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Concientization among People in Support and Opposition of President Trump

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ABSTRACT

Civic engagement in the United States has increased since the election of President Trump. This increase is evident online as people are using Twitter to assert their digital citizenship by voicing their opinions regarding President Donald J. Trump and demonstrating solidarity with various civic movements. President Trump's election has caused many people to recognize how policies impact their daily lives and shed previous understandings as described by Freire (2005) as concientization. This study employed a Content Analysis to classify Tweets from #DisruptJ20 posted during inauguration week according to concientization and Support or Opposition of President Trump. A Sentiment Analysis revealed that supporters of President Trump were much more negative than those who oppose President Trump. Results of the Logistic Regression found that variables related to network structure (Friends, Followers, and Likes) were more likely to predict Retweets than concientization. Results of Hierarchical Linear Modeling indicate the average level of concientization was positively related to being Retweeted. Implications include recognizing that digital citizens value content that illustrates how matters of state are impacting their lives. As concientization increases in America, the more likely it is for people with opposing viewpoints to understand one another and work for mutually beneficial social change.

Keywords

Hierarchical linear modeling, Logistic regression, Concientization, Twitter, Digital citizenship

Introduction

The value of civic engagement can be seen as greater levels of participation in civic engagement increasing the chances for society to reflect the values of its citizens because there will be less of a disconnect between citizens and those elected to represent them (Coleman & Gotze, 2001). However, over a 25-year span, civic engagement has been decreasing at a rate of 9% in America (Montgomery, Gottlieb-Robles, & Larson, 2004). This trend of disengagement has changed course due to the election of President Donald J. Trump, which has catalysed Americans and people living abroad to engage in Social Action. Examples of Social Action associated with the election of President Trump are the Women's March and the March for Science. In part, these movements owe their existence to the common perception that the President is disrespectful toward women and his statements regarding the science behind climate change and environmental policies not favorable to energy-related industries. People are awakening from their state of apathy because the President is forcing them into a state of Dissonance (Festinger, 1957) by creating fundamental contradictions between their internal views of the world (e.g., women should be treated with respect and government should work to protect the environment) and what is actually taking place. With so many people struggling with the new realities introduced by Trump's presidency it begs the question, why did Americans elect Donald Trump in the first place?

The reasons Donald Trump was elected require further elucidation beyond existing interviews and exit polls because many instances of racism and anti-Semitism have surfaced since the election which threaten to disenfranchise large numbers of Americans. An examination of the statements made by people who support and oppose President Trump via the social medias site, Twitter, provides a unique opportunity to understand the identities of people on both sides and how they are exercising their freedom of speech in service of their digital citizenship. Twitter is an appropriate venue for this study because confidence in traditional methods of civic engagement is quite low (Coleman & Gotze, 2001) which ultimately drives people toward social media like Twitter to make their voices heard (Bonilla & Rosa, 2015). In addition, the combination of using Twitter and being an opinion leader on a given political topic has been found to significantly increase the chances of an individual increasing their civic engagement (Park, 2013). America currently stands as a house divided and the roots of these divisions must be identified in order to productively move forward as a nation.

Literature review

Imagined communities

Anderson (2006) developed the concept of Imagined Communities to describe nationalism as a sense of commonality regarding love for country regardless of the absence of direct intercourse among members. He provides the following definition: “It is an imagined political community - and imagined as both inherently limited and sovereign. It is imagined because the members of even the smallest nation will never know most of their fellow-members, meet them, or even hear of them, yet in the minds of each lives the image of their communion” (p. 5–6). He continues saying the nationalistic community is developed and maintained by participation in common activities. The idea that communities of people form based on interests, especially political interests, is important to this study because people who support and oppose President Trump are a subset of nationalists. These individuals will likely never meet (outside of Twitter) yet they all share similar views regarding the President and what they should or should not do to assert their views. Members of Imagined Communities form their identities based on prevailing stereotypes that exist within groups but also according to a person’s interpretation of how their actions are perceived by group members. Indeed Holland, Lachicotte, Skinner, and Cain (1998) note that “Persons develop through and around the cultural forms by which they are identified, and identify themselves, in the context of their affiliation or disaffiliation with those associated with those forms and practices” (p. 45). People who support and oppose President Trump form their own Imagined Communities. Within these communities, people are developing their identities through their talk about ideas surrounding societal and governmental issues and how they impact the lives of everyday Americans. This process is known as concientization.

