	Opinion leaders -> News Media	5	0.799
	Opinion leaders -> The public	5	4.300**
	The public -> News media	5	0.732
	The public -> Opinion leaders	5	4.190***
Retweet Network	News media -> Opinion leaders	2	0.216
	News media -> The public	2	5.075**
	Opinion leaders -> News Media	2	0.329
	Opinion leaders -> The public	2	2.423*
	The public -> News media	2	0.917
	The public -> Opinion leaders	2	0.929
Mention Network	News media -> Opinion leaders	3	1.203
	News media -> The public	3	1.525
	Opinion leaders -> News Media	3	0.411
	Opinion leaders -> The public	3	2.301 ($p < .08$)
	The public -> News media	3	0.431
	The public -> Opinion leaders	3	1.106

*** $p < .001$, ** $p < .01$, * $p < .05$

Table 27: Granger causality tests on Democratic #immigration issue networks (second-level).

	Direction (From -> To)	Degree of Freedom	Chi-Squared value
Entire Network	News media -> Opinion leaders	3	0.313
	News media -> The public	3	0.235
	Opinion leaders -> News Media	3	0.208
	Opinion leaders -> The public	3	2.244 ($p < .08$)
	The public -> News media	3	0.507
	The public -> Opinion leaders	3	1.714
Retweet Network	News media -> Opinion leaders	5	1.502
	News media -> The public	5	0.481
	Opinion leaders -> News Media	5	0.810
	Opinion leaders -> The public	5	0.949
	The public -> News media	5	1.564
	The public -> Opinion leaders	5	2.455*
Mention Network	News media -> Opinion leaders	1	3.378*
	News media -> The public	1	4.531*
	Opinion leaders -> News Media	1	1.696
	Opinion leaders -> The public	1	0.274
	The public -> News media	1	0.017
	The public -> Opinion leaders	1	0.138

*** $p < .001$, ** $p < .01$, * $p < .05$

SUMMARY AND DISCUSSION

Agenda-setting effects among the news media, opinion leaders, and the public were diversified and multidimensional. A total of 54 time-series relationships were measured. Research question 18 asked the first-level agenda-setting effects (n = 18) and Research question 19 examined the second-level agenda-setting effects (n = 36). Among a total of 54 relationships, 27 relationships exemplified top-down agenda-setting processes (from news media to opinion leaders / from news media to the public / from opinion leaders to the public), while the other 27 relationships demonstrated bottom-up agenda-setting effects (from opinion leaders to news media / from the public to news media / from the public to opinion leaders). A total of 10 significant top-down agenda-setting effects (10/27) and eight time-series bottom-up agenda-setting effects (8/27) were found by Granger causality tests.

To some degree, the news media set agendas for opinion leaders and the public, initiating traditional top-down processes. Of 18 total relationships initiated by news media, four significant relationships were found (4/18). As information resources in the intermedia agenda-setting process, news articles published in traditional news media outlets were embedded on tweets and transferred by Twitter users. Thus, hypothesis 6 was partly supported.

In a total of six significant cases, the news media and opinion leaders were found to influence the issue agenda of the public. In the Republican retweet network, the agenda of the public was influenced by both news media and opinion leaders; in the Democratic mention network, the news media set the agendas of both opinion leaders and the public, showing a clear top-down process. This top-down relationship suggests that many Twitter users may still perceive news media as a reliable information resource, even though other information sources such as blogs have gained increasing power in the age of social media. Also, the public relied on opinion leaders as information sources.

Opinion leaders could initiate agenda-setting process to the public and the news media, which can be categorized as top-down and bottom-up agenda-setting effects, respectively (7/18). Among nine possible top-down agenda-setting effects initiated by opinion leaders, six instances of top-down effects (including two marginally significant effects) were found. This finding suggests that Twitter opinion leaders were highly successful in attracting the attention of their followers. However, among another nine bottom-up agenda-setting effects initiated by opinion leaders, only one instance was found, suggesting the possibilities that (1) the news media agenda was rarely influenced by opinion leaders and (2) opinion leaders focused more on attracting the public in terms of agenda-setting process. Hypothesis 7 was supported partly, but presented the higher chance of setting the public agenda than the news media agenda.

Among a total of 18 cases, 7 significant time-series relationships initiated by the public were found. The public set the agenda of opinion leaders in five cases. Specifically, Twitter opinion leaders and ordinary Twitter users were also closely related, showing three mutual agenda-setting effects in the first-level retweet and mention (marginally significant) networks as well as in the entire second-level Republican network. This finding indicates a close association between these two types of Twitter. This result is similar to the finding of Russell Neuman et al. (2014) that Granger causality revealed a reciprocal agenda-setting relationship between traditional and social media. In this study, social media was considered as a networked public sphere for discussing social issues like US immigration policy, and Twitter opinion leaders and ordinary users performed mutual agenda-setting for one another.

The public set the agenda of news media directly, showing a reversed agenda-setting effect in two cases (the first-level entire and retweet networks). This is consistent with the Gruszczynski and Wagner's (2017) finding that the public can affect news organizations' agendas. Scholars (Russell Neuman et al., 2014; Gruszczynski & Wagner, 2017) have also argued that the transfer of salience among news media and the public is multidirectional, and the present study confirms this view. In some sense, the public is not a passive recipient of news media: some highly active users consumed information, distributed it, and thereby earned their reputation through Twitter, as illustrated by the example of highly retweeted users (e.g. @bfraser747 & @SandraTXAS) in the retweet network. Hypothesis 8 was partly supported.

The results of second-level agenda-setting tests highlighted the activeness of Twitter users who were conservative or supported stricter immigration policies. A total of five significant relationships (including one marginally significant relationship) were detected in the conservative network, while a total of four, including one marginally significant association, were found in the democratic network. The public (or ordinary Twitter users) in the Republican network were recipients of agenda-setting effects from traditional news sources and opinion leaders. Numerically, conservative tweets (*n* = 121,262) outnumbered democratic ones (*n* = 31,395), showing active participation among conservative users in the US immigration issue network like findings of Conover et al., (2011) and Barberá (2015). The presence of highly active public users who recorded high degree centrality scores (e.g. @bfraser747 & @SandraTXAS) supported activeness of conservative public. Inbar, Pizzaro, & Bloom (2009) argued that conservatives tended to be more sensitive than liberals to perceived threats to their group identity; conservatives' disapproval and wariness toward US immigrants were reflected in their Twitter activities.

Also in second-level agenda-setting clusters, tweets posted by the public showed more spikes compared to news media and opinion leaders. For example, when President Trump announced the travel ban at the late January, a large amount of tweets was posted by the public, compared to different time periods when the longitudinal changes of the number of news articles reported by news media and tweets posted by opinion leaders and the public were comparably parallel. Ordinary Twitter users who have more personal relevance might retweet other tweets posted by sources they perceive as credible, and they also mention other users who might have personal relevance.

Republican Twitter users were also active in initiating mutual agenda-setting effects between opinion leaders and the public. Especially in the entire and retweet networks, such mutual agenda-setting effects were detected. The entire network consisted of tweets, retweets and mentions, and it could allow the author to observe overall agenda-setting effects. Retweet networks were shaped to disseminate more information to followers and based on the activeness of Twitter users who were conservative or supported stricter immigration policies, opinion leaders and the public transfer their opinions actively using retweet functions. Flores (2017) analyzed Twitter data discussing

SB 1070 (The Support Our Law Enforcement and Safe Neighborhoods Act) and found that anti-immigration sentiment on Twitter was driven by specific groups of active Twitter users who motivated inactive users to post negative messages about immigrants. The finding suggested by Flores (2017) can be supported by the present study, which can explain the activeness of opinion leaders who interacted with the public.

Six significant agenda-setting effects were found in each network, which can be summed as 18 out of a total of 54 relationships. While more than half of significant agenda-setting effects were bottom-up processes in the entire (n = 4) and retweet (n = 3) networks, only one bottom-up and reversed agenda-setting effect was detected in the mention network, evidenced by a significant effect from the public to opinion leaders in the entire mention network. Also, news media set the agenda of the public in the entire and Democratic mention networks, indicating traditional top-down agenda-setting effect. The mention network is oriented to entice other Twitter users into discussions, and in order to offer informative and persuasive information to others, users can rely on traditional news sources and opinion leader tweets by embedding hyperlinks of traditional news sources and opinion leaders’ tweets while mentioning others on tweets.

Chapter 7: Discussions, Conclusions and Implications

This study is a comprehensive examination of Twitter issue opinion leadership and agenda-setting effects on Twitter. It comprises three steps: 1) social network analysis to detect opinion leaders who had a high level of in-degree centrality scores (the number of inbound links sent to each node) and to observe divisions of Twitter conversations into a variety of groups based on similar characteristics among clusters in the retweet, mention, and hashtag networks; 2) hierarchical linear regression analyses to understand predictors of opinion leadership and the frequency of being retweeted; and 3) time-series Granger-causality tests to investigate the directions of agenda-setting effects on Twitter issue networks among three main groups (news media, opinion leaders, and the public).

The author employed DiscoverText, Twitter open API (Application Programming Interface), to glean tweets that included the hashtag #immigration through a 4-month period from October 1, 2016 to January 31, 2017 (n = 397,655). This four-month period encompassed the month before the election of Donald Trump, the three months leading to his inauguration, and the first days of his administration. This study differentiated retweet and mention networks to provide a more detailed understanding of network shapes and different characteristics of opinion leaders.

The author chose US immigration policy as a case study to discover network structures and the role of opinion leaders who could lead the discussion in the network. US immigration policy is a highly contested issue between groups who support more humane immigration policies (whose political orientation is usually liberal and pro-immigration) and others who seek stricter restrictions on entrance to the US (whose political orientation is usually conservative and anti-immigration) on Twitter.

DETECTING OPINION LEADERS AND NETWORK STRUCTURES

Research question 1 explored the visual representation of the retweet and mention networks, and research question 2 inquired about the degree of divisions among clusters in each network. Both research questions were exploratory and descriptive; their purpose was to understand the visual structure of the retweet and mention networks. These research questions did not address the causes that led to the structures of these networks. The author aimed at drawing visual figures of two networks and measuring modularity scores of each network to understand how clusters in the networks were divided. Pew Research Center (2014) suggested various types of networks, and the author identified that the retweet network can be classified as a polarized network, and the mention network can be described as a community cluster. While two political groups were presented in the retweet network (Figure 1), the mention network looked like a bicycle tire, with Twitter accounts with high in-degree centrality scores located at the center, and lines extending outward like spokes connecting these accounts to various other groups (Figure 2).

For RQ1 and RQ2, the author expected that retweet and mention networks would both be clustered, but that they would be clustered differently. First of all, the author expected that both networks would be divided into sub-groups based on political orientations. Second, the author predicted that because the reasons to retweet (to disseminate information) are different from the reasons to mention (to engage others into Twitter conversations), the network clusters would be organized differently. Both of these expectations were confirmed by visual representations of both networks. The network graph of the retweet network supported the belief that the retweet network would be divided into two large groups based on political orientations. Users often retweeted contents from mainstream media or Twitter elites (Paßmann, Boeschoten, & Schäfer, 2014) to endorse or criticize their ideas. Political agonism (we-they relationship), one of the main characteristics of the networked public sphere, appeared in the retweet network; conflicting ideas were prevalent on Twitter and the direct representations of agonistic expressions boosted diversity of ideas, but resulted in polarization. Thus, a division into two groups based on political orientations was expected and a network figure in the retweet network supported this assumption.

On the other hand, the mention network featured as a community network because numerous small clusters that focused on specific characteristics such as discussants' occupations, nationalities and news organizations related to US immigration policy were found. Users had different intentions to mention others. Mentioning is usually similar to an offline conversation among close friends and family who already share similar characteristics or who have had a mutual relationship (Bruns & Moe, 2013). Also, Twitter users mentioned celebrities or famous figures in a hope to engage them in conversations (Marwick & boyd, 2011b). Thus, diverse clusters based on multiple intentions to mention others could be expected in the mention network. A visual graph of the mention network (Figure 2) supported this assumption.

The author assumed Twitter constituted a networked public sphere where individual users connected with others based on similarities. These findings reaffirmed the view that homophily was a key to connect members in Twitter issue networks (Himelboim, McCreery, & Smith, 2013), indicating that clusters in retweet and mention networks were gathered based on similarities among users, such as political orientations (mainly in the retweet network), and types of occupations such as lawyers, politicians, educators, journalists, and government personnel. Himelboim, Smith, and Shneiderman (2013) introduced the selective exposure cluster (SEC) method, and this study applied it to observe the homophily among members. Methodologically, this study confirmed the SEC is applicable to the analysis of the Twitter immigration issue network. This study also supported the theory of homophily, evidenced by similar characteristics of members in clusters, especially in the retweet network.

Research question 3 examined characteristics of influential users including their verified status and their elite occupations to determine who are active influential users in each cluster. The author expected that the percentage of these influential users who were officially verified was higher those of ordinary users. Also, the author expected that such influential users had elite occupations, including academic organizations and scholars, politicians or governmental officials, lawyers, authors, journalists and news organizations, and social movement organizations. After conducting manual content analysis for the top 50 degree centrality scored accounts in each cluster (*n* of the retweet network = 15, *n* of the mention network = 47), the author found that the percentage of verified users was 26.7% for the retweet network, and 34% for the mention network, which is a higher percentage of officially verified users (0.061 %) in the entire Twittersphere. Moreover, 63.1% for the retweet network and 55% for the mention network were engaged in elite occupations, outnumbering ordinary citizens. Thus, top 50 users in each cluster were highly likely to be categorized as opinion leaders.

In the retweet network, activists and social movement organizations were found most. In the mention network, journalists and news organizations appeared most, which was in line with the finding by Chen, Tu, and Zheng (2017) examining types of actors on #PM2.5 (particulate matters with a diameter less than 2.5 micrometers). Influential users in each network were elite Twitter users who were active in Twitter posting or famous figures who got a large number of retweet and mentions endorsing their opinions. The higher percentage of influential users who were verified users and Twitter users with elite occupations indicated the public's high level of attention to celebrity and the public's reliance on other mainstream news sources, which can be considered as credible and valid information sources (Zhang et al., 2014). Higher percentages of verified users and users with elite occupations in both networks supported the author's assumption.

