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Framing North Korea on Twitter: Is Network Strength Related to Sentiment?

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Research on the news coverage of North Korea has been paying less attention to social media platforms than to legacy media. An increasing number of social media users post, retweet, share, interpret, and set agendas on North Korea. The accessibility of international users and North Korea's publicity purposes make social media a venue for expression, news diversity, and framing about the nation. This study examined the sentiment of Twitter posts on North Korea from a framing perspective and the relationship between network strengths and sentiment from a social network perspective. Data were collected using two tools: Jupyter Notebook with Python 3.6 for preliminary analysis and NodeXL for main analysis. A total of 11,957 tweets, 10,000 of which were collected using Python and 1,957 tweets using NodeXL, about North Korea between June 20-21, 2020 were collected. Results demonstrated that there was more negative sentiment than positive sentiment about North Korea in the sampled Twitter posts. Some users belonging to small network sizes reached out to others on Twitter to build networks and spread positive information about North Korea. Influential users tended to be impartial to sentiment about North Korea, while some Twitter users with a small network exhibited high percentages of positive words about North Korea. Overall, marginalized populations with network bonding were more likely to express positive sentiment about North Korea than were influencers at the center of networks.

Keywords: Twitter, framing, sentiment, North Korea, network strength

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1. Introduction

North Korea is a nation that is difficult to access both physically and politically. Only select people screened by the North Korean authority can enter the country, and those admitted are under strict surveillance (Connell, 2019). Any behavior the authorities perceive as anti-government is subject to strict government scrutiny, to which violators are prosecuted for further investigation. As evidenced in the Otto Warmbier case, in which he died following the release to the United States (US) due to excessive torture during his imprisonment in North Korea, post-imprisonment death is common in North Korean prisoners (Kamp, 2019). Nonetheless, still not much is known in depth about the country except for what is provided by the news worldwide and anecdotes from neighboring China, which has remained an ally of North Korea for many years. A small number of international journalists visit North Korea and bring photos from the nation for their news reports. However, the photos and videos are not guaranteed to truly reflect on this highly media-censored nation (Holiday, Lewis, Anderson, & Nielsen, 2019). Recent misinformation about the Kim Jung Un death rumor attests to the lack of information honesty (Farhi, 2020).

Major international news outlets (e.g., *Agence France-Presse-AFP*, *Associated Press-AP*, and *Reuters*) have bureaus in North Korea. Other news agencies such as NK Korea cover a comprehensive picture of North Korea. The news coverage of North Korea is idiosyncratic in view of limited access to the nation and information credibility. Topics covered in news on North Korea vary including diplomacy, the economy, the military, politics, sports, culture, arrests, and accidents (Seo, 2018). The news framing on North Korea is more likely negative than positive (Lee, Baek, & Jeong, 2020) and conflict-oriented (Curran & Gibson, 2020).

A drawback of past research on the news coverage of North Korea is neglecting digital power in news circulation. YouTube, Facebook, TikTok, Twitter, and Instagram users share, interpret, set agendas, and generate virality on North Korea (Carroll & Hotham, 2020). The coexistence of international users and controlled North Korean webpages on the Internet suggests that social media is a crucial venue for diverse views about the nation (Sui & Paul, 2020). Users retweet what they find worth sharing and add their commentary to others' posts, which creates audience framing of news on social media channels. The current study focuses on the role of social media posts made by global users on North Korea. Although social media arises as a platform for news and information about North Korea, little research attention has been paid to the framing of social media posts by international users about the nation. Despite the role of social media as an information outlet about North Korea (Kim, 2018), empirical research on the content from over the world is scarce.

This study has two research purposes. The first purpose of this study is to measure the sentiment of international users' Twitter posts on North Korea from a framing perspective through sentiment analysis, which is a process of driving feelings of a particular statement or word (Mostafa & Nebot, 2020). The second purpose of this study is to examine the relationship between network strengths on Twitter and sentiment from a social network perspective. Positive and negative sentiment have both been significant predictors of network cluster density on Twitter (Himelboim, Xiao, Lee, Wang, & Borah, 2020). Using the framing perspective and social network theory, this study compared network strengths to sentiment to gauge Twitter's ability to shape public opinion.

2. Literature Review

2.1 Framing theory and sentiment

When a news agenda is framed in the media, some attributes are either overemphasized or underemphasized. Frames of information refer to the main idea of establishing and offering meaning to a group of attributes by selection, representation, inclusion, and exclusion (Nelson, Oxley, & Clawson 1997). The information originator chooses, crafts, and emphasizes themes and aspects in the forms of events, issues, and actors. Audiences receive, perceive, organize, and evaluate the forms of news through multiple communication channels (de Vreese, Peter, & Semetko, 2001; Kang, Shim, & Kim, 2019). As a result, audiences perceive an object, entity, or issue in a certain image delivered from the communication channels. Framing imparts the meaning of media agenda to the public.

Framing theory assumes that the attributes emphasized by the message sender and presented to the audience influence the way people process that information (Scheufele, 1999). Framing, therefore, is a precondition to affecting audiences' perceptions, evaluations, and behavior. Sentiment analysis intersects with framing theory in terms of information delivered to the audience. Such contrasting aspects and sentiment viewed as either favorable or unfavorable, positive or negative, and beneficial or detrimental create an information frame that can shape the views of the audience (Zukas, 2017). In this sense, sentiment is a part of framing theory that contributes to accounting for audience effects.