Concientization

Freire (1970) defines concientization as “learning to perceive social, political and economic contradictions, and to take action against the oppressive elements of reality” (p. 35). Concientization represents changes in consciousness that reorient people to view their realities in a more critical light. The stages of concientization per Freire (2005) are characterized as follows:

- Intransitive – silence about the circumstances of oppression and taking no action
- Semi-intransitive – submersion in historical processes characterized by introverted communities which cannot apprehend problems outside of their sphere of biological necessity. Represents a near disengagement between a person and existence.
- Naïve Transitive – oversimplification of problems and romantic view of the past that tend to have little interest in investigation and focus on polemics instead of dialogue
- Transitive – contending with problems outside their sphere of biological necessity by testing evidence which eventually replaces disengagement with almost total engagement and dialogue

Oppressed people generally start in the Intransitive stage and move gradually to the Transitive stage. To develop a critical consciousness oppressed people (e.g., minorities, people of low socioeconomic status, etc.) must engage in a critical confrontation of reality. In essence, the oppressed must critically state the nature of their oppression and name it as a first step in freeing themselves from their circumstances. However, when an oppressed people start to engage in sustained dialogue and reflection about the circumstances of their oppression, they often take action upon the world to initiate transformation, which is known as praxis (Freire, 1970). Praxis from a Transitive consciousness is the ideal outcome of concientization. However, not everyone reaches the Transitive stage because people tend to fear freedom due to the difficulties involved in recognizing the way one has lived his or her life is built on oppressive constructs (Freire, 1970). To that end, the power of social media to move people from a passive role of information consumers to information producers facilitates the ability to participate in Social Action (Gleason, 2013). Digital Activism specifically encompasses the online actions that people take to initiate change in society.

Digital activism and identity negotiation

Digital Activism is defined by Whyte and Joyce (2010) as “the use of electronic tools to increase the effectiveness of a social or political change campaign” (p. 218). For example, research by Juris (2012) on the Occupy Wall Street movement linked Twitter activity to face-to-face actions finding when the city of Boston was trying to dismantle the protester’s encampment, activists got the word out on Twitter and people started to sing and dance in the streets until the city relented. Furthermore, Digital Activism is reported in the work of Bonilla and Rosa (2015) who studied #Ferguson organizing. Their research found that very soon after news of Michael Brown's death hit social networks, people organized digital protests as a sign of solidarity with those who protested in person. As people from across the globe unite in solidarity with those protesting racial violence, they are exposed to a deluge of viewpoints that ultimately provides them with the opportunity to negotiate their own identities based on what they think of the points being made. Bakhtin (1981) speaks to this negotiation process saying, "The importance of struggling with another's discourse, its influence in the history of an individual's coming to ideological consciousness, is enormous. One's own discourse and one's own voice, although born of another or dynamically stimulated by another, will sooner or later begin to liberate themselves from the authority of the other's discourse" (p. 348). In other words, people initially engage in Social Action via Digital Activism using their own voice which is largely a product of socialization and experiential learning. As an individual engages in Digital Activism, he or she is provided with the opportunity to assess values and morals surrounding the subject of their activism. This assessment process is what Freire is referring to with concientization. As such, the resulting decision to continue to portray external values (remaining oppressed) or to formulate an original position (toward freedom) is what liberates people from external discourses.

When the negotiation of identity via concientization occurs at a group level the impact on society is often great. Perhaps the most powerful example of consciousness raising on social media is the Arab Spring Movement which was responsible for overthrowing former Egyptian President Hosni Mubarak. The role of social media like Twitter, Facebook, and YouTube was so important to the success of the Arab Spring Movement that it is referred to as a "Facebook Movement" (Brym, Godbout, Hoffbauer, Menard, & Zhang, 2014). Specifically, this Facebook Movement owes its inception in large part to previous movements that allowed Egyptians to voice their concerns about social issues in their country including "We are all Khaled Said." This online movement was organized around the Egyptian police beating Khaled Said to death in the streets reportedly because he was in possession of videotaped evidence incriminating police in sharing the spoils from a drug bust (Lim, 2012). Previously Egyptians were weary of police brutality but "We are all Khaled Said" provided Egyptians the opportunity to negotiate their identities and coalesce around a shared sense of victimization. This communal sentiment was vital in successfully overthrowing Hosni Mubarak. The advent of social media, such as Twitter, allows people to raise their consciousness regarding contradictions in society by providing a place to negotiate personal and group identity.