Research question 4 examined hashtag networks produced by co-occurrences with #immigration and other immigration-related hashtags. The author expected to observe that several hashtags would have ideologically related connections with the #immigration and further formed clusters. After extracting hashtag nodes which appeared at least 200 times (Borgatti, Everett, & Johnson, 2013), the author found five clusters with 212 hashtags from a total of 31,484 hashtags. The modularity score (.619) implies a high level of divisions among clusters shaped by hashtags sharing similar meanings. The main cluster consisted of a combination of politically liberal and conservative hashtags (e.g., #obama, #hillary for Democratic hashtags & #trump, #maga (Make America Great Again, President Trump's presidential campaign slogan), #tcot (Top Conservatives On Twitter) for Republican hashtags). There were no smaller clusters under this main cluster. An additional four clusters were found. Similarities across these four clusters included: (1) immigrants' interest in staying in the US and pursuing legal citizenship (ordinary citizens including #usa, #immigrants, #us, and #law), (2) liberal publics (e.g., #daca, #latism, #notmypresident, and #uniteblue), (3) protesters' interest in the borders between the US and Mexico (favoring a border wall or focusing on more humanitarian immigration policies including #mexico and #border), and (4) the interest in employment of US immigrants expressed through the hashtags #jobs, #economy, #visa, #trade, and #policy by hashtag posters (immigrants themselves who asked for helping find jobs and other individuals who tried to find jobs for immigrants). Like the retweet and mention networks, the hashtag network presented some divisions of clusters, indicating that Twitter users used hashtags that represented their interests. Basically, a pair of hashtags which co-occurred within a same tweet shared higher chance of similarity than randomly selected pairs of hashtags in the Twittersphere (Pöschko, 2011).

Research question 5 examined the distribution of in-degree centrality scores, and research question 6 inquired the distribution of the number of tweets each user posted in the issue retweet and mention networks. The author observed a skewedness of in-degree centrality scores and the number of tweets posted by individual users, examining whether a few individuals recorded higher in-degree centrality scores (RQ5) and whether a few individuals posted the majority of tweets in the retweet and mention networks (RQ6). Gini coefficients measure the skewedness of distributions. A value of zero 0 indicates perfect equality (every Twitter account recorded same in-degree centrality scores or posted same amount of tweets) and a value of 1 means maximal inequality (only one Twitter account recorded the highest in-degree centrality score or posted entire tweets). A value closer to 1 can visually represent a long-tail distribution.

The results indicated that while a few individuals recorded higher in-degree centrality scores than the rest of the members, individual participation in posting tweets with #immigration was not limited to a few individuals in the retweet and mention networks. Like the result of Research Question 3, a few individuals got more in-links from the rest of the members who occupied the majority of each network due to (1) the public's desire to have conversations and (2) the public's reliance on credible information sources from mainstream media and elite users. On the other hand, lower Gini coefficients for the number of tweets individual users posted indicated that every discussion participant had a chance to express their ideas equally on Twitter.

The author found evidence of a few key persons in an entire network based on the traditional concept of opinion leaders (Katz & Lazarsfeld, 1955). Also, the author confirmed that in-degree centrality scores can be used as a measure of opinion leaders in Twitter issue networks (Guo, Rohde, & Wu, 2018; Kim, 2007; Shi & Salmon, 2018; Valente, 2012). In terms of the number of tweets posted by individual users, the author also found that other users could equally participate in Twitter discussions, arguing that the number of tweets posted by individual users could not be a proper measure of opinion leaders. Twitters can be a networked public sphere that can be characterized as decentralized, egalitarian and participatory nature (Habermas, 1991; Benkler, 2006). Twitter is decentralized in the sense that any users can post tweets, but it is centralized in the sense that a few key persons whose tweets were retweeted and whose accounts were mentioned by others frequently, and these users' opinions were consumed by a large number of followers. This finding supports the traditional concept of opinion leaders.

PREDICTING OPINION LEADERSHIP

Research questions 7 and research question 8 investigated the associations between Twitter's communication affordances (the number of hashtags and mentions) and opinion leadership in the retweet and mention networks. Hypotheses 1, 2, 3, and 4 and research question 9 examined the predictive powers of contextual factors on opinion leadership in both networks. Hypothesis 5 tested the association between individual issue involvement and opinion leadership. Individual issue involvement was measured by the average number of tweets users posted with #immigration. The author expected statistical associations between contextual factors, and individual issue involvement, and opinion leadership. Research question 10 examined the strongest predictor of opinion leaders in both networks. Among several centrality scores, in-degree centrality calculated by social network analysis was used to measure individual opinion leadership because it can measure popularity by focusing on in-links from others, evidenced by RQ5.

The result of hierarchical linear regressions indicated that the number of followers, verified status, users' elite status measured by knowledge-intensive occupations and individual issue involvement were common predictors of opinion leadership in the retweet and mention networks, supporting H2, H4, and H5. Twitter users perceive that a large number of followers, officially verified status, and users' elite occupations determined opinion leadership. Officially verified users in social media were individuals who had verified accounts that signaled that they were famous or of public interest. This finding supports Han and Wang's (2015) argument that verified users were credible and occupied the dominant position in diffusing information on social media. Also, Chen, Tu, and Zheng (2017) found a positive relationship between elite occupations like professional and political elites and media workers, and higher in-degree centrality scores. This study found a positive relationship between the number of followers and in-degree centrality scores, like previous studies (Chen, Tu, & Zheng, 2017; Bakshy et al., 2011). The more followers users have, the more likely their message reaches its intended audiences. This finding supported the presence of Twitter opinion leaders, who have been explained by traditional theories of opinion leadership: a few key persons who were credible (being officially verified), knowledgeable (having elite occupations), and gregarious (having a large number of followers) (Katz & Lazarsfeld, 1955; Park, 2013).

Basically, ordinary person relied on experienced and knowledgeable individuals for advice (Boster et al., 2011). Authors, journalists, or bloggers with elite occupations published their works, and followers could find assurance of reliability by encountering these works on Twitter and reading biographical information on the authors' Twitter profiles. Users especially retweet breaking news and trending topics (boyd, Golder, & Lotan, 2010), produced by Twitter accounts of news organizations or journalists, suggesting the public reliance on elite information sources. Wu et al. (2011) found that authors and bloggers on Twitter played a significant role in mediating niche information from the mass media to the public. Open participation among bloggers allowed individuals to play “an active role in the process of collecting, reporting, sorting, analyzing and disseminating news and information” (Lasica, 2003, p. 71). Thus, bloggers shared similarity with the traditional opinion leaders as mediators of information from the news media to the public.

The positive relationship between the number of followees and opinion leadership was found only in the retweet network, while the number of tweets and followees were not associated with opinion leadership in the mention network. The mention network is a form of directed communication, and it is usually oriented toward expanding Twitter conversation. Users who received more “mentions” than others did not need to post a large number of tweets: if they are already famous, they might be mentioned more than others due to users’ desires to make conversation (Marwick & boyd, 2011b; Bruns & Moe, 2013). The number of followees (the number of people users follow), in itself, the potential information resources for Twitter users by following other’s accounts and consuming their tweets, was not associated with opinion leadership in the mention network. Existing relationships (having mutual acquaintances such as colleagues, friends and family) and the user’s popularity, factors out of the Twitter networks, can be decisive factors in being mentioned by others, further determining opinion leadership.

In answering RQ10, the most significant predictor among independent variables was individual issue involvement, which indicated that US immigration policy could significantly affect some Twitter users' lives. Hashtags can be used for Twitter users to find relevant discussions on specific issues (Chang, 2010), so opinion leaders need to know how to use hashtags proficiently. The finding of a positive relationship between issue involvement and opinion leadership was in line with Xu et al. (2014) which emphasized the association between users' issue involvement and leadership roles. On the other hand, like RQ6, Twitter activeness, measured by the total number of tweets, did not influence opinion leadership. While the total number of tweets was negatively associated with opinion leadership in the retweet network, there was no significant relationship between the total number of tweets and opinion leadership. The key to becoming an opinion leader in the Twitter issue network is to post relevant tweets in the network with hashtags. While some scholars (Bakshy et al., 2011; Park & Kaye, 2017) argued that opinion leaders frequently posted tweets regardless of the topic, this study discovered that Twitter users who posted topically relevant tweets (as opposed to a large quantity of tweets) were more likely to be opinion leaders.

Specifically, some Twitter elite users who have more expertise or in-depth knowledge on given issues can attract followers. Twitter users appeared less willing to consider active users who posted large numbers of tweets in general but had widely disseminated interests in other areas (e.g., same-sex marriage, gun control, or tax) as reliable discussion partners. Some general Twitter discussants can be actively involved in Twitter discussions of US immigration policy because some changes in immigration policy may have "significant consequences for their own lives" (Apsler & Sears, 1968, p. 162). Merton (1957) argued that people who exerted influence in discussing "local issues" differed from those who were influential in “cosmopolitan spheres.” Merton’s (1957) argument showed that it is possible to define the traits of opinion leaders in different ways. Some define opinion leadership based on generalized traits, while others define opinion leadership in more specialized ways based on their discussions of specific issues. Consistent with Merton’s (1957) argument, this study found that a focused and in-depth discussion about a specific issue was less likely to happen when discussants had broad interests rather than in-depth knowledge about the topic at hand. In addition, the influence of opinion leaders on social media was topic-sensitive, which means that opinion leaders had expertise in their own specialized areas (Shi & Salmon, 2018; Weng et al., 2010). This study supported that a large amount of general discussions about multiple issues could not guarantee opinion leadership status; more involvement in discussions of one specific issue matters.

The author differentiated the unit of analysis between Twitter users and tweets. The author expected to find statistical associations between the number of hashtags and mentions (Twitter communication affordances. RQ11 and 12), tweets posted by verified and elite users (contextual factors. RQ13 and 14), and the characteristics of tweets (content factors. RQ15, 16, and 17), and the frequency of being retweeted.

To answer those research questions, the author conducted an additional hierarchical linear regression analysis to measure the influence of the number of hashtags and mentions, contextual factors, and content factors on the frequency of being retweeted. The results indicated that the number of hashtags and mentions on tweets, and tweets offering personal opinions were all positively associated with the frequency of being retweeted. Using more hashtags and mentioning more people on a tweet indicate a higher chance to be detected by other users, leading them to retweet it when they consider it is worth to share with their followers (Wang et al., 2016). Also, the positive relationship between verified users and opinion leadership was confirmed in Weibo, a Chinese social media (Han & Wang, 2015). Traditional opinion leaders could interpret media messages based on their personal perspectives and disseminate them, ultimately influencing other's opinion and behaviors (Katz & Lazarsfeld, 1955). Tweets which offered personal information might be opinionated, supporting US immigration policy or asking for stricter immigration regulation. US immigration policy is an opinionated issue, and the author found polarized or clustered discussion networks in the network structure in RQ1. Users might retweet other tweets which were in line with their ideas, suggesting a possibility of tweets with personal opinions to be retweeted frequently. Such retweet behavior could lead to the formation of filter bubbles by retweeting tweets with like-minded ideas.

LONGITUDINAL AGENDA-SETTING EFFECTS AND OPINION LEADERS

Research question 18 and research question 19 examined the first-level and second-level agenda-setting effects in the entire, retweet and mention networks, respectively. Hypothesis 6 tested top-down agenda-setting effects initiated by news media. Hypothesis 7 tested the role of opinion leaders as agenda-setters to news media (bottom-up) and the public (top-down). Hypothesis 8 tested bottom-up agenda-setting effects initiated by the public. Among a total of 54 relationships, 27 relationships could belong to top-down agenda-setting processes (from news media to opinion leaders / from news media to the public / from opinion leaders to the public). The other 27 relationships were categorized into bottom-up agenda-setting effects (from opinion leaders to news media / from the public to news media / from the public to opinion leaders).

The author tried to link Twitter opinion leaders to agenda-setting. Brosius and Weimann (1996) originally suggested the role of early recognizers in the traditional agenda-setting process and Weiss-Blatt (2015) conducted time-series analyses to find opinion leaders' agenda-setting effects in the blogosphere. The networked public sphere can feature multiple and intertwined information flows initiated by individual curators who perform as active selectors and shapers of digital contents (Thorson & Wells, 2015).

The results discovered 18 significant agenda-setting effects among a total of 54 relationships. 36 cases were not significant. In the mention networks of the second-level agenda-setting, no reversed-agenda-setting was found. Also, fewer significant relationships were detected in Republican (n = 5) and Democratic (n = 4) agenda-setting effects than the first-level agenda settings (n = 9). Among them, a total of 10 significant top-down agenda-setting effects and 8 bottom-up agenda-setting effects were found. All hypotheses were supported partly, indicating that there was no fixed direction of setting the agenda in the issue network.

Like the traditional definition of agenda-setting, news media and opinion leaders could be sources of the agenda, initiating top-down agenda-setting effects. Top-down relationship suggested that many ordinary Twitter users still perceived news media and opinion leaders as a reliable information resource. First, Twitter opinion leaders might concentrate on attracting followers to persuade them to do specific activities, such as signing petitions or participating in protests like the Occupy Wall Street protest (#OWS), mobilizing the public (Park, 2013). This finding confirmed the traditional concept of opinion leadership. Also, ordinary Twitter users might be exposed to online news in the form of hyperlinks in tweets combined with personal opinions suggested by opinion leaders on Twitter, which spurred them to follow news media and opinion leaders.

However, news media and opinion leaders could be influenced by ordinary Twitter users. In this study, individual Twitter users posted tweets to support US immigrants or criticize them. Journalists can monitor such tweeting activities and use them as news sources by citing users' tweets and utilizing their opinions in the news (Kim et al., 2015). Murthy (2011) also argued that tweets posted by the public played a prominent role in producing and disseminating breaking news about disasters, because ordinary citizens can use their mobile devices to post tweets rapidly in response to breaking news moments. Twitter can facilitate distribution of user-generated contents that could affect the news-making process (Bruno, 2011). Specific story could be reported by ordinary Twitter users firsthand and grab the attention of others, including journalists (Bruns & Highfield, 2015).

In terms of second-level agenda-setting, Republicans and Twitter users who requested stricter immigration policies were active in Twitter. Tweets posted by Republican users (n = 121,262) outnumbered Democratic ones (n = 31,395). Conservative people have voiced concerns about US immigrants because they assume that immigrants threaten traditional American values (Suro, 2009). Also, Flores (2017) detected specific groups of active Twitter users such as advocates who had direct interests in US immigration policy, and individuals who drove anti-immigration sentiments. The finding in this study that Republican opinion leaders were active in setting the public agenda (3 out of a total of 3) could support active Republican Twitter users who are critical of US immigration policy. Also, Yoo, Kilgo, and Johnson (forthcoming) found a positive association between conservative Reddit users and opinion leadership personalities measured by the personality strength (PS) scale (Noelle-Neumann, 1985). On Reddit, a social news site, some subreddits (forums oriented to a specific topic on Reddit) with memes were used to promote Trump or criticize Hillary Clinton (Hale & Grabe, 2018), being dominated by conservative users. Like Reddit, Twitter was filled with active, conservative Twitter users who wished to take on opinion leadership roles, evidenced by @bfraser747 and @SandraTXAS. Those two Twitter accounts were not officially verified but they recorded the top 2 high centrality scores in the retweet network. They produced tweets to support stricter immigration policy and show their aversions toward US immigrants, dominating the retweet network.