A frame is accepted by the audience in different forms spanning from emotional pleasure to displeasure (Jaeger, Roigard, Jin, Vidal, & Ares, 2019). Sentiment is embedded in a variety of methods in expressive posts on social media. With sociodemographic and sociopolitical backgrounds, social media posts mirror users' contextual aspects. Several aspects of news media (Herman & Chomsky, 2002) illustrate the framing process of news. News media tend to rely on powerful sources, because the sources secure news credibility and acceptance by the public. Another filter are governments. Governments' political orientation can shape news coverage on social media (Giglietto, Valeriani, Righetti, & Marino, 2019). Under a conservative government, the news is able to oppose North Korea and vice versa under a liberal government.

Past research found that audiences tended to read North Korean news in two frames: conflict and human interest (Moon, 2018). In the study, international news organizations such as the *New York Times* or *BBC* often framed North Korean issues (e.g., the Cheonan Corvette incident) as conflicts. Metaphors to describe the North Korean regime and the leader in Australian media were military threat, unpredictable, isolated, and secretive (Dalton, Jung, Willis, & Bell, 2016). Korean national news outlets, including the *Yonhap* or the *DongA Daily* used the human-interest frame on the Cheonan Corvette issue (Moon, 2018). The news coverage on North Korea in recent years has highly revolved around crises from conflicts with South Korea and the US regarding tests on intercontinental ballistic missiles (ICBM) (Brennan, 2020). Another frame on North Korea is the ideology of anti-communism. Similar to media censorship, the ideological conflict can affect both the issues and sources of news on North Korea. The *Xinhua News Agency of China* and the *Korean Central News Agency of North Korea* showed respective valence on news coverage of the Six-Party Talks. The *Chinese Xinhua News Agency* exhibited a positive attitude toward South Korea, whereas the North Korean agency encompassed a strongly negative attitude toward the US and Japan (Jang, Hong, & Frederick, 2015).

Recent political talks in South Korea, North Korea, and the US have brought optimism regarding the regional peace and denuclearization of the Korean peninsula. However, the accumulation of opposition against North Korea over the past decades has drawn skepticism as well. Amidst an unpredictable geopolitical mood, the center of attention was on Kim Jong Un. His appearance in international politics is unprecedented in his leadership career. News media internationally covered the US-North Korea summit in addition to the multiple summits of the two Koreas in 2018. The recent demolition of the inter-Korean liaison office in Kaesung, North Korea (June 17, 2020) by Kim Yo Jung, the younger sister of Kim Jung Un, has elevated not only tension among South Korea, the US, and North Korea, but also the coverage of related news on the Korean peninsula (Shim, 2020).

Traditional and untraditional news framing is represented as two distinct values: ethical and material frames (Shah, Domke, & Wackman, 1996). Ethical frames refer to the value of news as being based on the moral values of right or wrong. When South Korean news media frame North Korea in a favorable manner, it is an ethical frame that imposes a moral value regarding reconciliation rather than confrontation. Material frames refer to tangible values in terms of gain and loss purposes. For example, South Korean news media positively frame the economic alliance with North Korea as a gain rather than a loss. Exposure to political issues of North Korea and social network heterogeneity on social media decreased opinion polarization (Lee & Choi, 2020). Such political divide regarding North Korea may be framed on Twitter either favorably or unfavorably.

Social media may be relatively free from the influence of the government in news frames because the news network is decentralized, and Block Chain based. News sources on social media are as divisive as the users, who share and retweet what they deem newsworthy. These posts go viral when they are uniquely controversial. Controversiality and conflicts hold true more for North Korea due to its idiosyncratic stance in the global political landscape (Curran & Gibson, 2020). News on North Korea is often incorrect as verified by reliable sources. For example, the news reported that a North Korean diplomat was executed. However, the diplomat turned out to be alive after all (Ripley, 2019). Additionally, Kim Yo Jung, the younger sister of Kim Jong Un, was also rumored to have fallen from power after the failure of the Hanoi Summit. Yet, she appeared at a mass game event performed by the North Korean people (Baker, 2019). In their news framing of North Korea's nuclear weapons, Cho, Saifuddin, Park, and Keum (2016) found that both anti-North Korean and anti-American sentiment was prevalent.

Overall, the media coverage of North Korea has likely not been favorable given research evidence. Photojournalist David Guttenfelder's posts about images of North Korea on Instagram revealed the totalitarian aspects of the nation (Holiday et al., 2019). Six-party talks covered by the six nations' news media (China, Japan, North Korea, Russia, South Korea, and the US) reflected on the national interests of each nation (i.e., China and North Korea framed pro-North Korea) (Jang et al., 2015). News frames of North Korea by international press entail threats, war on terror, and nuclear tests (Dai & Hyun, 2010). Like most news outlets frame North Korea adversely, posts on Twitter may constitute a dichotomy that is more negative than positive.