Twitter features and discourse support

Twitter provides specific technological features that mediate the ability of people to negotiate their identity and communicate online. Twitter (2016) offers the following definitions of these unique features:

- Hashtags – A hashtag is any word or phrase immediately preceded by the # symbol. When you click on a hashtag, you'll see other Tweets containing the same keyword or topic.
- Retweet – A Tweet that you forward to your followers is known as a Retweet. Often used to pass along news or other valuable discoveries on Twitter, Retweets always retain original attribution.
- Follower – A follower is another Twitter account that has followed you to receive your Tweets in their Home timeline.
- Like – Liking a Tweet indicates that you appreciate it. You can find all of your likes by clicking or tapping the Likes tab on your profile.

In this study Retweets are operationalized as a measure of network diffusion and by proxy a measure of popularity. Research has identified that Twitter mediates communication in an examination of informal (self-directed outside of traditional classroom) learning. This research asserts that people learn on Twitter by structuring their communication according to Twitter hashtags which expose them to various perspectives (Gleason, 2013). Another unique feature of communication on Twitter is the limit of 140 characters enforced for all tweets. Blair (2013) found that the limit of 140 characters (recently changed to 280 characters) helps create engagement online and makes it easy to consume information. In a similar vein, Risse, Peters, Senellart, and Maynard (2014) note that the limit of 140 characters reduces the effort needed to engage in communication and focuses the message on core information. Puschmann, Bruns, Mahrt, Weller, and Burgess (2014) even go so far as to state Twitter's character limit makes previously impossible discourses a reality. An example of such a discourse is found in this study where people who represent the far left (anarchists and socialists) and far right (religious fundamentalists and racists) of the American political spectrum communicate with one another and are ultimately exposed to totally opposing viewpoints. Interaction among these two groups is unheard of, especially outside of sanitized and mediated sessions, because their viewpoints are so incendiary to one another. Freire (1970) states, "Without dialogue there is no communication, and without communication there can be no true education" (p. 92–93). In other words, the exposure to diverse viewpoints allows ample opportunity for people to learn from one another and begin developing their consciousness. Therefore, the purpose of this study is to compare people who support President Trump with people who oppose him in terms of Retweets accounting for average levels of concientization for people contributing to #DisruptJ20 and #OccupyInaguration on Twitter just prior to Inauguration Day. In addition, this study seeks to describe the sentiment of the messages sent by people who support or oppose President Trump.

Research questions

Sentiment Analysis, logistic regression, and Hierarchical Linear Modeling (HLM) were conducted to complete this study. The research questions that will be addressed in this study according to these methods are as follows:

Sentiment Analysis Question:

- How does the sentiment of people who support President Trump compare to people who oppose him in terms of the words they use in their tweets?

Logistic Regression Questions:

- Can the likelihood of a Tweet being Retweeted be accurately predicted by concientization, Friends, Followers, and Likes?
- Which variables are most important to predicting the likelihood of a Tweet being Retweeted?

HLM Level 1 Questions:

- How does a tweet's level of concientization impact the number of Retweets?
- How does a tweet's number of Followers impact the number of Retweets?

HLM Level 2 Questions:

- How does supporting President Trump impact the number of Retweets?
- How does being an individual impact the number of Retweets?

Method

The data for this study was analyzed according to (1) Logistic Regression and (2) HLM. Prior to conducting any analysis, data was scraped from Twitter. Data scraping is defined by Batrinca and Treleaven (2015) as "collecting online data from social media and other Web sites in the form of unstructured text" (p. 90). Twitter data was scraped using the OILS Twitter Scraper (Flor, 2014). This tool uses the Twitter API to transfer data from Twitter servers into an Excel spreadsheet. Data was delimited according to the search string used to search for tweets on Twitter.com. A sample search string used to scrape data is provided below:

q=%23OccupyInauguration OR %23DisruptJ20 since%3A2017-01-17 until%3A2017-01-18&src=typd