METHODOLOGICAL IMPLICATIONS

This study contributes to Twitter opinion leadership studies by developing a systematic procedure to explain the position of opinion leaders. This study could be described as a holistic methodology in opinion leadership studies by combining three methodologies. All methodologies used in this study worked together. Three methodologies, social network analysis, hierarchical linear regressions, and time-series Granger-causality tests were linked to explain opinion leaders in Twitter issue networks.

The author followed previous scholars who conducted social network analysis to detect opinion leaders (Choi, 2015; Kim, 2007, Xu et al., 2014), re-affirming the explanatory power of social network analysis in Twitter issue network. While many opinion leadership studies have relied on surveys to assess causal relationships among variables gathered by self-reported data, survey data is not free from self-report bias due to its reliance on survey participants' memories and individual overrepresentation as opinion leaders (Kim, 2007). In contrast, social network analysis can examine actual relationships shaped by Twitter conversations with a higher degree of accuracy, detecting influential users in the network. Also, social network analysis was used to provide detailed explanations of Twitter usages by focusing on the assumption that two networks had different purposes (retweet network: disseminating information & mention network: expanding Twitter conversations). Thus, this study could minimize bias and arbitrariness initiated by conducting a social network analysis only.

The author used the results of social network analysis for further studies that examined predictors of opinion leadership and agenda-setting processes among news media, opinion leaders, and the general public on Twitter. In-degree centrality scores calculated by social network analyses were used as dependent variables in hierarchical linear regression based on a large set of data. Because social network analysis observes relations between nodes, ordinary statistical analysis based on the assumption of independence among variables cannot be applicable (Choi, 2012). Thus, the author chose a hierarchical linear regression analysis to focus on individual characteristics extracted from Twitter metadata and explained the association between each independent variable and opinion leadership in a direct manner. Lastly, the results of social network analysis and hierarchical linear regressions were also linked to longitudinal Granger causality tests by operationally defining opinion leaders as users who were officially verified and scored top 10% of in-degree centrality scores.

THEORETICAL IMPLICATIONS

This study extends our understanding of opinion leaders based on traditional theories including two-step flow of information and agenda-setting effects. First, this study confirms pre-existing theories and yields new insights regarding opinion leaders. The result stated that the number of followers, verified status, and elite status of each user were significant predictors of opinion leadership. Based on RQ5, the retweet and mention networks were highly skewed by a few Twitter users who recorded high in-degree centrality scores, suggesting a presence of a few opinion leaders. Such a few key persons in the networks were socially credible (being officially verified), knowledgeable (having elite occupations) and gregarious (having a large the number of followers, Katz & Lazarsfeld, 1955), confirming the pre-existing definition of opinion leaders. Also, traditional theories of agenda-setting effects have assumed a top-down transfer of issue salience from the news media to the public. News media and opinion leaders did set the agenda of the public in 10 out of a total of 18 cases and remained influential as information resources.

On the other hand, this study suggested new insights regarding agenda-setting effects. The results of longitudinal Granger-causality tests indicated that agenda-setting should not be considered a unidirectional top-down process. Rather, this study demonstrated multiple directions of agenda setting initiated by news media, opinion leaders, and the public, like the findings of previous studies (Russell Neuman et al., 2014; Gruszczynski & Wagner, 2017). News media, opinion leaders, and the public all have the potential to set the agendas of others. Reversed agenda-setting effects (from the public to opinion leaders, and then to news media) were found in a total of 8 out of 27 cases, especially for the entire retweet network measuring the first-level agenda-setting effects.

Also, three mutual agenda-setting effects between opinion leaders and the public (circular agenda-setting processes in which opinion leaders set the agenda of the public, and the public, in turn, influenced opinion leaders' agenda) suggest that both opinion leaders and the public rely on each for issue saliences in the agenda-setting process. The circulation of issue salience was active among Twitter opinion leaders and the public. Through this circulation, rapid transfers of news and other forms of information like editorials on tweets could happen, influencing each agenda.

Based on the assumption suggested by Brosius and Weimann (1996), who emphasized the role of early recognizers in mediating agenda-setting effects between the news media and the public, this study added Twitter opinion leaders to the classic agenda-setting process to examine the possibilities of new diversified agenda-setting patterns. This is one of the very first studies to combine two-step flow of information and agenda-setting effects on Twitter. While some studies considered agenda-setting effects between traditional news media and social media (Conway et al., 2015; Groshek & Groshek, 2013; Russell Neumann, et al., 2014; Vargo et al., 2014) and blogs (Meraz, 2011), the author added Twitter opinion leaders between the news media and the public. While some scholars have raised doubts about the presence of opinion leaders online by arguing for a direct one-step flow from niche media to the public (Bennett & Manheim, 2006), this study asserts that a few key opinion leaders still exist on the Twittersphere. These opinion leaders were officially verified and initiated agenda-setting effects from the news media to the public, and reversed agenda-setting effects from the public to the news media. This study suggested the explanatory power of classic agenda-setting effects and two-step flows of information on Twittersphere, a social media platform where multiple directions of agenda setting were found.

Lastly, this study offered detailed understanding of "influence" by discriminating between individual opinion leadership and the frequency of being retweeted. Two different units of analysis allowed the author to measure the concept of influence on Twitter. In-degree centrality and the frequency of being retweeted were used to measure the influence of individual persons and tweets, respectively. The findings of this study, which pursued a detailed understanding of opinion leadership and posting activities, suggested several ways for a Twitter user to be influential. These ways include being socially verifiable persons who have a large number of followers; getting involved in discussions about specific issues; using hashtags, and mentions frequently, and posting personal ideas to disseminate their messages widely.

In addition, this study broadened the range of agenda-setting studies by focusing on one specific issue: US immigration policy. While agenda-setting studies have traditionally focused on the public responses selecting "What is the most important problem facing this country (MIP)?" among multiple issues (McCombs & Shaw, 1972) as a measure of public salience, some scholars narrowed down to one issue and examine the agenda-setting process around it, such as the issue of immigration reform (Dunaway, Branton, & Abrajano, 2010), same-sex marriage (Hester & Gibson, 2007), economy (Lee, 2015), mass shooting (Jashinsky et al., 2017), and the association of race and school shooting (Park, Holody, & Zhang, 2012). This study concentrated on agenda-setting effects about US immigration policy, suggesting the presence of a few opinion leaders and reversed agenda-setting effects in issue networks.

PRACTICAL IMPLICATIONS

This study found that active Twitter users can set agendas regarding US immigration policy. Immigration campaign organizers or social movement activists might consider recruiting such Twitter opinion leaders to promote or disseminate information to target audiences. Such leaders may be engaged in academic occupations, or they may be who provide credible information and expertise on the issue of immigration for their followers; they may be affiliated with social movement organizations; or they may be ordinary citizens who are active in Twitter discussions. This study suggested that more use of hashtags, mentions, and tweets to offer personal opinions were (marginally) associated with the frequency of being retweeted. For ordinary Twitter users, or for immigration activists who want to promote their ideas widely, proper uses of Twitter affordances (such as mentions and hashtags) can expand their readership. The use of hashtags that were chosen deliberately by users could lead others to identify ad hoc discussion groups (Wang & Fikis, 2017). More usages of hashtags and mentions can lead tweets to be retweeted by a large number of Twitter users. Also, it is helpful to express personal opinions frequently, rather than merely posting facts on tweets. Social elites, such as immigration lawyers and academic scholars, have an advantage of giving personal opinions on Twitter, due to their expertise in US immigration policy, access to information resources, and communication skills.

In addition, the negative association between general Twitter activities and opinion leadership and the positive association between issue involvement and opinion leadership indicated that Twitter discussants need to concentrate on the specific issues being discussed in the hashtag network. This means that the individuals who focus on one issue would be more influential than others who tweet about multiple issues. For social movement organizations and activists, such findings gave ideas of how to make effective user of Twitter. To promote their activities through Twitter, they need to show their consistent devotion to US immigration issues by actively tweeting personal but persuasive ideas. Also, the mix of #immigration with other hashtags with political orientations could expand Twitter discussions, by attracting more users who had similar interests in US immigration policy.

This study also emphasized that journalists and news organizations should pay attention to public Twitter activities. The finding that both Twitter opinion leaders and ordinary Twitter users can be agenda-setters in the issue networks suggests that the direction of information flow is not a simply top-down process. Journalists and traditional news media organizations need to pay attention to public Twitter discussions in order to understand the opinions of members of the Twitter public to specific issues; these discussions can be further developed into potential news sources (Kim et al., 2015).

In sum, this study provided a guideline to understand opinion leadership in the new media environment of Twitter. Methodologically, this study offers a systematic process (detecting opinion leaders, examining their characteristics, and analyzing agenda-setting effects) based on voluminous social media data. This study chose US immigration policy as a case study, and theoretically, Twitter discourses about this controversial issue confirmed several pre-existing theories, like clustered networks in the network public sphere and a discussion dominated by a few opinion leaders suggested by traditional two-step flows of information. However, Twitter voluminous data offered new insights supplementing traditional theories, like multi-directional agenda-setting effects. In practical terms, this study suggested several ways to be influential on Twitter to promote their ideas to a wide range of audiences, ultimately contributing to US immigration discourses.

LIMITATIONS AND FUTURE RESEARCH

Despite these theoretical and practical contributions, this study is not free from limitations. The biggest challenge of this study is a lack of demographic information about Twitter users. Only metadata purchased through DiscoverText was incorporated into this study; this includes the profile of the account, the number of followers of accounts, the number of following accounts, hashtags, Twitter messages, and verified status attached to each tweet. While this study relied on elite status as a proxy for education level, such classifications could not explain all the demographic characteristics associated with users. No exact personal information such as gender, age, ethnicity and income level was found in the metadata gathered by DiscoverText due to the possibility of secondary accounts that were used for organizations or administrations, being described on Twitter profiles. Without demographic variables, it is difficult to generalize results to the general Twitter population or to determining differences between different genders, races, and ages (Salkind, 2010). For future, profile photos can be used to extract demographic variables to roughly measure demographic variables, such as gender, age and race. Similarly, the author equated "ordinary Twitter users" with "the public" when analyzing agenda-setting on Twitter. Due to the limited demographic data available, this study offered an incomplete understanding of public discussions and opinion leadership about immigration issues on Twitter.

Also, the author focused only on the Twittersphere; the characteristics of Twitter opinion leadership cannot explain other opinion leaders in different social media platforms. The author chose Twitter as a main platform because Twitter can be examined as a public sphere that democratic engagement occurs (Murthy, 2013). The findings in this study might not be generalizable to other social media platforms such as Facebook. Even though Facebook has restricted access to users' personal data (Wilson, Gosling, & Graham, 2012), different contextual factors such as the number of friends and the frequency of posts can result in new relationships that this study could not explain. Such different forms of affordances indicate that measuring opinion leadership needs to be changed in different social media platforms. The result of this study could be generalized mainly to Twitter issue networks. Further research is needed to investigate opinion leadership in other social media platforms.

While immigration has triggered clustering based on political orientation on Twitter, the framework used in this study needs to be tested again with other issues such as same-sex marriage, gun control policy, and Black Lives Matter. They share similarity with US immigration policy in terms of clustered discussions between conservatives and liberals, so the methodological frame in this study can be applied to the analysis of opinion leadership on these issues. While this study can be generalized by studying other issues, this methodology may generate different results when users' opinions are affected by additional demographic variables not available for this study. For example, religion is likely to be associated with Twitter discussions of same-sex marriage, and race is likely to be connected to Black Lives Matter (#BLM) discussions. Lack of access to demographic data for Twitter users will remain as a limitation.

This study did not consider the usage of bots in creating tweets, although opinion leaders were contacted to confirm they were not bot. Some influential users might adopt algorithms or technology like bots to post tweets, retweet other tweets and mention other users on tweets. Pew Research Center (2018b) discovered that about two-thirds of tweeted hyperlinks to popular websites were posted by automated accounts. In this study, highly active users (e.g. @bfraswer747, and @SandraTXAS) created a large volume of tweets each day. While the author confirmed that both Twitter accounts were managed by ordinary citizens, future studies should consider impact of automated accounts in political discussions, as a way to influence ordinary Twitter user's opinions.

Lastly, the author relied on manual content analysis to analyze the influence of content factors on the frequency of being retweeted. While 1,116 randomly selected tweets could represent the entire retweet network, a computer-assisted content analysis could help with classifying tweets based on content factors (disseminating information, offering personal information and calling for specific actions). This study relied on a computational analysis to classify users' political orientation based on keywords on users' profiles for clustering and second-level agenda-setting studies, but more advanced computational methodology such as classification of words based on users' intention is required to classify content factors. Future studies could incorporate this suggestion by classifying the entire set of tweets using more advanced computational data analysis methods such as automated classifications of document using machine learning.

Despite these limitations, this study advances understanding of opinion leadership and the Twitter issue network. It finds that these Twitter opinion leaders exhibit characteristics similar to those of traditional opinion leaders, in terms of a few key persons who were credible. As flows of information are becoming more diversified, the answer to the question, "who sets the agenda on Twitter?," is "everyone." The findings of this study reinforce the validity of two theories within the field of communications—opinion leadership of which two-step flow of information is a part and agenda-setting—and confirm these theories' explanatory potential in a digital media environment.