2.2 Networks, sentiment, and North Korea

Social network theory views social relationships as ties, which determine the social capital of individual actors in the networks. The emphasis is on the strength of the network rather than individual attributes (Biehl, Kim, & Wade, 2006). The connections within the network influence other members' opinions and perceptions. Network density and the network's normative performance standards (i.e., required levels of members' performance in an organization) determine network influencers' ability to constrain members to either high or low performance standards (Manata, 2019). Online conversational communities can emerge from dynamic communication on social media. Community participants conduct endogenous selection and self-organization in the social network strength building process at individual, dyadic, and triadic levels (Sun, 2020).

Twitter builds clusters of users in the form of information networks, ties, and strengths. Framing and social networks on social media are intertwined with each other. Twitter posts are framed by what the network members feature pervasively. For example, celebrity news topics on Twitter, which are derived from the dominant network strength including news features and celebrity attributes, were topic-driven (Yan & Zhang, 2020). The most powerful social network members formed homogeneity in affective terms on Twitter (Robles, Velez, De Marco, Rodríguez, & Gomez, 2020). As such, Twitter creates network strengths by aggregating common characteristics and attributes of the members. Network strengths generate content flows and frame what is discussed in the networks (Bennett, Segerberg, & Yang, 2018).

A combination of network and sentiment analyses demonstrates that network density is positively associated with positive perspectives on human papillomavirus (HPV) on social media (Himelboim et al., 2020). Organizations that actively tweet build strong ties in the social media networks by forming in degree (the number of arrows that go to the user) and out degree (the number of arrows that go out from the user) (Jiawei, 2019). In another study on emotional expression in response to a crisis issue, the researchers found that interaction strength among social media users influenced sentiment (Zhou, Cai, & Ye, 2019). In other words, as a social network is formed and strengthened online, participating members self-disclose, exchange support, and experience sentiment (Yang, Zhong, Kumar, Chow, & Ouyang, 2018). Sentiment toward a topic indicates that the users expressing emotion tend to exhibit strong ties between them (Cabling et al., 2018). The networked sentiment may create influencers, set agendas, and influence public opinions.

Network strength can be an important indicator of interest in North Korea because of the nation's geopolitical locus in the ideological landscape. The tension in multilateral talks among the two Koreas, the US, and other surrounding nations has placed confronting issues at the epicenter of global politics. Only limited research resources provide the findings regarding the sentiment of North Korea on social media and network strength. Pro-North Korean sentiment in strong networks has been highly pronounced in South Korea in the past decade (Owen, 2014). In turn, network homogeneity on North Korea triggers opinion polarization that solidifies the cohesion of ideological groups (Lee & Choi, 2020). Although not Twitter, a social network on YouTube demonstrated the possibility to build international communities for publicity purposes (Park & Lim, 2020).

Social networks among news agencies and international allies are represented in news media so that their posts conform to respective national interests (Lee & Wang, 2016). Social media network intimacy was a prominent indicator of positive sentiment among politicians. A study on the relationship between politician-follower strength and positive sentiment toward the politician found a positive association between the strength and sentiment, called "sentiment democracy" (Ceron, 2018). Past research on network strengths and sentiment suggests that varying forms of network strengths are either positively or negatively related to sentiment.

2.3 Twitter for sentiment analysis

Twitter is a global social media platform frequently used for data analysis because of its role as an outlet for communicative outcomes. Past research using Twitter as a database for analysis examined public opinion (Sanger & Warin, 2018), debate (Tuñón Navarro & Carral Vilar, 2021), real time views (Navarro, Delgado, Paz, Garcia-Muñoz, & Mendoza, 2021), and the social scientific research (Wignell, Tan, O'Halloran, & Chai, 2021).

This study focused on whether international users' Twitter posts framed North Korea positively or negatively. Therefore, the analysis is about how North Korea is framed by Twitter users, an outside perspective rather than by North Korea. The way users frame the nation may influence the views on North Korea by people and shape their attitudes toward North Korea. Given the widespread use of social media for news and information today, examining the framing and sentiment about North Korea on Twitter can offer a public opinion climate about the nation.

2.4 Hypothesis and research question

The review on the framing of North Korea leads to a hypothesis predicting that North Korea is likely negatively framed on Twitter. The majority of research found that the media emphasized totalitarian regime (Holiday et al., 2019), threats and war or terror (Dai & Hyun, 2010), and conflicts (Curran & Gibson, 2020) when framing North Korea. Therefore, this study hypothesizes that Tweets are framed likely more negatively than positively toward North Korea

H: The sentiment of North Korea on Twitter will be more negative than positive.

Although there might be network homogeneity on North Korea (Lee & Choi, 2020), no empirical evidence of a positive relationship between network strengths and the sentiment of North Korea on Twitter exists. Given the review, a research question addresses whether there is a relationship between Twitter users' network strengths and sentiment of North Korea.

RQ: Do social network strength indicators relate to the sentiment of North Korea on Twitter?

3. Methods

3.1 Data collection

Data were collected from Twitter using two analytical tools: Jupyter Notebook with Python 3.6 for preliminary analysis and NodeXL for hypothesis testing. Twitter is a mediated public sphere that offers an open forum where users can post views and retweet others' posts and news with a low barrier to entry. Jupyter Notebook is a big data analysis platform that enables users to adapt computer languages to network and sentiment analysis with built-in libraries. NodeXL is a network analysis and visualization software package that identifies key actors, documents, and networks in social media (Matei, 2011). The search keyword, "North Korea" was used for both Python and NodeXL.