Data was scraped from Jan 16 - 21, 2017 but only data from Jan 16 - 18 was used in this study to avoid the potential influence of confounding variables introduced on Jan 19 - 21 due to live events and demonstrations that happened on those days. The dataset used for this study is considered "big data," which means that data cleaning must be completed after data collection. Batrinca and Treleaven (2015) define data cleaning as the "correction or removal of erroneous (dirty) data caused by disparities, keying mistakes, missing bits, outliers, etc." (p. 93). Data cleaning first limited the data only to the users who posted on all of the days that were going to be used in the analysis. This process yielded a total of 65 users who posted to all days. Assuring the consistency of the users helps to enumerate the ideologies of the tweeters because the analysis of their continued interactions over time elucidates their unconscious tendencies. Next, duplicate data was removed by examining Retweets using Excel's Remove Duplicates function. 874 original tweets spread across three days remained upon the conclusion of this process. Note that the unit of analysis for this study is the original tweets. Having completed the data cleaning, the process moved to qualitative coding.

A Content Analysis (Krippendorff, 1980) was performed to code the tweets according to the four stages of concientization (Freire, 2005). Content Analysis involves forming an in-depth understanding of information contained in transcripts which is not discernible by a cursory viewing (De Wever, Schellens, Valcke, & Van Keer, 2006). This approach involves a close reading of the data to identify themes. The data was coded on a 4-point scale. 1 represented the first level of concientization and 4 represented the final level. Data was also coded according to the general sentiment of the tweet regarding whether it was in support or opposition of President

Trump. Support was coded as a 0 and opposition was coded as a 1. Finally, the users who contributed to the hashtags of interest were coded according to whether they were an individual or organization with 0 representing organizations and 1 representing individuals. Table 1 presents samples of Tweets according to the phases of concientization grouped by their support or opposition of President Trump.

Table 1. Sample tweet concientization coding

Concientization phases	Support	Opposition
Intransitive	I TOLD YOU, LIBS Prefer Islamic Terrorists, Over You, America! #ObamasDomesticTerrorists #BLM #ISIS #DisruptJ20… https://t.co/Wp5lciEZJk	Jesus supports the ACA #DisruptJ20 https://t.co/0Ot0KoB0Ik
Semi-Intransitive	The very same globalist forces opposing Donald Trump are aligned with nazis in Ukraine #PopularFront #DisruptJ20… https://t.co/MFifK8nLsm	Godspeed Brandon. Maybe consider offering tips for kids being exploited by #DisruptJ20 thugs on how to get out https://t.co/4mtrB5vcF6
Naïve-Transitive	Trump is a pragmatist, not an ideologue. He could be an FDR or a Ronald Reagan, largely depending on what "progressives" do #DisruptJ20	Trump's attacks on John Lewis was another racist dog whistle appeal to white supremacists.'… https://t.co/mjF9diCbxM
Transitive	Undercover investigation expose groups plotting criminal activity at Trump inauguration @TuckerCarlson #disruptj20 https://t.co/tnmNK1Afmu	We are tooootally going to FB Live this #J20 event https://t.co/45zf5VvrVE thank you @dcmj2014 for THE GREATEST DEMO EVER! #DisruptJ20

Study 1 – Sentiment analysis

A Sentiment Analysis, defined by Batrinca and Treleaven (2015) as "the application of natural language processing, computational linguistics and text analytics to identify and extract subjective information in source materials" (p. 90), was performed in Excel using the OILS Twitter Scrapper. First a parser was used to generate frequency counts of both the most commonly occurring single words (unigrams) and word pairs (bigrams) in the dataset by running a preprogrammed routine. Note unigrams and bigrams are the most common features used in topic-based text classification (Liu, 2012). The unigrams and bigrams were manually reviewed to determine which ones should be included in the positive and negative lexicons. Specific words that were included in the positive lexicon include "join us," "resilient," and "bridges" while examples of words included in the negative lexicon include "demolish," "crying," and "Libtard." The positive lexicon also included general sentiment words like "wonderful" or "fantastic" while the negative lexicon contained words such as "horrible" or "awful." These lists were then used to produce a sentiment score which determines positive or negative sentiment by summing the numbers of positive and negative words in the data set (Liu, 2012). Positive words are counted as +1 while negative words are counted as -1 (Hu & Liu, 2004). Outcomes of the Sentiment Analysis are presented in the first subsection in Results.