Appendices

APPENDIX A – THE 5 NON-PARTISAN CLUSTERS IN THE RETWEET NETWORK

Clusters[6]	Twitter account	Bio	Degree	Verified?
Global immigration Workers (*n* = 1,795)	@WWICSReviews	WWICS Immigration Consultants provides Consultancy in Business Immigration, Student Visa, Permanent Resident, Skilled Worker Immigration and Work Permit Visa.	384	No
	@WorldBank	The official World Bank Twitter feed. The World Bank's mission is to end extreme poverty and promote shared prosperity.	245	Yes
	@simongerman600	German #geographer and #demographerin #Melbourne. Love #maps and #datathat explain how the #world works. Views my own.	118	No
	@GLD_Law	Davis & Associates are your Dallas immigration attorneys of choice. We care about families, not files.	108	No
	@GDXryerson	A think & do tank @TRSMRyersonU that identifies & amplifies links between prosperity, diversity & migration & anchors these in policy, research & practice.	102	No
U.K. & U.S. Immigration Workers (*n* = 1,359)	@Harryslaststand	Survivor of the Great Depression, RAF veteran Activist for the Welfare State Author of Harry's Last Stand Love Among the Ruins, 1923 & The Empress of Australia	562	Yes
	@GovBillWeld	Two-term governor of Massachusetts, Honorary Chair for @OurAmericaInfo, and 2016 Libertarian candidate for Vice-President.	546	Yes
	@pdacosta	Journalist. Economics and the Fed. Market News. International, @Forbes, @MarketWatch and more.	272	Yes
	@BrookesTimes	Political cartoonist for @TheTimes	108	Yes
	@Whippenz	Artist Seeking The Perfect Medium #Pacifist #Vergetarian #AnimalRights #TheResistance #DAESH I Will Not Buy Followers	107	No
Immigration workers & News media (*n* = 352)	@WashTimes	Built on traditional American values, delivering breaking news and commentary on the issues that affect the future of our nation.	614	Yes
	@CathieMarie2014	Educate yourself...don't just follow blindly. Take a stance on what is right. search the truth and you will find it.	335	No
	@drudgeheadlines	(empty information on bio)	305	No

[6] The author did not include (1) clusters that did not have similarities among members and (2) others that members were lower than 30 in the retweet network. A total of 5 clusters were not examined in this study.

Clusters	Twitter account	Bio	Degree	Verified?
	@supermorgy	Editor in Chief	289	No
	@mkopNY	Global strategist ~ American immigrant enthusiast ~ AI/Deep Learning Innovator ~ 2016 NYC Triathlon Team MS Member ~ Medalist 2017 Ellis Island Medal of Honor	229	No
Neutral Immigration workers (n = 293)	@anirb_das	Engineer. Building roads and bridges...literally! Supporter of skilled immigration reform	225	No
	@WeAreSIIA	Making America aware about the significance of skilled immigration again! #Immigration #I140EAD #GCBacklogs #AskForFairness	221	No
	@helpSiiA	Advocating for Skilled Immigrants' rights and their fair treatment in US. we are a 135k+ members growing grassroots organization.	220	No
	@USCISmediaTX	Press Officer for USCIS for Texas, New Mexico, and Oklahoma. Follow for #immigration info.	90	No
	@DHSgov	The #DHS Mission: "With honor and integrity, we will safeguard the American people, our homeland, and our values."	63	No
Global critics (n = 119)	@DailyRasp	#MAGA UN #Brexit #TRUDEXIT | I Israel | #Gab | https://www.minds.com/DailyRasp	32	No
	@CandiceMalcolm	Journalist, best-selling author, syndicated columnist for the Toronto Sun	31	Yes
	@amlozyk	Curiosity is one of the great secrets of happiness.	23	No
	@Joe_Meyer1	(empty information on bio)	22	No
	@breakinnewz1	Up to date USA Newz and from around the Globe. Not affiliated with any one reporting service. RT's do not necessarily equal endorsements. #MAGA#WalkAway	18	No

APPENDIX B – THE 24 CLUSTERS IN THE MENTION NETWORK

Clusters[7]	Twitter account	Bio	Degree	Verified?
Politicians & Washington D.C. based workers (*n* = 1,716)	@RushHolt	CEO, AAAS; Executive Publisher, Science; fmr. Member of Congress; physicist	381	No
	@CAPAction	Hard-hitting news + analysis paired with action on the issues that matter most. Working alongside @AmProg & @ThinkProgress.	251	Yes
	@HouseDemocrats[8]	House Democratic Caucus of the United States Congress.	238	Yes
	@benjaminwittes	Senior Fellow at Brookings. Editor in Chief: Lawfare (@lawfareblog). It was evening all afternoon. It was snowing And it was going to snow.	186	Yes
	@GOP	Join our team and get official updates from the Republican National Committee.	143	Yes
Politicians & immigration workers (*n* = 1,651)	@immcouncil	Through research, policy analysis, and litigation, we seek to shape a twenty-first century vision of the American immigrant experience.	317	No
	@MayorGimenez	Mayor Gimenez is Miami-Dade County's highest-ranking elected official & administrator. He oversees a government of 26,000 employees with a $7.8 billion budget.	233	Yes
	@FWD_us	Fixing the failed immigration & criminal justice systems that have locked too many out of the American dream for too long. Together we can move America forward.	229	Yes
	@marcorubio	US Senator for Florida. Follow @SenRubioPress for official updates. @TeamMarco for campaign updates.	195	Yes
	@SenatorSessions	(empty information on bio)	188	No
Immigration Services & mixed (*n* = 1,383)	@DHSgov	The #DHS Mission: "With honor and integrity, we will safeguard the American people, our homeland, and our values."	975	Yes
	@CustomsBorder	International Customs Modernization & Border Management Advisor contracted to the Border Management Task Force, Afghanistan.	542	No
	@USCIS	Official Twitter channel of U.S. Citizenship and Immigration Services	323	Yes
	@SpeakerRyan	Office of the 54th Speaker of the House, Paul Ryan.	235	Yes
	@DallasMetro360	Dallas and Ft Worth Texas Metropolitan Area. Great people , Great State, Great Football, Great Beef, Great Freedom, Great Industry&Tech, Its all good!!!	172	No

[7] The author did not include (1) clusters that did not have similarities among members and (2) others that members were lower than 30 in the mention network. A total of 11 clusters were not examined in this study.

[8] While there are some politically partisan Twitter accounts like (@HourseDemocrats, @GOP, and etc.), clusters having politically partisan Twitter accounts in Appendix were not politically opinionated. Also, some clusters consisted of liberal or conservative Twitter accounts, thus author could not identify political orientations of such clusters.

Clusters	Twitter account	Bio	Degree	Verified?
U.K. news media & politicians (*n* = 1,233)	@thetimes	The best of our journalism. Subscribe here: http://thetim.es/subscribe Speak to our customer service team	1,046	Yes
	@BBCr4today	@BBCRadio4 flagship news programme, on air 6-9am weekdays and 7-9am on Saturday. Talk about the programme #r4today	125	Yes
	@theresa_may	Prime Minister and @Conservatives Leader.	81	Yes
	@TheEconomist	News and analysis with a global perspective.	70	Yes
	@jeremycorbyn	Leader of the Labour Party.	51	Yes
CNN outlets & ordinary users (*n* = 1,089)	@CNN	It's our job to #GoThere & tell the most difficult stories. Join us! For more breaking news updates follow @CNNBRK	275	Yes
	@CathieMarie2014	Educate yourself...don't just follow blindly. Take a stance on what is right. search the truth and you will find it.	231	No
	@bdevil89	(empty information on bio)	160	Yes
	@costareports	National political reporter, @WashingtonPost; Moderator, @WashingtonWeek; Political analyst, @NBCNews and @msnbc	109	No
	@CNNPolitics	Political news, campaign stories and Washington coverage from CNN's political team.	101	Yes
Mixed & immigration workers (*n* = 1,068)	@thenation	The place for debate on the left.	376	Yes
	@TheBNN	Started in 2009, now the largest, most comprehensive local news media network covering 400 cities	350	No
	@NILC_org	Defending and advancing the rights and opportunities of low-income immigrants and their family members.	318	No
	@WhiteHouse	Welcome to @WhiteHouse! Follow for the latest from President @realDonaldTrumpand his Administration.	170	Yes
	@MarielenaNILC	Executive Director of @NILC_org & @ImmJusticeFund. Proud #Colombian#immigrant #Workers'/ #immigrants' rights attorney. Passionate re #civilrights& #justice	159	Yes
Canada (*n* = 969)	@JobSearchTech	(empty information on bio)	194	No
	@JustinTrudeau	Account run by the 23rd Prime Minister of Canada and staff… Compte géré par le 23e premier ministre du Canada et personnel.	169	Yes
	@AndyRodriguez	Regulated Canadian Immigration Consultant at Nexus Canada.	131	No
	@paceimmigration	We provide immigration representation in 32 languages to people from all over the world. If you have any questions about immigration, let us know.	123	No
	@HonJohnMcCallum	Canada's Ambassador to China	54	Yes

Clusters	Twitter account	Bio	Degree	Verified?
Vice President Mike Pence & African American activists (*n* = 439)	@mike_pence	Vice President of the United States	183	Yes
	@HR_PAC	After deaths of men of color in NY & the US #Action & #Justice are needed! We support those who support needs of OUR #Community #Jobs #Education	132	No
	@RNunezLawrence	#Entrepreneur #HigherEd Administrator #Professor #Progressive #PoliticalStrategist #NonProfit Management #Tech#ClimateChange #Fitness #Foodie	131	No
	@AfroLatinoAssoc	Afro-Latino Association for Policy & Advocacy Nonprofit to create awareness of #AfroLatino's & support public policy positively impacting Blacks, Latinos,& #POC	107	No
	@NYSHEPAC	Registered PAC in NYS, endorsing & campaigning for political candidates who support progressive #HigherEd policy while also supporting #Dreamers in #NYS	92	No
Immigration publishers (*n* = 412)	@cm_thompson3	writer for @MarshallProj. Tweets usually about prisons & immigration.	60	No
	@torchmktg	Lighting the way in b2b marcomms. Event Organisers and Support Services, Marketing Strategies, Video Production, Design & Print, Digital Media, PR, we can help.	54	No
	@ImmRefColorado	Chronicling Colorado's local news and breaking national news on the progress of immigration reform.	50	No
	@POLSBoulder	The most important news about politics in Boulder	50	No
	@POLSDenver	The most important news about politics in Denver	49	No
News outlets & mixed (*n* = 351)	@MSNBC	The place for in-depth analysis, political commentary and informed perspectives.	198	Yes
	@marty_walsh	Mayor, City of Boston. Tweets by staff with tweets from the Mayor signed MJW.	83	Yes
	@CFNAStLouis	We are focused on partnering with congregations to meet needs and proclaim Christ among immigrant and refugee people groups in the greater St. Louis region.	61	No
	@HuffPost	Know what's real.	54	Yes
	@NBCDFW	The first TV station in #Texas & the place to go for exclusive local stories, the latest breaking news, weather updates	42	Yes
News outlets (*n* = 260)	@Reuters	Top and breaking news, pictures, and videos from Reuters.	106	Yes
	@washingtonpost	Breaking news, analysis, and opinion. Founded in 1877	76	Yes
	@WSJ	Breaking news and features from the WSJ.	63	Yes
	@TheAtlantic	Politics, culture, business, science, technology, health, education, global affairs, more.	53	Yes
	@ImmigNewsDigest	Please send us social media-worthy #immigration news and stories, and we'll RT them. We also post immigration services using #CommunityBulletin.	36	No
Immigrants & Mixed (*n* = 233)	@MELANIATRUMP	The official profile for Melania Trump	1329	Yes
	@ElGerryChicago	Fauno del Peloponeso, más o menos. Basado en hechos reales.	118	No
	@bobwiederhold	(empty information on bio)	33	No

Clusters	Twitter account	Bio	Degree	Verified?
	@couchbase	The world's best open source database for building scalable, high performance web, mobile & IoT applications.	32	Yes
	@MichiganUnited	Fighting for our families on issues of #Labor #immigration #Environment & #Justice. Fighting against #Racism#inequality & #Greed in #Michigan	29	No
News & International activists (*n* = 217)	@FilipinoAmazing	#FilAm #Immigrant #FilAmsResist #FBR#SaveACA #DACA #Resist #FBRParty#TheResistance #BlueWave#BlueWave2018 #UniteBlue #P2 #CTL#StrongerTogether	145	No
	@guardian	The need for independent journalism has never been greater. Become a Guardian supporter: https://support.theguardian.com	127	Yes
	@OECD	The Organisation for Economic Co-operation & Development promotes #policies that improve people's #wellbeing around the world	124	Yes
	@JessicaValenti	Feminist author, @Medium columnist, Queens native. My bitch face never rests.	38	Yes
	@ub2bad2	Democrats Against Illegal Immigration	38	No
Eastern U.S. politicians & activists (*n* = 213)	@SenatorCollins	United States Senator from Maine. All tweets originate from the Press Office of Senator Susan Collins.	60	Yes
	@TheBuffaloNews	News alerts, headlines and notes from Buffalo's daily newspaper.	43	Yes
	@craigieonmain	The long-awaited #CraigieVeggie is officially here! Get it at the Craigie bar every Tuesday, 5:30pm until we run out.	15	No
	@tmaws	Oysters, pork belly, crispy skin, charred gristle, roasted bones, wife Karolyn and son Charlie are a few of my favorite things	13	No
Washington State based workers & mixed (*n* = 203)	@TrumpHotels	Iconic architecture, unrivaled views, bold design, entrepreneurial spirit and uncompromising attention to detail.	116	Yes
	@repjohnlewis	Congressman, Georgia's Fifth Congressional District	73	Yes
	@absolutelynot13	Mass organized resistance trumps fascism.	69	No
	@AGOWA	Official Twitter account of the Washington State Attorney General's Office	64	Yes
	@PramilaJayapal	Congressmember, WA 07. Bold, Progressive & Unafraid. Life long organizer for immigrant, civil & Human Rights. Proud mom!	35	Yes
	@TIME	Breaking news and current events from around the globe. Hosted by TIME staff.	8	Yes
Media outlets & Washington D.C based immigration workers (*n* = 193)	@MTV	snapchat/musical.ly/everything: mtv	189	Yes
	@Iam360WISE	Personal Account of Robert Alexander CEO Of @360WiseMedia #PR#Entertainment #Journalist #News#Business	165	Yes
	@BPC_TBrown	Theresa Cardinal Brown, Director, Immigration & Cross-Border Policy @BPC_Bipartisan. Opinions are my own; RT=interest,	21	No
	@ElectThis	Super PACs. Electoral College. Attack ads. You're sick of it, and so are we. This year, we're flipping the bird to the same old politics and saying: ELECT THIS.	21	Yes