A total of 10,000 Twitter posts about North Korea were collected between June 20-21, 2020. The data collection period was selected for several reasons. The dates were the days Kim Yo Jung, the first vice director of the United Front Department of the Workers' Party of North Korea, announced a plan to send leaflets of punishments in response to South Korea's anti-North Korea leaflets (Shin, 2020). This period was also during the peak of tensions between the two Koreas amid the explosion of the liaison office on June 17 in Gaesung, North Korea (Bicker, 2020). The 10,000 posts were set by factoring in the server capacity without system breakdown and the interruption of information processing speed. The NodeXL version collected 1,957 tweets about North Korea between June 20-21, 2020.

The sentiment analysis with Python used the Maximum Entropy Classifier Model (MECM), in which the positive-negative structure took no assumptions regarding the relations between featured keywords. The basic steps for conducting sentiment analysis consist of data collection, pre-processing of data, feature extraction, selecting baseline meanings, and carrying out classification using machine learning approaches (Gupta, Negi, Vishwakarma, Rawat, & Badhani, 2017). The MECM uses the following formula to draw classifications.

$$P_\lambda(y|X) = \frac{1}{Z(X)} exp \sum_i \lambda_i f_i(X, y)$$

where X is the feature vector and y the class label. $Z(X)$ is the normalization factor and λ_i the weight coefficient $f_i(X, y)$, which is the feature function defined as

$$f_i(X, x) = \begin{cases} 1, \\ 0, \end{cases} X = x_i \; and \; y = y_i \; otherwise$$

The MECM using the Python language yielded a 90% accuracy in sentiment classifications (Gupta et al., 2017). The model always attempts to maximize entropy of a system by computing its conditional distribution of its class labels (Neethu & Rajasree, 2013). Python packages for sentiment analysis encompassed Tweepy, Pandas, Matplot, Seaborn, and natural language processing (NLP). NLP adapts the MECM to the text processing and classification of sentiment. NLP allows Python 3.6 to perform tokenization, tagging, filtering, and text manipulation in the sentiment analysis process (Htet & Myint, 2018).

The pre-processing in Python was obtained by cleaning and adjusting original posts into the data format. This was done by a) converting all uppercase letters to lowercase, b) removing URLs, handles, @, hashtags, #, emoticons, re-tweets, stop words, and repeated characters, and c) expanding slangs and abbreviations, d) collecting spelling, e) generating a dictionary for words, and f) retweets.

3.2 Measurement instruments

3.2.1 Sentiment

For sentiment analysis using Python, this study used a polarity-based sentiment analysis (Nagalakshmi & Radhika, 2018). The sentiment analysis using Python followed procedures provided by Polarity from negative to positive on the machine learning was categorized into numbers from -1.0 (negative sentiment), -.75, -.5, -.25, 0.0, .25, .5, .75, to 1.0 (positive sentiment) in Python 3.6. Sentiment for NodeXL was programmed based on vocabularies with either positive or negative connotations. Two parameters were used to measure sentiment in NodeXL. Positive sentiment was assessed with the values as frequencies (from 0 = Not positive to higher numbers = Positive). Negative sentiment was evaluated in the same way as positive sentiment (from 0 = Not negative to higher numbers = Negative). Positive word percentage was measured with respect to the percentage of positive words included in a tweet (from 0% = Not positive to higher percentage = Positive). Negative word percentage was assessed by the percentage of negative words in a tweet (from 0% = Not negative to higher percentage = Negative).

3.2.2 Network strengths

The data obtained from NodeXL consist of categories that represent network strength indicators (Csardi & Nepusz, 2006; Hansen, Himelboim, Shneiderman, & Smith, 2019; Masserra, 2014). Each Twitter user is measured by a) in degree, b) out degree, c) betweenness centrality, d) closeness centrality), e) eigenvector centrality, f) page rank, g) clustering efficiency, h) followed, i) follower, j) tweets, k) favorites, l) positive counts, m) positive counts percentage, n) negative counts, and o) negative counts percentage (Table 1).

Table 1

Characteristics of Network Strength Indicators (N = 1,957)

	M	*SD*	Range
In Degree	0.99	17.73	0 – 749
Out Degree	0.99	0.62	0 – 17
Betweenness Centrality	408.23	12,863.80	0 – 560,252
Closeness Centrality	0.10	0.26	0 – 1
Eigenvector Centrality	0.0005	0.0006	0 – 0.01
Page Rank	0.99	8.12	0.40 – 344.67
Cluster Coefficient	0.09	0.06	0 – 0.50
Followed	3,395.87	10,806.23	0 – 225,879
Follower	190,154.73	2,766,363	0 – 82,343,695
Tweets	63,469.39	125,600.87	0 – 1,849,678
Favorites	37,928.44	69,911.99	0 – 808,906
Positive Word Counts	0.14	0.53	0 – 10
Positive Word Percentage	0.63	2.30	0 – 25
Negative Word Counts	0.18	0.48	0 – 6
Negative Word Percentage	0.85	2.33	0 – 25

"In degree" indicates a count of the number of arrows that go to the person, whereas "out degree" is a count of the number of arrows that go out from the user. "Betweenness centrality" is the strength of the user's centrality in the network. A high number of betweenness centrality indicates that the user is in a central position in the network. "Closeness centrality" is measured by the speed of access to information. The higher the number, the faster the person reaches the central point of the network. Users with a high closeness central score have the shortest distance (inverse distance) to all central users. "Eigenvector centrality" is assessed by the influence of a user in a network. High scoring users imply that many other users point to the users (high network strengths). "Page rank" is the fraction of the time spent by the user over other vertices. Higher numbers demonstrate a large network and vivid activity. "Clustering efficiency" measures the degree to which a user's friends know each other. As the number is closer to 1.0, the strength of friend networks is more warranted.