Study 2 – Logistic regression

A Logistic Regression was identified to analyze the data because many tweets (n = 577) were never Retweeted. These null values mean that using HLM to analyze the entire dataset would have produced misleading results because the effects would have been heavily influenced by the high number of tweets that were never Retweeted. SPSS was used to conduct the Logistic Regression to determine which independent variables (concientization, Friends, Followers, Likes, Support or Opposition, and Individual or Organization) were predictors of whether a tweet was Retweeted. Data screening led to the elimination of five outliers based on their Mahalanobis distance which left a total of 868 cases to be entered into the analysis. Note that the variable that served as the case number for data screening was the ID variable. The regression method selected to conduct the analysis was Forward Likelihood Ratio. This method enters independent variables one at a time into the model and uses the Likelihood Ratio to determine which variables are included in the final model. The model completed four steps to finalize the model. Outcomes of the Logistic Regression are presented in the second subsection in Results.

Study 3 – HLM

To conduct the HLM the tweets that were never Retweeted were removed from the dataset in order to address the potential for producing misleading results. After tweets that were never Retweeted were removed, a total of 297 samples remained. An additional step was necessary to prepare the data for the HLM because the distribution of some study variables (Retweets, Followers, and Likes) exhibited a substantial positive skew. For example, some tweets were Liked thousands of times while others received only a handful of Likes. To address this, these variables were all log transformed which allowed the data to meet the assumption of normality. The log transformed variables were used in the HLM. Note that upon the completion of the HLM, the inverse log was calculated for each effect size to increase the fidelity of the interpretation.

Once the data was prepared, the effects of study variables on the number of Retweets were modeled in R. The variables included in the Level 1 equation are Retweets (Ret), concientization (Conc), and number of Followers (Follower). Variables included in the Level 2 equations are Support or Opposition (Supp) and Individual or Organization (Ind). The final equations are as follows:

Level 1

$$Ret_{ij} = \beta_{0j} + \beta_{1j}Conc_{ij} + \beta_{2j}Follower_{ij} + r_{ij}$$

Level 2

$$\beta_{0j} = \gamma_{00} + \gamma_{01}Supp_j + \gamma_{02}Ind_j + u_{0j}$$
$$\beta_{1j} = \gamma_{01} + u_{1j}$$
$$\beta_{2j} = \gamma_{02} + u_{2j}$$

Concientization was used as a Level 1 variable to capture the effects of the content of individual tweets. HLM Level 1 Research Question 1 will be assessed using the concientization variable. Followers were used as a Level 1 variable because each tweet is sent individually to all followers. HLM Level 1 Research Question 2 will be assessed using the Followers variable. Support was used as a Level 2 variable because the people who support or oppose President Trump generally share the same sentiment as a group. Note that to operationalize Support at the group level, the mode of all messages posted by a user was used in the data analysis. Finally, the Individual variable which captures whether the tweet came from an individual or an organization was used as a Level 2 variable because individuals and organizations fundamentally have different degrees of network penetration that can be expected to influence the likelihood of a tweet being Retweeted. HLM Level 2 Research Questions 1 and 2 will be answered by the Support and Individual variables respectively. Outcomes of the HLM are presented in the third subsection in Results.

Results

Study 1 – Sentiment analysis

A parser in the OILS Twitter Scrapper was used to generate frequency counts for unique words (n = 2567) and unigrams and bigrams for the Support and Opposition groups. Note that bigrams have a distinct advantage over unigrams because the pairing of words provides context that is vital to correct data interpretation (Bespalov, Bai, Qi, & Shokoufandeh, 2011). Table 2 displays the top 10 bigram noun phrases for both groups.

Table 2. Top 10 Bigrams from support and opposition groups

Support		Counts	Opposition		Counts
plotting	criminal	21	the	Streets	19
undercover	investigation	20	we	Will	14
groups	plotting	20	resist	Trumps	13
investigation	exposes	20	we	Need	12
exposes	groups	18	to	Resist	9
criminal	activity	15	20-Jan	3pm	9
plot	to	9	e	Colorado	9
you	are	9	stand	Up	9
trump	inauguration	8	trumps	antiworker	8
acid	attacks	6	join	Us	8

Note that the bigrams with the highest frequencies in both groups were all combinations of hashtags and URLs (e.g., #disruptj20 and [url]). While these bigrams are useful for determining the classification of tweets, they are not as useful as noun phrases in illustrating the actual message content. From the bigrams, it is clear that the Support and Opposition groups had very different messages. The Support group was mostly discussing the video made by a political activist who documented some people associated with organizing the Disrupt J20 protests planning activities like stink bombing a party for Trump supporters. Notice that the word “criminal” is mentioned several times which speaks to the tendency of those in the Support group to vilify everyone associating themselves with Disrupt J20. The Opposition group was mostly discussing the need for action and attempting to organize people to attend various face-to-face protests. Notice that the language of the Opposition group uses collective words like “we” and “us” painting a picture of the Opposition group as a community.