Clusters	Twitter account	Bio	Degree	Verified?
	@BPC_Bipartisan	The Bipartisan Policy Center is a think tank that combines the best ideas from both parties to promote health, security, and opportunity for all Americans.	18	Yes
Tech companies (*n* = 179)	@Google	News and updates from Google	105	Yes
	@Apple	Apple.com	68	Yes
	@tim_cook	Apple CEO Auburn Duke National Parks "Life's most persistent and urgent question is, 'What are you doing for others?'" - MLK	65	Yes
	@facebook	Give people the power to build community and bring the world closer together.	51	Yes
	@sundarpichai	CEO, Google	19	Yes
California based Politicians & figures (*n* = 165)	@kdeleon	Officially Endorsed Candidate for U.S. Senate by the California Democratic Party (@CA_Dem). Current State Senator; Fmr. CA Senate President pro Tempore.	85	Yes
	@flySFO	Official Twitter account of San Francisco International Airport (SFO) - Gateway to the Pacific. Twitter hours are Monday - Friday, 9AM-5PM, excluding holidays.	52	Yes
	@mehdirhasan	Columnist, The Intercept. Contributing Editor, New Statesman. Host, Al Jazeera English. Adjunct Professor, Georgetown University. A Brit based in DC.	48	Yes
	@SupDaveCortese	Santa Clara County Board Supervisor representing District 3: Sunnyvale, Milpitas, Alviso, North San Jose, Berryessa, East Hills, Evergreen	39	No
Educators (*n* = 153)	@MIT	The Massachusetts Institute of Technology is a world leader in research and education.	90	Yes
	@JohnTirman	Executive Director & Principal Research Scientist, MIT Center for International Studies. I write/act on the human costs of war, U.S. foreign policy, & migration	83	No
	@seabird7	Semi-retired psychoanalytic psychotherapist. Systems. Phenology. Integral theory. Social Justice. Subtle energy practices.	37	No
	@facinghistory	Facing History and Ourselves combats racism and antisemitism by using history to teach tolerance in classrooms around the globe.	34	Yes
	@FernandoReimers	Professor of International Education, studying innovative policies and programs around the world that empower youth to achieve Sustainable Development Goals	19	No
Boston Globe related workers (*n* = 142)	@GlobeOpinion	Dispatches from the @BostonGlobeeditorial board and op-ed page.	128	Yes
	@madeleine	Author of the #1 New York Times bestseller, Fascism: A Warning. 64th SecState, refugee, prof, bizwoman, pin collector & occasional drummer. Grateful American.	77	Yes
	@Presbyterian	For over 200 years, Presbyterians have been responding to the call of Jesus Christ. Follow us as we share what God continues to do in the world.	48	Yes
	@speechboy71	Columnist Boston Globe. Author, American Maelstrom	43	No

Clusters	Twitter account	Bio	Degree	Verified?
	@DanielPAldrich	Professor of comparative public policy: social capital, disaster recovery, environment, energy and resilience	22	No
SHRM (Society for Human Resource Management) (*n* = 138)	@Global_imm	The Council for Global Immigration (CFGI) is the leading employer network of companies, universities and research institutions dedicated to #immigration.	42	No
	@SHRMRoy	Talent Acquisition Editor at SHRM	37	No
	@SHRM	We are the world's largest professional association of #HR pros. Follow us for updates on all things #HR!	35	Yes
	@HRMagSHRM	The official Twitter page of HR Magazine, published by the Society for Human Resource Management	19	No
	@SHRMnextchat	Learn. Share. Network. Host of #NextChat on Wednesdays at 3 p.m. ET.	16	No
Activists (*n* = 130)	@NDLON	NDLON's mission is to improve the lives of day laborers in the United States.	28	Yes
	@MartinOMalley	Katie O'Malley fan. Celtic rock Singer/Songwriter. 61st Governor of Maryland, former Mayor of Baltimore. On a mission to win back our states.	26	Yes
	@MichelleObama	Girl from the South Side and former First Lady. Wife, mother, dog lover. Always hugger-in-chief.	21	Yes
	@Agnes_Politics	Nigerian & lived in South Africa | RTs, tweets, & likes are NOT endorsements | #Immigration Law | Former Chicago @OFA Fellow |	17	No
	@sg_ndlon	People, politics, and social imagination; campaigns and legislative for @ndlon	14	No
Immigration lawyers & Washington D.C. Based workers (*n* = 116)	@PaulJeffPerez	Family Immigration Lawyer, Political Opinions, Latino Issues, Husband and Dad, Mets, Giants & Knicks Fan, Beginner Cook, Marine Corps veteran	83	Yes
	@AccentLegal	A dedicated immigration lawyer with a world of experience.	67	No
	@TheHalliCJShow	Halli hosts THE HALLI CASSER-JAYNE PODCAST To hell with whine.	38	No
	@racrutcher	President and Professor of Music at the University of Richmond; Educational and cultural leader; Cellist in the Klemperer Trio	28	No
	@LatAmFr	GOD & the Constitution FREEDOM & LIBERTY from worldwide Marxist Socialists Communists oppressors destroying Latin America	22	No
Universities & California professors (*n* = 90)	@JosephICastro	Dad | Beach Lover | Berkeley & Stanford Alumnus|Professor of Educational Leadership & President, California State University, Fresno. @Fresno_State#BeBold	71	No
	@Fresno_State	Official California State University, Fresno | #FresnoState | Pres. @JosephICastro | #GoDogs | Day of Giving is Thursday	55	Yes
	@SLNazario	Pulitzer Prize winning journalist focusing on social issues and author of national best-selling book Enrique's Journey.	17	No
	@calstate	CSU is a leader in high-quality, accessible, student-focused higher education. Tweets by the CSU Public Affairs Office. http://www.calstate.edu	16	Yes
	@RiderUniversity	The official Twitter account of Rider University	15	No

APPENDIX C – CLASSIFICATION OF TWEETS BASED ON KEYWORDS

```
import java.util.*;
import org.apache.poi.sl.usermodel.Sheet;
import org.apache.poi.ss.usermodel.Cell;
import org.apache.poi.ss.usermodel.CellType;
import org.apache.poi.ss.usermodel.Row;
import org.apache.poi.ss.usermodel.Workbook;
import org.apache.poi.xssf.usermodel.XSSFSheet;
import org.apache.poi.xssf.usermodel.XSSFWorkbook;

import java.io.File;
import java.io.FileInputStream;
import java.io.FileNotFoundException;
import java.io.FileOutputStream;
import java.io.IOException;
import java.util.Iterator;
public class Excel {
   private static final String FILE_NAME = "Final_Retweet_Network.xlsx";
   private static final String DEMO_FILE = "Demcrat.xlsx";
   private static final String REPUB_FILE = "Republican.xlsx";
   private static final String[] DEMO_LIST = {"Democratic", "Liberal", "Iamwithher",
"Hillary",
          "Clinton", "HillaryClinton", "Uniteblue", "withHillary", "refugee", "Democrat",
          "Progressive", "LGBT", "LGBTQ", "BLM", "BlackLivesMatter", "Feminist",
"Obama"};
   private static final String[] REPU_LIST = {"Republican", "Conservative", "Donald",
          "Trump", "DonaldTrump", "TrumpTrain", "TCOT", "CCOT", "Christian",
"Neverhillary",
          "1A", "2A", "Breitbart", "ProTrump", "BuildTheWall", "Patriot", "MAGA",
          "MakeAmericaGreatAgain","Make America Great Again", "TrumpPence16",
"VoteTrump",
          "CrookedHillary", "NRA", "Illegal", "Undocumented", "NoReFugees"};

     public static void main(String[] args) throws Exception {
      ArrayList<ArrayList<String>> data = new ArrayList<ArrayList<String>>();
      readData(data);
      writeData(data);
     }
     public static void writeData(ArrayList<ArrayList<String>> data) {
          XSSFWorkbook repub = new XSSFWorkbook();
          XSSFWorkbook demo = new XSSFWorkbook();
```

```
        XSSFSheet sheet_repub = repub.createSheet("Republican");
        XSSFSheet sheet_demo = demo.createSheet("Democrat");
        int demo_row = 0;
        int repu_row = 0;
        for (int row = 0; row < data.size(); row++) {
          int result = check(data.get(row).get(3));
          if(result == 1) { // Democrat
              Row r = sheet_demo.createRow(demo_row++);
                    int colNum = 0;
                    for (int col = 0; col < data.get(row).size(); col++){
                          Cell cell = r.createCell(colNum++);
                          cell.setCellValue((String) data.get(row).get(col));
                    }
          }else if(result == 2) { // Republican
              Row r = sheet_repub.createRow(repu_row++);
                    int colNum = 0;
                    for (int col = 0; col < data.get(row).size(); col++){
                          Cell cell = r.createCell(colNum++);
                          cell.setCellValue((String) data.get(row).get(col));
                    }
          }

        }

        try {
              FileOutputStream outputStream1 = new FileOutputStream(DEMO_FILE);
              FileOutputStream outputStream2 = new FileOutputStream(REPUB_FILE);
              demo.write(outputStream1);
              repub.write(outputStream2);
              demo.close();
              repub.close();
        } catch (FileNotFoundException e) {
              e.printStackTrace();
        } catch (IOException e) {
              e.printStackTrace();
        }


  }
  public static int check(String list){
    int demo_count = 0;
    int repub_count = 0;
    for(int i = 0; i < DEMO_LIST.length; i++){
```

```
            if( list.toLowerCase().contains(DEMO_LIST[i].toLowerCase()))
               demo_count++;

         }
         for(int i = 0; i < REPU_LIST.length; i++) {
            if(list.toLowerCase().contains(REPU_LIST[i].toLowerCase()))
               repub_count++;
         }
         if((demo_count == 0 && repub_count == 0) || demo_count == repub_count){
            return 0;
         }else if (demo_count > repub_count) {
            return 1;
         }else {
            return 2;
         }
        }
        public static void readData(ArrayList<ArrayList<String>> data) {
             try {
               int index = 0;
                  FileInputStream excelFile = new FileInputStream(new
File(FILE_NAME));//Îç∞Ïù¥ÌÑ∞ Î∞õÏïÑÑ
                  Workbook workbook = new XSSFWorkbook(excelFile);
                  org.apache.poi.ss.usermodel.Sheet datatypeSheet =
workbook.getSheetAt(0);//create a sheet
                  Iterator<Row> iterator = datatypeSheet.iterator();

                  // row
                  while (iterator.hasNext()) {
                        Row currentRow = iterator.next();
                        Iterator<Cell> cellIterator = currentRow.iterator();
                        data.add(new ArrayList<String>());
                        // column
                        while (cellIterator.hasNext()) {
                              Cell currentCell = cellIterator.next();
                              if (currentCell.getCellTypeEnum() == CellType.STRING){
                                String x =currentCell.getStringCellValue();
                                   data.get(index).add(x);
                              } else if (currentCell.getCellTypeEnum() ==
CellType.NUMERIC) {
                                String y = "" + currentCell.getNumericCellValue();
                                   data.get(index).add(y);
                              }
                        }
```

```
                index++;
            }
        } catch (FileNotFoundException e) {
            e.printStackTrace();
        } catch (IOException e) {
            e.printStackTrace();
        }
    }
}
```

References

Adam, S. (2008). Do mass media portray Europe as a community? German and French debates on EU enlargement and a common constitution. *Javnost-The Public*, *15*(1), 91-112.

Amiri, A., & Ventelou, B. (2012). Granger causality between total expenditure on health and GDP in OECD: Evidence from the Toda–Yamamoto approach. *Economics Letters*, *116*(3), 541-544.

Apsler, R., & Sears, D. O. (1968). Warning, personal involvement, and attitude change. *Journal of Personality and Social Psychology*, *9*(2), 162.

Arranz, M. A. (2005). Portmanteau test statistics in time series. *Time Orientated Language*, 1-8.

Ausserhofer, J., & Maireder, A. (2013). National politics on Twitter: Structures and topics of a networked public sphere. *Information, Communication & Society*, *16*(3), 291-314.

Bakshy, E., Hofman, J. M., Mason, W. A., & Watts, D. J. (2011). Everyone's an influencer: quantifying influence on twitter. In *Proceedings of The Fourth Association for Computing Machinery (ACM) International Conference on Web Search and Data Mining* (pp. 65-74). ACM.

Barabási, A. L. (2003). *Linked: How everything is connected to everything else and what It means for business, science, and everyday Life*: New York, NY: Penguin Group.

Barash, V., & Golder, S. (2010). Twitter: Conversation, entertainment, and information, all in one network. *Analyzing Social Media Networks with NodeXL: Insights from a connected world*, 143-164.

Barberá, P. (2015). Birds of the same feather tweet together: Bayesian ideal point estimation using Twitter data. *Political Analysis*, *23*(1), 76-91.

Bastos, M., Piccardi, C., Levy, M., McRoberts, N., & Lubell, M. (2018). Core-periphery or decentralized? Topological shifts of specialized information on Twitter. *Social Networks*, *52*, 282-293.

Beck, P. A., Dalton, R. J., Greene, S., & Huckfeldt, R. (2002). The social calculus of voting: Interpersonal, media, and organizational influences on presidential choices. *American Political Science Review*, *96*(1), 57-73.

Becketti, S. (2013). *Introduction to time series using Stata*. College Station, TX: Stata Press.

Benkler, Y. (2006). *The wealth of networks: How social production transforms markets and freedom*. Yale University Press.

Bennett, W. L., & Manheim, J. B. (2006). The one-step flow of communication. The ANNALS of the American Academy of Political and Social Science, 608(1), 213-232.

Blondel, V. D., Guillaume, J. L., Lambiotte, R., & Lefebvre, E. (2008). Fast unfolding of communities in large networks. *Journal of Statistical Mechanics: Theory and Experiment*, *2008*(10), P10008.

Bode, L., Hanna, A., Yang, J., & Shah, D. V. (2015). Candidate networks, citizen clusters, and political expression: Strategic hashtag use in the 2010 midterms. *The ANNALS of the American Academy of Political and Social Science*, *659*(1), 149- 165.

Bodendorf, F., & Kaiser, C. (2009). Detecting opinion leaders and trends in online social networks. In *Proceedings of the 2nd ACM Workshop on Social Web Search and Mining* (pp. 65-68). ACM.

Borgatti, S. P. (2006). Identifying sets of key players in a social network. *Computational & Mathematical Organization Theory*, *12*(1), 21-34.

Borgatti, S. P., Mehra, A., Brass, D. J., & Labianca, G. (2009). Network analysis in the social sciences. *Science*, *323*(5916), 892-895.

Borgatti, S. P., Everett, M. G., & Johnson, J. C. (2013). *Analyzing Social Networks*. Thousand Oaks: SAGE.

Borge Bravo, R, & Del Valle, M. E. (2017). Organization Still Matters: Parties' Characteristics, Posting and Followers' Reactions on Facebook. *International Journal of E-Politics (IJEP)*, *8*(1), 30-49.