"Followed" is the number of other users the user follows. "Follower" is the number of people who follow the vertex. "Tweets" are the number of tweets the user posted. "Favorites" are the number of likes the user received in posts. "Positive counts" indicate the number of positive words in the user's network. "Positive count percentage" refers to the ratio of positive words in the node's network. "Negative counts" are the number of negative words in the network. "Negative count percentage" is the ratio of negative sentiment in the vertex's network.

3.3 Data analysis

Python 3.6 was used as the tool for sentiment analysis on Jupyter Notebook. This study used Jupyter Notebook with Python for preliminary analysis because the analysis results provided not a statistical significance but a distribution difference in sentiment only. NodeXL Basic was used for statistical difference in sentiment and network strength analysis. SPSS 25.0 was also employed to conduct a paired sample *t*-test to compare positive sentiment with negative sentiment posts. Inferential relationships between network strength indicators and sentiment were discovered through multiple regressions.

4. Findings

A preliminary sentiment analysis with Python 3.6 yielded a bar graph showing a positive and negative sentiment distribution (Figure 1). The analysis of 10,000 tweets from June 20-21, 2020 demonstrated that there was more negative sentiment than positive sentiment in the posts about North Korea. The results indicated that the sentiment about North Korea would be more likely to be negative than positive.

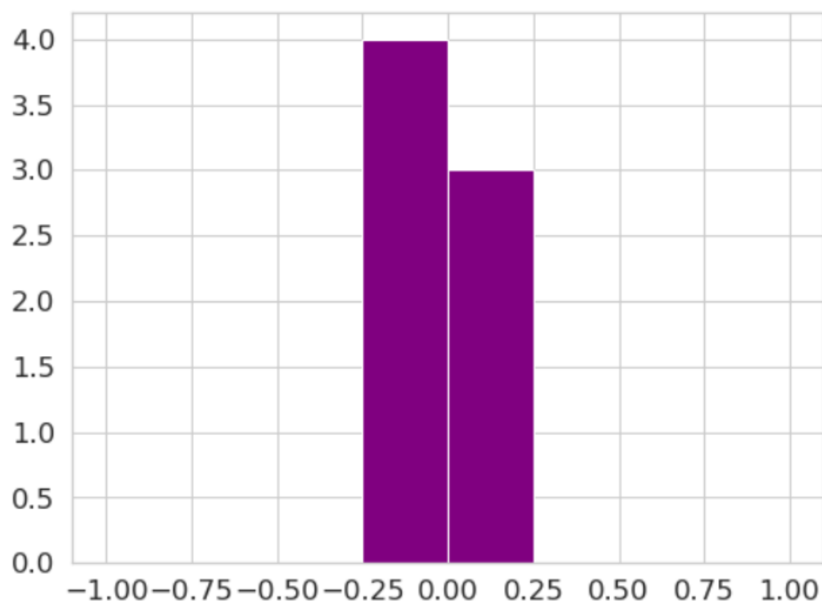

Figure 1. A sentiment analysis on North Korea (N = 10,000)

The hypothesis predicted that the sentiment about North Korea on Twitter would be more negative than positive. For statistical significance, a total of 1,957 cases from NodeXL provided both positive and negative sentiment data. A descriptive analysis for positive and negative word counts found that positive sentiment ranged from 0 to 10 (M = .14, SD = .53, N = 1,957) and negative sentiment from 0 to 6 (M = .18, SD = .48, N = 1,957). The positive word percentage demonstrated a similar pattern with the sentiment counts (positive: 0 – 25%, M = 0.63, SD = 2.30, N = 1,957; negative: 0 – 25%, M = 0.85, SD = 2.33, N = 1,957). A paired t-test revealed a significant difference between positive and negative word counts (t = -2.87, p < .01) (Table 2); therefore, there was more negative sentiment than positive sentiment about North Korea on the sampled Twitter posts, and the hypothesis was supported.

Table 2

Mean Difference Between Positive and Negative Sentiment

Sentiment	*N*	*Mean*	*SD*	*t*	*df*	*p*	*CI*
Positive	1,957	.14	.53				
Negative	1,957	.18	.48				
Paired-Sample *t*-test				-2.87	1,956	.004	-.07 - -.01

The research question asked if network strength indicators were related to sentiment about North Korea on Twitter (Table 3). The analysis found that the actors in the networks consisted of from individuals through news organizations. To name top 10 actors as influencers, they were @michaeljohns (National Tea Party movement co-founder and leader), @reuters, @hispantv (an Iranian Spanish language news channel), @reutersjapan, @ww3info (Third World Info), @coldnoodlefan (Anti-war, peace advocate and news on North Korea), @mi6rogue (Secret Intelligence Service Insider), @bordsystemnewsx (unidentified news source), @sdnylive (Matthew Russell Lee, an American journalist working for innercitypress.com) and @jagrannews (Indian journalist for Jagran News).