The Sentiment Analysis failed to classify 43% of the tweets in the Support group and 50% of the Opposition group as either positive or negative. The reason for this performance is many tweets do not use conventional language and only contain hashtags and links. An example of such a tweet is “https://t.co/O2WuIWWiPX #DisruptJ20 #LukeKuhn #altright #PresidentElectTrump #PresidentTrump #wolfblitzer #cnn… https://t.co/Uw8Zpift6m.” The results of the Sentiment Analysis are presented in Figure 1.

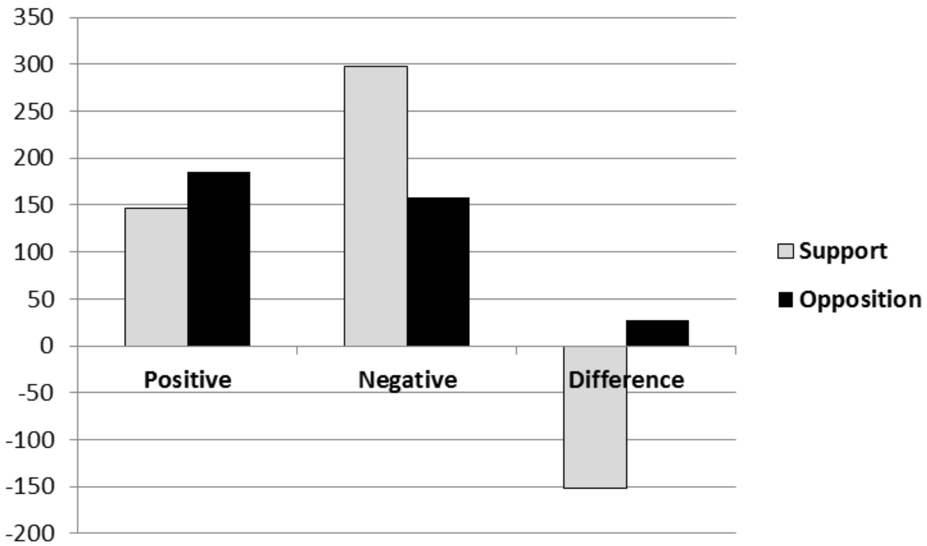

Figure 1. Sentiment analysis results

The sentiment score, represented by the difference between the positive and negative words, of the Support group was strongly negative (-152) while the sentiment of the Opposition group was slightly positive (29).

Study 2 – Logistic regression

Regression results indicated that the overall model of four predictors (concientization, Friends, Followers, and Likes) was reliable in distinguishing between whether the tweet would be Retweeted or not. The four steps in which variables were added to the model improved the -2 Log Likelihood from 953.38 to 907.44 which indicates an improvement of model fit but also that the model fit can be improved. Logistic Regression Research Question 1 is satisfied as the model correctly classified 69.1% of the cases. Concientization, Friends, Followers, and Likes significantly predict Retweets ($\chi^2 = 288.104$, $df = 4$, $p < .000$). Regression coefficients are presented in Table 3.

Table 3. Regression coefficients

	B	Standard Error	*df*	*P*	Odds Ratio
Concientization	-.190	.091	1	.037	.827
Number of Friends	.000	.000	1	.008	1.000
Number of Followers	.392	.110	1	$p < .000$	1.481
Number of Likes	4.109	.458	1	$p <.000$	60.863
Constant	-1.339	.338	1	$p <.000$	.262

Logistic Regression Research Question 2 is addressed by examining the odds ratios for these variables which indicate Likes are overwhelmingly more likely to predict the number of Retweets than the other variables included in the model. That is, tweets that are Liked are about 60 times more likely to be Retweeted than those that are not. Followers and Friends were also found to predict Retweets but to a much lesser extent being only about 1.5 times more likely. Concientization was least likely to predict the number of Retweets but was still statistically significant.

Study 3 – HLM

HLM results indicate that all the significant effects occurred at the first level when examining how concientization and Followers impacted the number of Retweets. Results of the HLM are presented in Table 4.