Boster, F. J., Kotowski, M. R., Andrews, K. R., & Serota, K. (2011). Identifying influence: Development and validation of the connectivity, persuasiveness, and maven scales. *Journal of Communication*, *61*(1), 178-196.

boyd, D., Golder, S., & Lotan, G. (2010). Tweet, tweet, retweet: Conversational aspects of retweeting on Twitter. In *System Sciences (HICSS), 2010 43rd Hawaii International Conference on System Sciences* (pp. 1-10). IEEE.

Box, G. E., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M. (2015). *Time series analysis: forecasting and control*. John Wiley & Sons.

Broersma, M., & Graham, T. (2012). Social media as beat: tweets as a news source during the 2010 British and Dutch elections. *Journalism Practice*, 6(3), 403-419.

Brosius, H. B., & Weimann, G. (1996). Who sets the agenda?: Agenda-setting as a two-step flow. *Communication Research*, 23(5), 561-580.

Bruno, N. (2011). Tweet first, verify later? How real-time information is changing the coverage of worldwide crisis events. Oxford: Reuters Institute for the Study of Journalism, University of Oxford. https://reutersinstitute.politics.ox.ac.uk/our-research/tweet-first-verify-later-how-real-time-information-changing-coverage-worldwide-crisis

Bruns, A., & Burgess, J. E. (2011). The use of Twitter hashtags in the formation of ad hoc publics. In *Proceedings of the 6th European Consortium for Political Research (ECPR) General Conference 2011*.

Bruns, A., & Moe, H. (2013). Structural layers of communication on Twitter. *Twitter and Society*, 89, 15-28.

Bruns, A., & Highfield, T. (2015). 18. From news blogs to news on Twitter: gatewatching and collaborative news curation. *Handbook of Digital Politics*, 325.

Burt, R. S. (2004). Structural holes and good ideas. *American Journal of Sociology*, 110(2), 349-399.

Cakim, I. (2007). Online opinion leaders: a predictive guide for viral marketing campaigns. *Connected Marketing*, *107*.

Cassell, J., Huffaker, D., Tversky, D., & Ferriman, K. (2006). The language of online leadership: Gender and youth engagement on the Internet. *Developmental Psychology*, *42*(3), 436.

Castillo, C., Mendoza, M., & Poblete, B. (2011). Information credibility on twitter. In *Proceedings of the 20th International Conference on World Wide Web* (pp. 675-684). ACM.

Cha, M., Haddadi, H., Benevenuto, F., & Gummadi, P. K. (2010). Measuring User Influence in Twitter: The Million Follower Fallacy. ICWSM, 10(10-17), 30.

Chaffee, S. H. (1972). *Longitudinal designs for communication research: Cross-lagged correlations*. Paper presented to the Annual Conference of the Association for Education in Journalism, Carbondale, IL.

Chaiken, S. (1987). The heuristic model of persuasion. In *Social Influence: The Ontario Symposium* (Vol. 5, pp. 3-39).

Chandler, C. R., & Tsai, Y. M. (2001). Social factors influencing immigration attitudes: an analysis of data from the General Social Survey. *The Social Science Journal*, *38*(2), 177-188.

Chang, H. C. (2010). A new perspective on Twitter hashtag use: Diffusion of innovation theory. *Proceedings of the American Society for Information Science and Technology*, *47*(1), 1-4.

Chen, W., Tu, F., & Zheng, P. (2017). A transnational networked public sphere of air pollution: analysis of a Twitter network of PM2.5 from the risk society perspective. *Information, Communication & Society*, *20*(7), 1005-1023.

Choi, S. (2012). Flows of Information/Influence and Diversity of Content within Online Public Fora in the Context of Civil Society. (Doctoral Dissertation). Retrieved from The University of Texas Libraries. http://hdl.handle.net/2152/ETD-UT-2012-12-6508.

Choi, S. (2014). Flow, Diversity, Form, and Influence of Political Talk in Social-Media-Based Public Forums. *Human Communication Research*, *40*(2), 209-237.

Choi, S. (2015). The two-step flow of communication in Twitter-based public forums. *Social Science Computer Review*, *33*(6), 696-711.

Chung, J. E. (2017). Retweeting in health promotion: Analysis of tweets about Breast Cancer Awareness Month. *Computers in Human Behavior*, *74*, 112-119.

Chung, W., & Zeng, D. (2016). Social-media-based public policy informatics: Sentiment and network analyses of US Immigration and border security. *Journal of the Association for Information Science and Technology*, 67(7), 1588-1606.

Cision (2016). Twitter in Crisis: 5 things to know. An article published at February 16, 2016. Retrieved from http://www.cision.com/us/2016/02/twitter-in-crisis-five-things-you-need-to-know/

Conover, M. D., Gonçalves, B., Ratkiewicz, J., Flammini, A., & Menczer, F. (2011). Predicting the political alignment of twitter users. In *2011 IEEE Third International Conference on Privacy, Security, Risk and Trust and 2011 IEEE Third International Conference on Social Computing* (pp. 192-199). IEEE.

Conway, B. A., Kenski, K., & Wang, D. (2015). The rise of Twitter in the political campaign: Searching for intermedia agenda-setting effects in the presidential primary. *Journal of Computer-Mediated Communication*, *20*(4), 363-380.

Dahlgren, P. (2005). The Internet, public spheres, and political communication: Dispersion and deliberation. *Political communication*, *22*(2), 147-162.

Daly, A. J. (Ed.). (2010). *Social Network Theory and Educational Change* (Vol. 8). Cambridge, MA: Harvard Education Press.

Dang-Xuan, L., Stieglitz, S., Wladarsch, J., & Neuberger, C. (2013). An investigation of influentials and the role of sentiment in political communication on Twitter during election periods. *Information, Communication & Society*, *16*(5), 795-825.

DeFleur, M. L. (1998). Where have all the milestones gone? The decline of significant research on the process and effects of mass communication. *Mass Communication and Society*, *1*(1-2), 85-98.

Deutschmann, P. J., & Danielson, W. A. (1960). Diffusion of knowledge of the major news story. *Journalism Quarterly*, *37*(3), 345-355.

Discovertext. (2014). Sifter - search the complete (undeleted) history of Twitter. Retrieved from https://discovertext.com/2014/02/24/sifter-search-the-complete-undeleted-history-of-twitter/

Domingos, P., & Richardson, M. (2001). Mining the network value of customers. In *Proceedings of the Seventh ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 57-66). ACM.

DreamGrow (2018). "Top 15 most popular social networking sites" Retrieved from https://www.dreamgrow.com/top-15-most-popular-social-networking-sites/

Dubois, E., & Gaffney, D. (2014). The multiple facets of influence: Identifying political influentials and opinion leaders on Twitter. *American Behavioral Scientist, 58*(10), 1260-1277.

Dunaway, J., Branton, R. P., & Abrajano, M. A. (2010). Agenda setting, public opinion, and the issue of immigration reform. *Social Science Quarterly*, *91*(2), 359-378.

Eder, K., & Kantner, C. (2000). Transnationale Resonanzstrukturen in Europa. Eine Kritik der Rede vom Öffentlichkeitsdefizit [Transnational resonance structure in Europe: A critique of the supposed deficit of the public sphere]. *Die Europäisierung nationaler Gesellschaften. Sonderheft*, *40*(2000), 306-331.

Ellison, N. B., Steinfield, C., & Lampe, C. (2007). The benefits of Facebook "friends": Social capital and college students' use of online social network sites. *Journal of Computer-Mediated Communication*, *12*(4), 1143-1168.

Erbring, L., Goldenberg, E. N., & Miller, A. H. (1980). Front-page news and real-world cues: A new look at agenda-setting by the media. *American Journal of Political Science*, 24(1), 16-49.

Everett, M., & Borgatti, S. P. (2005). Ego network betweenness. *Social Networks*, *27*(1), 31-38.

Farrell, H., & Drezner, D. W. (2008). The power and politics of blogs. *Public Choice, 134*(1-2), 15.

Flores, R. D. (2017). Do anti-immigrant laws shape public sentiment? A study of Arizona's SB1070 using Twitter data. *American Journal of Sociology*, *123*(2), 333-384.

Flores, R. D. (2018). Can Elites Shape Public Attitudes Toward Immigrants?: Evidence from the 2016 US Presidential Election. *Social Forces*, *96*(4), 1649-1690.

Flynn, L. R., Goldsmith, R. E., & Eastman, J. K. (1994). The King and Summers opinion leadership scale: Revision and refinement. *Journal of Business Research*, *31*(1), 55-64.

Fishel, J., Phelps. J., Mallin, A., & Sands, A. (2017). Trump orders suspensions of all refugees, immigrants from some Muslim nations. *ABC News*. Retrieved from http://abcnews.go.com/Politics/president-trump-signs-executive-actions-pentagon/story?id=45096609.

Fiske, J. (1989). Moments of television: Neither the text nor the audience. *Remote control: Television, audiences, and cultural power*, 56-78.

Freeman, L. C. (1979). Centrality in social networks conceptual clarification. *Social Networks*, 1(3), 215-239.

Freeman, J. R. (1983). Granger causality and the times series analysis of political relationships. *American Journal of Political Science*, 27(2), 327.

Friedland, L. A., Hove, T., & Rojas, H. (2006). The networked public sphere. *Javnost-the Public*, *13*(4), 5-26.

Friedrichs, J., Lepsius, M. R., & Neidhardt, F. (1994). Öffentlichkeit, Öffentliche Meinung, Soziale Bewegungen.

Garton, L., Haythornthwaite, C., & Wellman, B. (1997). Studying online social networks. *Journal of computer-mediated communication*, *3*(1), JCMC313.

Garcia, D., Abisheva, A., Schweighofer, S., Serdült, U., & Schweitzer, F. (2015). Ideological and temporal components of network polarization in online political participatory media. *Policy & Internet*, *7*(1), 46-79.

Gaver, W. (1991). Technology affordances. In Proceedings of SIGCHI Conference on Human Factors in Computing Systems (pp. 79–84). New York, NY: ACM.

Gibson, R. (2018). *Same-Sex Marriage and Social Media: How Online Networks Accelerated the Marriage Equality Movement*. Routledge.

Giglietto, F., Rossi, L., & Bennato, D. (2012). The open laboratory: Limits and possibilities of using Facebook, Twitter, and YouTube as a research data source. *Journal of Technology in Human Services*, *30*(3-4), 145-159.

Gil de Zúñiga, H., Correa, T., & Valenzuela, S. (2012). Selective exposure to cable news and immigration in the US: The relationship between FOX News, CNN, and attitudes toward Mexican immigrants. *Journal of Broadcasting & Electronic Media*, *56*(4), 597-615.

Gil de Zúñiga H, Jung N, & Valenzuela S. (2012) Social media use for news and individuals' social capital, civic engagement and political participation. *Journal of Computer-Mediated Communication.* 17: 319-336.

Gitlin, T. (1978). Media sociology. *Theory and society*, *6*(2), 205-253.

Gleason, B. (2013). # Occupy Wall Street: Exploring informal learning about a social movement on Twitter. *American Behavioral Scientist*, *57*(7), 966-982.

Golder, S. A., & Donath, J. (2004). Social roles in electronic communities. *Internet Research*, *5*(1), 19-22.

González-Bailón, S., Borge-Holthoefer, J., & Moreno, Y. (2013). Broadcasters and hidden influentials in online protest diffusion. *American Behavioral Scientist*, *57*(7), 943-965.

Granger, C. W. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica: Journal of the Econometric Society*, 424-438.

Groshek, J., & Groshek, M. C. (2013). Agenda trending: Reciprocity and the predictive capacity of social networking sites in intermedia agenda setting across topics over time. *Media and Communication*, *1*(1), 15.

Gruszczynski, M., & Wagner, M. W. (2017). Information flow in the 21st century: The dynamics of agenda-uptake. *Mass Communication and Society*, *20*(3), 378-402.

Gruzd, A., Wellman, B., & Takhteyev, Y. (2011). Imagining Twitter as an imagined community. *American Behavioral Scientist*, *55*(10), 1294-1318.

Guille, A., & Favre, C. (2015). Event detection, tracking, and visualization in twitter: a mention-anomaly-based approach. *Social Network Analysis and Mining*, *5*(1), 18.

Guo, L. (2012). The application of social network analysis in agenda setting research: A methodological exploration. *Journal of Broadcasting & Electronic Media*, *56*(4), 616-631.

Guo, L., Rohde, J. A., & Wu, H. D. (2018). Who is responsible for Twitter's echo chamber problem? Evidence from 2016 US election networks. *Information, Communication & Society*, 1-18.

Habermas, J. (1991). *The structural transformation of the public sphere: An inquiry into a category of bourgeois society*. MIT press.

Habermas, J. (2006). Political communication in media society: Does democracy still enjoy an epistemic dimension? the impact of normative theory on empirical research 1. *Communication Theory*, *16*(4), 411-426.

Habermas, J., Lennox, S., & Lennox, F. (1974). The public sphere: An encyclopedia article (1964). *New German Critique*, (3), 49-55.

Hair Jr., J. F., Anderson, R. E., Tatham, R. L. & Black, W. C. (1995). *Multivariate Data Analysis*, 3rd edn. New York: Macmillan.

Hale, B. J., & Grabe, M. E. (2018). Visual War: A Content Analysis of Clinton and Trump Subreddits During the 2016 Campaign. *Journalism & Mass Communication Quarterly*, *95*(2), 449-470.

Hambrick, M. E., Simmons, J. M., Greenhalgh, G. P., & Greenwell, T. C. (2010). Understanding professional athletes' use of Twitter: A content analysis of athlete tweets. *International Journal of Sport Communication*, *3*(4), 454-471.

Hämmerli, A., Gattiker, R., & Weyermann, R. (2006). Conflict and cooperation in an actors' network of Chechnya based on event data. Journal of Conflict Resolution, 50(2), 159-175.

Han, G., & Wang, W. (2015). Mapping user relationships for health information diffusion on microblogging in China: A social network analysis of Sina Weibo. *Asian Journal of Communication*, *25*(1), 65-83.

Hanneman, R. A., & Riddle, M. (2005). Introduction to Social Network Methods. Riverside, CA: University of California, Riverside.

Hansen, L. K., Arvidsson, A., Nielsen, F. Å., Colleoni, E., & Etter, M. (2011). Good friends, bad news-affect and virality in Twitter. In *Future Information Technology* (pp. 34-43). Springer Berlin Heidelberg.

Heclo, H. (1978). Issue networks and the executive establishment. *Public Adm. Concepts Cases*, *413*, 46-57.