Some indicators of network strengths provided by the dataset predicted sentiment of North Korea. Out degree (β = .12, p < .05) and closeness centrality (β = .10, p < .001) positively predicted positive word counts. When Twitter users had connections outward (out degree), they posted positive sentiment about North Korea. Similarly, those who responded quickly to the central point of the network on Twitter (closeness centrality) tended to post about North Korea positively. Eigenvector centrality (β = .18, p < .001) negatively predicted positive word counts, meaning that those who received attention by other Twitter users were likely to post negatively about North Korea. The model explained 24.6% of the total variance. Out degree (β = .09, p < .05) and closeness centrality (β = .07, p < .01) were positively associated with positive word percentage. Eigenvector centrality (β = -.20, p < .001) was a negative predictor of positive word percentage. The number of tweets (β = -.05, p < .05) negatively predicted positive word percentage, indicating that those who posted on tweets often tend to have a low percentage of posts about North Korea. The model explained 25.3% of the total variance.

Table 3

Network Strengths Predicting Sentiment (N = 1,957)

Independent Variable	Positive Word Counts	Positive Word Percentage	Negative Word Counts	Negative Word Percentage
In Degree	.48 (0.51)	-.22 (-0.23)	-.74 (-0.81)	-2.31 (-2.52)*
Out Degree	.12 (3.33)*	.09 (2.41)*	.08 (2.18)*	.01 (0.36)
Betweenness Centrality	-.13 (-1.10)	-.09 (-0.77)	-.21 (-1.80)	-.16 (-1.38)
Closeness Centrality	.10 (3.76)***	.07 (2.94)**	-.03 (-1.43)	-.02 (-0.85)
Eigenvector Centrality	-.18 (-7.49)***	-.20 (-8.25)***	-.31 (-13.27)***	-.29 (-12.38)***
Page Rank	-.34 (-0.35)	.31 (0.32)	.97 (1.03)	2.48 (2.63)**
Cluster Coefficient	-.03 (-1.38)	-.02 (-0.84)	-.01 (-0.33)	.02 (0.92)
Followed	.02 (0.81)	.02 (0.76)	.01 (0.24)	-.01 (-0.13)
Follower	-.02 (-0.87)	-.02 (-0.91)	-.02 (-1.08)	-.02 (-1.18)
Tweets	-.04 (-1.61)	-.05 (-2.29)*	-.01 (-0.48)	-.01 (-0.31)
Favorites	.01 (0.51)	-.01 (-0.15)	.04 (1.65)	.01 (0.46)
R-square (%)	24.6***	25.3***	32.2***	31.1***
Final *F* (11, 1,945)	11.37***	12.10***	20.40***	18.89***

Notes. The coefficients are standard Betas. The coefficients in parentheses are *t*-values. The models for each dependent variable are final.
*$p < .05$. **$p < .01$. ***$p < .001$.

Out degree (β = .08, $p < .05$) was a positive predictor of negative word counts. In turn, Twitter users who had outward connections in the network likely posted negative comments about North Korea. Eigenvector centrality (β = .31, $p < .001$) was negatively associated with negative word counts. In other words, Twitter users who were pointed to by many users tended to be negative toward North Korea in posts. The total variance of the negative word counts model was 32.2%. In degree (β = -2.31, $p < .001$) negatively predicted negative word percentage. Those who had inward arrows from others were more likely to post negative comments about North Korea than those who had limited inward connections. Eigenvector centrality (β = -.29, $p < .001$) was a negative predictor of negative word percentage. Page rank (β = 2.48, $p < .01$) was positively associated with negative word percentage. Those with vivid Twitter activities (does not always indicate a large network in numbers and size) tended to post negative sentiment about North Korea. The model explained 31.1% of the total variance.

5. Discussion

This study first investigated the positive and negative sentiment of Twitter posts about North Korea. In the second research objective, network strength indicators were used as predictors of sentiment to unravel any relationships between network strength and sentiment. An analysis of data sets found that there was more negative sentiment than positive sentiment toward North

Korea. Some unique network strength indicators explained either positive or negative sentiment about North Korea. Network strengths with central roles in network size were likely to show negative sentiment, whereas peripheral populations with network bonding were likely to demonstrate positive sentiment toward North Korea. The major actors of the posts about North Korea were either individual influencers or news organizations for international affairs. For example, Reuters (@Reuters) and Reuters Japan (@ReutersJapan) were at the center of networks and related to negative posts about North Korea. Meanwhile, Rogue Secret Intelligence Service Insider (@mi6rogue) and @ lokmankaradag1 were individual users who had positive posts about North Korea more than others.