Hester, J. B., & Gibson, R. (2007). The agenda-setting function of national versus local media: A time-series analysis for the issue of same-sex marriage. *Mass Communication & Society*, *10*(3), 299-317.

Himelboim, I. (2008). Reply distribution in online discussions: A comparative network analysis of political and health newsgroups. *Journal of Computer-Mediated Communication, 14*(1), 156-177.

Himelboim, I., Gleave, E., & Smith, M. (2009). Discussion catalysts in online political discussions: Content importers and conversation starters. *Journal of Computer-Mediated Communication*, *14*(4), 771-789.

Himelboim, I., McCreery, S., & Smith, M. (2013). Birds of a feather tweet together: Integrating network and content analyses to examine cross-ideology exposure on Twitter. *Journal of Computer-Mediated Communication*, *18*(2), 154-174.

Himelboim, I., Smith, M., & Shneiderman, B. (2013). Tweeting apart: Applying network analysis to detect selective exposure clusters in Twitter. *Communication Methods and Measures*, *7*(3-4), 195-223.

Honey, C., & Herring, S. C. (2009). Beyond microblogging: Conversation and collaboration via Twitter. In *System Sciences, 2009. HICSS'09. 42nd Hawaii International Conference on System Sciences* (pp. 1-10). IEEE.

Hong, K., & Shemer, S. (1976). Influence of media and interpersonal agendas on personal agendas. In annual convention of the Association for Education in Journalism, Madison, Wisconsin.

Huffaker, D. (2010). Dimensions of leadership and social influence in online communities. *Human Communication Research*, *36*(4), 593-617.

Hutchings, C. (2012). Commercial use of Facebook and Twitter–risks and rewards. *Computer Fraud & Security*, *2012*(6), 19-20.

Inbar, Y., Pizarro, D. A., & Bloom, P. (2009). Conservatives are more easily disgusted than liberals. *Cognition and Emotion*, *23*(4), 714-725.

Jacomy, M., Venturini, T., Heymann, S., & Bastian, M. (2014). ForceAtlas2, a continuous graph layout algorithm for handy network visualization designed for the Gephi software. *PloS one*, *9*(6), e98679.

Jang, S. M., & Park, Y. J. (2017). Redirecting the Focus of the Agenda: Testing the Zero-Sum Dynamics of Media Attention in News and User-Generated Media. *International Journal of Communication*, *11*, 20.

Jashinsky, J. M., Magnusson, B., Hanson, C., & Barnes, M. (2017). Media agenda setting regarding gun violence before and after a mass shooting. *Frontiers in Public Health*, *4*, 291.

Jin, S. A. A., & Phua, J. (2014). Following celebrities' tweets about brands: The impact of twitter-based electronic word-of-mouth on consumers' source credibility perception, buying intention, and social identification with celebrities. *Journal of Advertising*, *43*(2), 181-195.

Johnston, C. D., Newman, B. J., & Velez, Y. (2015). Ethnic change, personality, and polarization over immigration in the American public. *Public Opinion Quarterly*, *79*(3), 662-686.

Kadushin, C. (2012). *Understanding social networks: Theories, concepts, and findings*. OUP USA.

Katz, E., & Lazarsfeld, P. F. (1955). Personal Influence, the part played by people in the flow of mass communications. Transaction Publishers.

Kellstedt, P. M. (2003). *The mass media and the dynamics of American racial attitudes*. New York, NY: Cambridge University Press.

Kilgo, D. K., Yoo, J. J., Sinta, V., Geise, S., Suran, M., & Johnson, T. J. (2016). Led it on Reddit: An exploratory study examining opinion leadership on Reddit. *First Monday*, *21*(9).

Kim, D. K. (2007). Identifying Opinion Leaders by Using Social Network Analysis: A Synthesis of Opinion Leadership Data Collection Methods and Instruments (Doctoral Dissertation). Retrieved from https://etd.ohiolink.edu/rws_etd/document/get/ohiou1186672135/inline

Kim, Y., Kim, Y., Lee, J. S., Oh, J., & Lee, N. Y. (2015). Tweeting the public: Journalists' Twitter use, attitudes toward the public's tweets, and the relationship with the public. *Information, Communication & Society*, *18*(4), 443-458.

King, C. W., & Summers, J. O. (1970). Overlap of opinion leadership across consumer product categories. *Journal of Marketing Research*, 43-50.

Ko, H. C., Yin, C. P., & Kuo, F. Y. (2008). Exploring individual communication power in the blogosphere. *Internet Research*, *18*(5), 541-561.

Krippendorff, K. (2004). *Content analysis: An introduction to its methodology.* Second Edition. Thousand Oaks, CA: Sage.

Krosnick, J. A. (1990). Lessons learned: A review and integration of our findings. *Social Cognition*, 8, 154-158.

Kutner, M. H., Nachtsheim, C., & Neter, J. (2004). *Applied linear regression models*. McGraw-Hill/Irwin.

Kwak, H., Lee, C., Park, H., & Moon, S. (2010). What is Twitter, a social network or a news media? *In Proceedings of the 19th International Conference on World Wide We b* (pp. 591-600). ACM.

Lampe, C. A., Ellison, N., & Steinfield, C. (2007). A familiar face (book): profile elements as signals in an online social network. In *Proceedings of the SIGCHI conference on Human factors in computing systems* (pp. 435-444). ACM.

Laniado, D., Tasso, R., Volkovich, Y., & Kaltenbrunner, A. (2011). When the wikipedians talk: Network and tree structure of Wikipedia discussion pages. In *ICWSM* (pp. 177-184).

Larsson, A. O., & Moe, H. (2012). Studying political microblogging: Twitter users in the 2010 Swedish election campaign. *New Media & Society*, *14*(5), 729-747.

Lasorsa, D. L., Lewis, S. C., & Holton, A. E. (2012). Normalizing Twitter: Journalism practice in an emerging communication space. *Journalism Studies*, *13*(1), 19-36.

Lasica, J. D. (2003). Blogs and journalism need each other. *Nieman Reports*, *57*(3), 70-74.

Lasswell, H. D. (1927). *Propaganda technique in the world war* (p. 2). Cambridge, MA: MIT press.

Lazarsfeld, P. F., Berelson, B., & Gaudet, H. (1948). The People's Choice. New York: Columbia University Press.

Lee, N. Y. (2015). Two different motivations on agenda setting: Need for orientation and motivated reasoning. *International Journal of Public Opinion Research*, *28*(4), 484-510.

Lee, S. H., & Cotte, J. (2009). Moderating Role of Member Identification on the Relationship Between Network Centrality and Opinion Leadership/Satisfaction. *NA-Advances in Consumer Research Volume 36*.

Lee, J., & Sundar, S. S. (2013). To tweet or to retweet? That is the question for health professionals on Twitter. *Health Communication*, *28*(5), 509-524.

Lee, J., & Xu, W. (2018). The more attacks, the more retweets: Trump's and Clinton's agenda setting on Twitter. *Public Relations Review*, *44*(2), 201-213.

Lee, W.T., Cha, M.Y., & Yang, H.R. (2011). The network characteristic of social media influentials: Focusing on South Korea's twitter networks. *Journal of Communication Research*, 48(2), 44-79.

Lessig, L. (2005). *Free culture: The nature and future of creativity*. New York: Penguin.

Li, W., & Schuurmans, D. (2011). Modular community detection in networks. In *IJCAI Proceedings-International Joint Conference on Artificial Intelligence* (Vol. 22, No. 1, p. 1366).

Li, H., Dombrowski, L., & Brady, E. (2018). Working toward Empowering a Community How Immigrant-Focused Nonprofit Organizations Use Twitter during Political Conflicts. In *Proceedings of the 2018 ACM Conference on Supporting Groupwork* (pp. 335-346). ACM.

Lin, C. A. (2003). An interactive communication technology adoption model. *Communication Theory*, *13*(4), 345-365.

Loader, B. D., Vromen, A., & Xenos, M. A. (2014). The networked young citizen: social media, political participation and civic engagement. *Information, Communication & Society,17*(2), 143-150.

Lovejoy, K., & Saxton, G. D. (2012). Information, community, and action: How nonprofit organizations use social media. *Journal of Computer-Mediated Communication*, *17*(3), 337-353.

Lu, Y., Jerath, K., & Singh, P. V. (2013). The emergence of opinion leaders in a networked online community: A dyadic model with time dynamics and a heuristic for fast estimation. *Management Science*, *59*(8), 1783-1799.

Lu, S., Chen, W., Li, X., & Zheng, P. (2018). The Chinese Smog Crisis as Media Event: Examining Twitter Discussion of the Documentary Under the Dome. *Policy & Internet*.

Luhmann, N. (1971). Offentliche Meinung [Public opinion]. In N. Luhmann (Ed.), Politische Planung: Auf- sa ̈tze zur Soziologie von Politik und Verwaltung [Political planning: Essays on the sociology of politics and administration] (pp. 9–34). Opladen, Germany: Westdeutscher Verlag.

Lyons, B., & Henderson, K. (2005). Opinion leadership in a computer-mediated environment. *Journal of Consumer Behaviour: An International Research Review*, *4*(5), 319-329.

Marwick, A., & boyd, D. (2011a). I tweet honestly, I tweet passionately: Twitter users, context collapse, and the imagined audience. *New Media & Society*, *13*(1), 114-133.

Marwick, A., & boyd, D. (2011b). To see and be seen: Celebrity practice on Twitter. *Convergence*, *17*(2), 139-158.

McCombs, M. (2002). The agenda-setting role of the mass media in the shaping of public opinion. In *Mass Media Economics 2002 Conference, London School of Economic.*

McCombs, M. (2005). A look at agenda-setting: Past, present and future. *Journalism Studies 6*(4), 543-557.

McCombs, M. (2014). Setting the Agenda: The mass media and public opinion. John Wiley & Sons.

McCombs, M. E., & Shaw, D. L. (1972). The agenda-setting function of mass media. *Public Opinion Quarterly*, 176-187.

McGraw, M., Kelsey, A., & Keneally, M. (2017). A timeline of Trump's immigration executive order and legal challenges. An article published at June 29, 2017. Retrieved from http://abcnews.go.com/Politics/timeline-president-trumps-immigration-executive- order-legal-challenges/story?id=45332741

Meraz, S. (2011). Using time series analysis to measure intermedia agenda-setting influence in traditional media and political blog networks. *Journalism & Mass Communication Quarterly*, *88*, 176-194.

Merton, R. (1957). Patterns of influence: Local and cosmopolitan influentials. *Social Theory and Social Structure*, *2*, 387-420.

Miller, M. M., & Riechert, B. P. (2001). The spiral of opportunity and frame resonance: Mapping the issue cycle in news and public discourse. In S. D. Reese, O. H. Gandy, Jr., & A. E. Grant (Eds.), Framing Public Life: Perspectives on media and our understanding of the social world. Mahwah, NJ: Lawrence Erlbaum.

Mirer, M. L., & Bode, L. (2015). Tweeting in defeat: How candidates concede and claim victory in 140 characters. *New Media & Society*, *17*(3), 453-469.

Mouffe, C. (2005). *On the Political.* London: Routledge.

Muntean, C. I., Morar, G. A., & Moldovan, D. (2012). Exploring the meaning behind Twitter hashtags through clustering. In *Business Information Systems Workshops* (pp. 231-242). Springer, Berlin, Heidelberg.

Murthy, D. (2011). Twitter: Microphone for the masses? *Media Culture and Society, 33(5),* 779.

Murthy, D. (2013). Twitter: Social communication in the Twitter age. Cambridge: Polity.

Murthy, D. (2015). Twitter and elections: are tweets, predictive, reactive, or a form of buzz? *Information, Communication & Society*, *18*(7), 816-831.

Murthy, D., Powell, A. B., Tinati, R., Anstead, N., Carr, L., Halford, S. J., & Weal, M. (2016). Bots and political influence: A sociotechnical investigation of social network capital. *International Journal of Communication*, *10*, 4952-4971.

Mutz, D. C., & Young, L. (2011). Communication and public opinion: Plus Ça change?. *Public Opinion Quarterly*, *75*(5), 1018-1044.

Myers, R. H. (1990). *Classical and Modern Regression with Applications* (Vol. 2). Belmont, CA: Duxbury press.

National Immigration Law Center (2018). "What We Do" Retrieved from https://www.nilc.org/about-us/what_we_do/

Navarra, M. (2016). Twitter is verifying way more account, and here's the data to prove it. *TNW*. An article published at July 22th, 2016. Retrieved from https://thenextweb.com/twitter/2016/07/22/twitter-verification-rises/

Newman, M. E., & Girvan, M. (2004). Finding and evaluating community structure in networks. *Physical Review E*, *69*(2), 026113.

Nisbet, E. C. (2005). The engagement model of opinion leadership: Testing validity within a European context. *International Journal of Public Opinion Research, 18*(1), 3-30.

Nisbet, M. C., & Kotcher, J. E. (2009). A two-step flow of influence? Opinion-leader campaigns on climate change. *Science Communication*, *30*(3), 328-354.

Noelle-Neumann, E. (1985). Identifying opinion leaders. In Paper presented at the 38th Annual Convention of the European Society of Market Research, Wiesbaden, Germany.

O'Hara, K., & Stevens, D. (2015). Echo chambers and online radicalism: Assessing the Internet's complicity in violent extremism. *Policy & Internet*, *7*(4), 401-422.

Otterbacher, J., Hemphill, L., & Shapiro, M. A. (2012). Tweeting vertically? Elected officials' interactions with citizens on Twitter. In *CeDEM (Conference for E - Democracy and Open Government) Asia 2012*.

Pariser, E. (2011). *The filter bubble: What the Internet is hiding from you*. Penguin UK.

Pallant, J. (2013). *SPSS Survival Manual*. McGraw-Hill Education (UK).

Panek, E. T., Nardis, Y., & Konrath, S. (2013). Mirror or Megaphone?: How relationships between narcissism and social networking site use differ on Facebook and Twitter. *Computers in Human Behavior*, *29*(5), 2004-2012.

Papacharissi, Z. (2008). The virtual sphere 2.0: The Internet, the public sphere, and beyond. In *Routledge Handbook of Internet Politics* (pp. 246-261). Routledge.

Papacharissi, Z., & de Fatima Oliveira, M. (2012). Affective news and networked publics: The rhythms of news storytelling on# Egypt. *Journal of Communication, 62*(2), 266-282.

Park, C. S. (2013). Does Twitter motivate involvement in politics? Tweeting, opinion leadership, and political engagement. *Computers in Human Behavior*, *29*(4), 1641-1648.

Park, C. S., & Kaye, B. K. (2017). The tweet goes on: Interconnection of Twitter opinion leadership, network size, and civic engagement. *Computers in Human Behavior, 69*, 174-180.

Park, S. J., Park, J. Y., Lim, Y. S., & Park, H. W. (2016). Expanding the presidential debate by tweeting: The 2012 presidential election debate in South Korea. *Telematics and Informatics*, *33*(2), 557-569.

Park, S. Y., Holody, K. J., & Zhang, X. (2012). Race in media coverage of school shootings: A parallel application of framing theory and attribute agenda setting. *Journalism & Mass Communication Quarterly*, *89*(3), 475-494.

Parmelee, J. H., & Bichard, S. L. (2012). Politics and the Twitter revolution. *Lanham, MD: Lexington*.

Paßmann, J., Boeschoten, T., & Schäfer, M. T. (2014). The gift of the gab: Retweet cartels and gift economies on Twitter. *Twitter and Society*, 331-344.

Peng, T. Q., Liu, M., Wu, Y., & Liu, S. (2016). Follower-followee network, communication networks, and vote agreement of the US members of congress. *Communication Research*, *43*(7), 996-1024.

Penney, J., & Dadas, C. (2014). (Re) Tweeting in the service of protest: Digital composition and circulation in the Occupy Wall Street movement. *New Media & Society*, *16*(1), 74-90.

Pew Research Center (2014). Mapping Twitter topic networks: From polarized crowds to community clusters. Retrieved from http://www.pewinternet.org/2014/02/20/mapping-twitter-topic-networks-from-polarized-crowds-to-community-clusters/

Pew Research Center (2016). Americans' view of immigrants marked by widening partisan, generational divides. Retrieved from http://www.pewresearch.org/facttank/2016/04/15/americans-views-of-immigrants-marked-by-widening-partisan-generational-divides/

Pew Research Center (2018a). Social media update 2018. Retrieved from http://www.pewinternet.org/2018/03/01/social-media-use-in-2018/

Pew Research Center (2018b). Bots in the Twittersphere. Retrieved from https://www.pewinternet.org/2018/04/09/bots-in-the-twittersphere/

Poell, T., & Rajagopalan, S. (2015). Connecting activists and journalists: Twitter communication in the aftermath of the 2012 Delhi rape. *Journalism Studies, 16*(5), 719-733.

Pöschko, J. (2011). Exploring twitter hashtags. *arXiv preprint arXiv:1111.6553*.

Ravid, G., & Rafaeli, S. (2004). Asynchronous discussion groups as small world and scale free networks. *First Monday*, *9*(9).

Recuero, R., Araujo, R., & Zago, G. (2011). How does social capital affect retweets? International Association for the Advancement of Artificial Intelligence on Web and Social Media.

Reynolds, A., & McCombs, M. (2002). News influence on our pictures of the world. In *Media effects* (pp. 11-28). Routledge.

Reynolds, M. (2014). Tweeters Focus on Immigration Reform, Not Deportation Halt. *NBC News*. An article published at April 11, 2014. Retrieved from https://www.nbcnews.com/news/latino/tweeters-focus-immigration-reform-not-deportation-halt-n78206

Rhoades, J., & Rhoades, R. (2013). The complexity of online discussion. *Journal of Online Learning & Teaching*, *9*(1).

Roberts, M., Wanta, W., & Dzwo, T. H. (Dustin). (2002). Agenda setting and issue salience online. *Communication Research*, 29(4), 452–465.

Robinson, J. P. (1976). Interpersonal influence in election campaigns: Two step-flow hypotheses. *Public Opinion Quarterly*, *40*(3), 304-319.

Rogers, E. M. (2010). Diffusion of Innovations. Simon and Schuster.

Rudalevige, A. (2016). Trump says he'll cancel Obama’s ‘unconstitutional’ executive actions. It’s not that easy. *Washington Post*. An article published at December 3, 2016 retrieved from https://www.washingtonpost.com/news/monkey-cage/wp/2016/12/03/trump-says-hell-cancel-obamas-unconstitutional-executive-actions-its-not-that-easy/?utm_term=.2deb2176ff5f

Russell Neuman, W., Bimber, B., & Hindman, M. (2011). The Internet and four dimensions of citizenship. *The Oxford handbook of American public opinion and the media*, 22-42.

Russell Neuman, W., Guggenheim, L., Mo Jang, S., & Bae, S. Y. (2014). The dynamics of public attention: Agenda-setting theory meets big data. *Journal of Communication, 64*(2), 193-214.

Salkind, N. J. (2010). *Encyclopedia of measurement and statistics*. SAGE publications.

Shahin, S., Seroka, L., & Islam, M. R. (2018). "What's racist about deporting criminal illegal 'Felons'?" Examining the link between emotion and cognition in tweets about immigration. Paper presented at the AEJMC annual conference, Washington, D.C.

Schier, S. E. (2016). *Polarized: The Rise of Ideology in American Politics*. Rowman & Littlefield.

Sherif, C. W., Kelly, M., Rodgers Jr., H. L., Sarup, G., & Tittler, B. I. (1973). Personal involvement, social judgment, and action. *Journal of Personality and Social Psychology*, *27*(3), 311-328.

Shi, J., & Salmon, C. T. (2018). Identifying opinion leaders to promote organ donation on social media: network study. *Journal of Medical Internet Research*, *20*(1).

Slavakis, K., Giannakis, G. B., & Mateos, G. (2014). Modeling and optimization for big data analytics: (statistical) learning tools for our era of data deluge. *IEEE Signal Processing Magazine*, *31*(5), 18-31.

Small, T. A. (2011). What the hashtag? A content analysis of Canadian politics on Twitter. *Information, communication & society*, *14*(6), 872-895.

Soares, F. B., Recuero, R., & Zago, G. (2018). Influencers in Polarized Political Networks on Twitter. In *Proceedings of the 9th International Conference on Social Media and Society* (pp. 168-177). ACM.

Stroud, N. J. (2010). Polarization and partisan selective exposure. *Journal of Communication*, *60*(3), 556-576.

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

Sun, T., Youn, S., Wu, G., & Kuntaraporn, M. (2006). Online word-of-mouth (or mouse): An exploration of its antecedents and consequences. *Journal of Computer-Mediated Communication*, *11*(4), 1104-1127.

Sunstein, C. (2001). Republic.com. Princeton University Press.

Sunstein, C. R. (2018). *# Republic: Divided democracy in the age of social media*. Princeton University Press.

Suro, R. (2009). America's views of immigration: The evidence from public opinion surveys. *Migration, Public Opinion, and Politics*, 52-76.

Tajfel, H., & Turner, J. C. (1986). The social identity theory of inter group behavior. Worchel & WG Austin (Eds.). Psychology of Intergroup Relations (pp. 7-24). Chicago: Nelson Hall.

Tan, Y., & Weaver, D. H. (2007). Agenda-setting effects among the media, the public, and congress, 1946–2004. *Journalism & Mass Communication Quarterly*, *84*(4), 729-744.

Thelwall, M., Buckley, K., Paltoglou, G., Cai, D., & Kappas, A. (2010). Sentiment strength detection in short informal text. *Journal of the American Society for Information Science and Technology*, *61*(12), 2544-2558.

Theocharis, Y., Lowe, W., Van Deth, J. W., & García-Albacete, G. (2015). Using Twitter to mobilize protest action: online mobilization patterns and action repertoires in the Occupy Wall Street, Indignados, and Aganaktismenoi movements. *Information, Communication & Society*, *18*(2), 202-220.

Thorson, K., & Wells, C. (2015). Chap 2: Understanding Media Effects in an Era of Curated Flows. *Gatekeeping in Transition*. Routledge New York.

Toda, H. Y., & Yamamoto, T. (1995). Statistical inference in vector autoregressions with possibly integrated processes. *Journal of Econometrics*, *66*(1-2), 225-250.

Trammell, K., & Keshelashvili, A. (2005). Examining the new influencers: A self-presentation study of A-list blogs. *Journalism & Mass Communication Quarterly*, *82*(4), 968-982.

Treem, J. W., & Leonardi, P. M. (2013). Social media use in organizations: Exploring the affordances of visibility, editability, persistence, and association. *Annals of the International Communication Association*, *36*(1), 143-189.

Tremayne, M., & Minooie, M. (2013). Opinion leadership on gun control in social networks: Preferential attachment versus reciprocal linking. *American Communication Journal*, *15*(4). 34-52.

Tumasjan, A., Sprenger, T. O., Sandner, P. G., & Welpe, I. M. (2010). Predicting Elections with Twitter: What 140 Characters Reveal about Political Sentiment. ICWSM, 10, 178-185.

Twitter (2018a). About Twitter. Retrieved from https://about.twitter.com/company

Twitter (2018b). About verified accounts. Retrieved from https://help.twitter.com/en/managing-your-account/about-twitter-verified- accounts

Valente, T. W. (2012). *Social Networks and Health: Models, methods, and applications*. Oxford University Press.

Valente, T. W., & Pumpuang, P. (2007). Identifying opinion leaders to promote behavior change. *Health Education & Behavior*, *34*(6), 881-896.

Valenzuela, S., Correa, T., & Gil de Zúñiga, H. (2018). Ties, likes, and tweets: Using strong and weak ties to explain differences in protest participation across Facebook and Twitter use. *Political Communication*, *35*(1), 117-134.

Valverde, M. (2016). Compare the candidates: Clinton vs. Trump on immigration. *Politifact*. An article published at July 15, 2016. Retrieved from https://www.politifact.com/truth-o-meter/article/2016/jul/15/compare-candidates-clinton-vs-trump-immigration/

van den Ban, A. W. (1964). A revision of the two-step flow of communication hypothesis. *International Communication Gazette*, *10*(3), 237-249.

van Haperen, S., Nicholls, W., & Uitermark, J. (2018). Building protest online: Engagement with the digitally networked #not1more protest campaign on Twitter. *Social Movement Studies*, 1-16.

Vargo, C. J., Guo, L., McCombs, M., & Shaw, D. L. (2014). Network issue agendas on Twitter during the 2012 US presidential election. *Journal of Communication, 64*(2), 296-316.

Vicari, S. (2017). Twitter and Non-Elites: Interpreting Power Dynamics in the Life Story of the (#) BRCA Twitter Stream. *Social Media + Society*, *3*(3), 1-14.

Vickery, J. R. (2016). # YesAllWomen (have a collective story to tell): Feminist hashtags and the intersection of personal narratives, networked publics, and intimate citizenship. *AoIR Selected Papers of Internet Research*, *6*.

Vigil, J. M. (2010). Political leanings vary with facial expression processing and psychosocial functioning. *Group Processes & Intergroup Relations*, *13*(5), 547- 558.

Wang, Y., & Fikis, D. J. (2017). Common core state standards on Twitter: Public sentiment and opinion leaders. *Educational Policy*, 0895904817723739.

Wang, Y., Luo, J., Niemi, R., Li, Y., & Hu, T. (2016). Catching Fire via “Likes": Inferring Topic Preferences of Trump Followers on Twitter. In *ICWSM* (pp. 719-722).

Wanta, W., & Wu, Y. C. (1992). Interpersonal communication and the agenda-setting process. *Journalism & Mass Communication Quarterly*, 69(4), 847-855.

Ward, M. D., Stovel, K., & Sacks, A. (2011). Network analysis and political science. *Annual Review of Political Science*, *14*, 245-264.

Wasserman, S., & Faust, K. (1994). Social network analysis: Methods and applications (Vol. 8). Cambridge University Press.

Watts, D. J., & Dodds, P. S. (2007). Influentials, networks, and public opinion formation. Journal of Consumer Research, 34(4), 441-458.

Watts, S. A., & Zhang, W. (2008). Capitalizing on content: Information adoption in two online communities. *Journal of the Association for Information Systems*, *9*(2), 73- 94.

Wei, Z., He, Y., Gao, W., Li, B., Zhou, L., & Wong, K. F. (2013). Mainstream Media Behavior Analysis on Twitter: A Case Study using UK General Election. *Labour*, *498*(356), 48.

Weimann, G. (1994). *The influentials: People who influence people*. SUNY Press.

Weimann, G., & Brosius, H. B. (2017). Redirecting the agenda. *The Agenda Setting Journal*, *1*(1), 63-102.

Weiss-Blatt, N. (2015). Role of Tech Bloggers in the Flow of Information. *The Power of Information Networks: New Directions for Agenda Setting*. Routledge.

Weng, J., Lim, E. P., Jiang, J., & He, Q. (2010). Twitterrank: finding topic-sensitive influential twitterers. In *Proceedings of the Third ACM International Conference on Web Search and Data Mining* (pp. 261-270). ACM.

White, C. M. (2016). *Social media, crisis communication, and emergency management: Leveraging Web 2.0 technologies*. CRC Press.

Williams, H. T., McMurray, J. R., Kurz, T., & Lambert, F. H. (2015). Network analysis reveals open forums and echo chambers in social media discussions of climate change. Global Environmental Change, 32, 126-138.

Wilson, R. E., Gosling, S. D., & Graham, L. T. (2012). A review of Facebook research in the social sciences. *Perspectives on psychological science*, *7*(3), 203-220.

Wu, S., Hofman, J. M., Mason, W. A., & Watts, D. J. (2011). Who says what to whom on Twitter. In *Proceedings of the 20th International Conference on World Wide Web* (pp. 705-714). ACM.

Xu, W. W., Sang, Y., Blasiola, S., & Park, H. W. (2014). Predicting opinion leaders in Twitter activism networks: The case of the Wisconsin recall election. *American Behavioral Scientist*, 1278-1293.

Yoo, J. J., Kilgo, D. K., & Johnson, T. J. (forthcoming). Blindly following opinion leaders?: Examining opinion leadership in the anonymous Reddit network. A paper submitted to *Computers in Human Behavior*.

Young, L. E., & Leonardi, P. M. (2012). Social issue emergence on the Web: A dual structurational model. *Journal of Computer-Mediated Communication*, *17*(2), 231-246.

Zaichkowsky, J. L. (1985). Measuring the involvement construct. *Journal of Consumer Research*, *12*(3), 341-352.

Zhang, L., Peng, T. Q., Zhang, Y. P., Wang, X. H., & Zhu, J. J. (2014). Content or context: Which matters more in information processing on microblogging sites. *Computers in Human Behavior*, *31*, 242-249.

Zolberg, A. R., & Zolberg, A. R. (2009). *A nation by design: Immigration policy in the fashioning of America*. Harvard University Press.