Past framing research on North Korea (Moon, 2018) was congruent with the current result, negative sentiment-oriented posts (H). Some examples that were categorized as negative posts were, “#NorthKorea and #SouthKorea are childish. Is it children war?”, “The world's first woman dictator? #NorthKorea Kim Jong Un’s equally scary sister is spitting venom at South Korea.”, “Tyrannical Regimes”, “Leafleting: decisive propaganda or empty provocation?”, and “North Korea is gearing up to send propaganda leaflets over its southern border, denouncing North Korean defectors and South Ko...”

Some examples of positive sentiment posts encompassed, “RT @KimJoongUnnn: Birthday Wishes To @actorvijay On Behalf Of All #NorthKorea Fans 😍. Best Wishes To His Upcoming Project #Mastar 🔥 ”, “Welcome sir. #KimJongUn #Northkorea”, “This presidency shows that #America is the most divided country on earth right up there with #NorthKorea”, “Even though he left the #TrumpKimSummit empty handed— Donald was still excited to see that #NorthKorea rolled out…”, and “A great opportunity for anyone looking to work on #NorthKorea.” The sentiment analysis through NLP detected more negative words than positive ones about North Korea, as found in past research (Dalton et al., 2016). In a broader sense, social media sentiment may reflect on a part of the current agenda and have the potential to influence user perceptions (Kraft, Krupnikov, Milita, Ryan, & Soroka, 2020).

Six predictors (in degree, out degree, closeness centrality, eigenvector centrality, page rank, and tweets) were most powerful in the association of network strengths with sentiment (RQ). Those at the center of networks were individual Tweeters or news organizations (e.g., @ReutersJapan) that covered North Korea (Figure 2). As seen in Figure 2, Some news organizations are at the center of the networks in covering North Korea. HispanTV (@hispantv1) is an Iranian Spanish language news channel operated by IRIB, Iran’s state-controlled broadcaster. NK News (@nknewsorg) is an independent, privately owned specialist information source that focuses on North Korea. Daily NK (@The_Daily_NK) Japan is a Japanese news channel that covers North Korea. Reuters Japan was a hub of news on North Korea. The Figure also shows some individual users. A user at the center of the networks was Michael Johns (@michaeljohns), a National Tea Party movement co-founder and leader, former White House speechwriter, and Heritage policy analyst. Further, the editor of a China’s foreign affairs magazine (@dankurtzphelan) posted positive tweets about North Korea often.

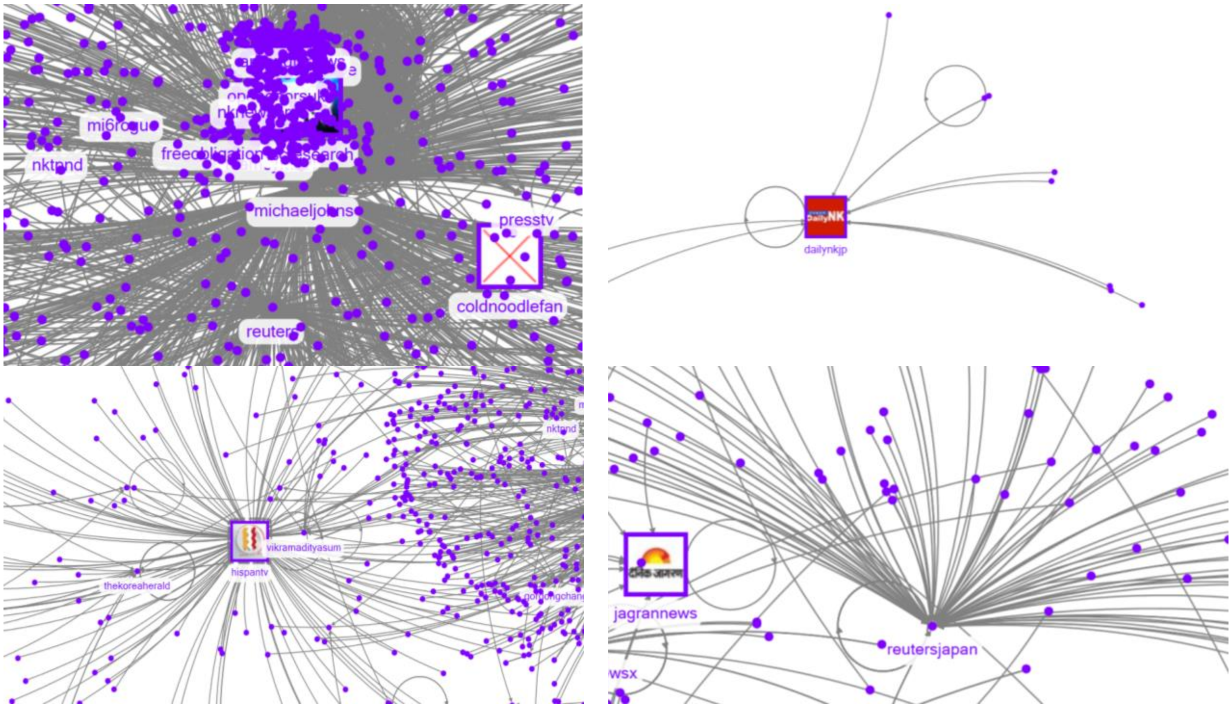

Figure 2. Network strength connections of key Tweeters (*N* = 1,957)

According to the results, these six network strength indicators may play a certain role in shaping either positive or negative sentiment about North Korea on Twitter. The high in degree implicates a large network. Users with a large network were less likely than users with a small network to express negative sentiment as was found in this study. The users with a large network may influence the perception of other users on North Korea. Out degree (a user with outreach to multiple networks) tended to have positive sentiment toward North Korea. This may be interpreted that some select users intentionally reach out to others on Twitter to build networks and spread positive publicity of North Korea. The entities of out degree may be those with pro-North Korea attitudes or other pro-North Korean news agencies such as Uriminzokkiri (https://twitter.com/uriminzok, uriminzokkiri, @uriminzok) and individual users including @ giulioterzi (Italian Ambassador) as found in the data. As social media and news channels are still the most powerful publicity tools for North Korea (Altenberger, 2014; Richey, 2019), such pro-North Korea publicity channels can play a role in framing positive sentiment about the nation.

Closeness centrality significantly predicted both positive word counts and percentage but did not predict negative word counts or percentage. The indicator of closeness centrality measures the extent to which the user is intimate with the center of the given network. Positive word counts assess the number of positive words about North Korea within the network. A probable implication of the result is that those who frame North Korea positively tend to be not influencers but peripheral users trying to be part of the strong network so that they can enter the network to promote North Korea. Some Twitter users may express positive sentiment about

North Korea but not be in central networks. For example, the data showed that some unknown users such as @drunkpamaster and @silvestro52 were some of the users who posted positive tweets about North Korea indicating that Twitter provides a sphere that individual users may influence others.

Instead, they appear to utilize strong networks to spread positive sentiment. In fact, North Korea has been involved in communicating on social media such as Twitter. A summit between the US and North Korea was initiated and set via Twitter by North Korea's response to President Donald Trump's tweet (Reddy, 2019). North Korea's networks or other pro-North Korea Tweeters may access central networks to spread positive sentiment about North Korea.

A notable finding is the negative predictability of eigenvector centrality for both positive and negative sentiment. Eigenvector centrality measures an influencer in a network. A user with high eigenvector centrality indicates that the user is in a powerful position in the network. In turn, those influential users were likely neither positive nor negative in sentiment about North Korea. This result suggests that Twitter influencers are likely to avoid ideologically oriented discussions about North Korea. Rather, their expression appeared to be in the middle ground without either significantly positive or negative sentiment.

Those who spent a large amount of time on Twitter (high page rank) showed a positive association with negative word percentage (the ratio of negative words in the user's network). Vivid Twitter users tended to have higher percentages of negative words toward North Korea than did inactive users. The result may mean that although there are some social media users who introduce North Korea to the world (e.g., Carson, 2016), active Twitter users mention human rights and are satirical about North Korea proactively (The Indian Express, 2019). Another finding that the number of tweets was negatively related to positive word counts (the number of positive words about North Korea in the user's network) might imply that those who frequently post on Twitter are not favorable toward North Korea.

In summary, Twitter is an outlet for cosmopolitan access and a forum for freely discussing North Korea. A significant observation from this 'big data' analysis suggests that both positive and negative sentiment exists on Twitter, but those users expressing positive sentiment toward North Korea are likely marginalized populations. The network strength indicators discover the pattern of peripheral use regarding positive sentiment about North Korea. The marginalized populations on Twitter may use strong social media networks to promote North Korea. Although they are not influencers, they approach and connect with influencers (center of network) to spread positive sentiment about North Korea throughout entire social media networks.

5.1 Theoretical and practical implications

Both framing theory and social network theory provided grounds for a sentiment landscape analysis of North Korea on Twitter. Sentiment can be a part of information framing so that it may influence the public's views on an issue. This study applied framing theory to sentiment analysis. Regarding network strengths and sentiment based on social network theory, the strength indicators (e.g., in degree and eigenvector centrality) in this study may be developed as independent variables to predict public opinion about North Korea. With a created scale for network strengths, such research attempts may provide an answer to the influence of social media on public opinion about North Korea or other social issues. The diverse indicators of network strength provided by NodeXL can offer a delicate model for predicting sentiment. The current study might have offered a theoretical model to test the predictability of network strengths on public opinion among social media users. News organizations or governments may be able to utilize this study's framework to gauge the present trends of opinions about North Korea or other sociopolitical issues.

5.2 Limitations, suggestions, and conclusion

This sentiment analysis about North Korea was not able to find categorical frames, including issues and actors. The present analysis provided only positive and negative slants. Therefore, for a detailed content structure of posts about North Korea, future research can code posts to investigate a distribution of issues, sources, aspects, and images (e.g., Holiday et al., 2019; Seo, 2018). The data size may be too small to generalize the results. A larger sample in multimodal platforms may offer a valid structure of the content. This study set only a short period of time for data collection. Future research could extend the period to multiple points in time and conduct longitudinal studies to see changing patterns overtime.

In conclusion, the present study about framing North Korea on Twitter found the sentiment to be more negative than positive. Network strengths were significant indicators predicting sentiment. Those who were relatively marginalized tended to express positive sentiment. Meanwhile, those with strong network power were likely either objective or negative toward North Korea. The results suggest that Twitter is a media outlet that may have the potential to frame and influence public opinion about North Korea.

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