Table 4. HLM Results

Outcome measures	*df*	Effect Size (Log)	Effect Size (Inverse Log)	Standard Error	*t*-value	*p*
Intercept	245	-0.2048075	0.624011	0.4056303	-0.504912	0.6141
Concientization	245	0.0604927	1.149457	0.0305596	1.979499	0.0489
Followers	245	0.3034410	2.011134	0.0913375	3.322194	0.0010
Support	47	-0.2480536	0.564867	0.1758478	-0.760808	0.1649
Individual	47	-0.1150564	0.767262	0.1512293	-1.410615	0.4506

Concientization and Followers are both significant as $p < .05$ for both variables. Note that the t-values for these two measures provide additional evidence that the variables are significant because concientization can be rounded up to 2 and Followers is greater than 2. The effects for concientization and Followers were quite large. The effect size of 1.14 indicates that the higher the average level of concientization the more likely the possibility of a Retweet, which addresses HLM Level 1 Research Question 1. The effect size of 2.01 for Followers indicates that the more Followers are exposed to a tweet the more likely it is to be Retweeted, which addresses HLM Level 1 Research Question 2. Note that the effect of Followers is almost twice that of concientization which means that network structure is more important to determining the likelihood of a Retweet than the content of the message. Note that the value of the Level 1 random effects is .3827 standard deviations for the intercept while the value of the residual is .358 standard deviations. Neither of the second level effects were significant as $p > .05$ and the *t*-values for Support and Individual are below 2. Therefore, for both of the HLM Level 2 Research Questions it can be concluded that neither variable has any significant impact on the level of Retweets. These findings suggest that the most important factor in determining Retweets is network structure rather than the polarity (Support) or who the tweeter is (Individual).

Discussion

A primary finding of this study is that variables related to the network structure of Twitter (Followers and Friends) were strongly related to the likelihood of being Retweeted. Boyd, Golder, and Lotan (2010) confirm this result saying, “Retweeting for Social Action is most successful when the Retweeter has a large network and occupies structural holes, or gaps in network connectivity between different communities” (p. 7). People who occupy structural holes are often known as information brokers because they use their membership in various online communities to pass content into new domains (Bizzi, 2013). As mentioned earlier, Followers receive tweets from people they follow in their timelines. It follows that the more people who belong to different groups see a tweet, regardless of its content, the more chances the tweet has to find people who resonate with its content enough to Retweet it. Additional support of the impact of Followers and Friends is provided by Suh, Hong, Pirolli, and Chi (2010) who found that Followers are positively associated with Retweets in their random sample of 73 million tweets. Another Twitter network structure variable, Likes, was found to predict the likelihood of Retweets in the Logistic Regression. However, this finding is contested by Suh et al. (2010) who found that Likes were not used much by Twitter users and that Likes also explained little regarding the potential to be Retweeted. By definition, the random sample of tweets taken by Suh et al. (2010) did not focus on specific communities which have developed their own unique uses of Likes. The focused nature of this study on Imagined Political Communities means that by and large the people tweeting in this dataset are likely to have formed their own online practices. That being said, it also seems if someone “appreciates” a tweet enough to Like it, they would also Retweet the content.

A second finding is concientization positively influences the number of Retweets. Holland et al. (1998) notes that media messages are evaluated through the lenses of everyday communities. If true, the finding that tweets with a higher average level of concientization are more likely to be Retweeted and reach wider audiences can be interpreted as a potential shift in the overall American political consciousness toward developing a critical understanding of how individuals are influenced by government policies. The actions people take in affiliation with Imagined Communities help people to imagine their own identities in light of their affiliations and disaffiliations (Holland et al., 1998). The Sentiment Analysis results are particularly important in this regard because they paint a clear picture of the messages people are exposed to. For instance, a Trump Supporter following the tweets associated with #DisruptJ20 would have been immersed in negativity among his peers. However, being exposed to positive messages coming from the Opposition group would create Dissonance. As such, the Trump Supporter would either change his beliefs and move toward freedom or continue falling in line with his peers. This process of negotiation is at the heart of concientization and such critical evaluation of positionality is what may ultimately lead to lasting changes in the American political consciousness.

A shift in political consciousness has been considered regarding its potential impact on society. For example, Wojcieszak (2009), in her study of online extremist groups, writes that "Many—if not most—Internet users may go online simply to vent or express opinions. Feeling empowered by self-expression or seeing it as a sufficient way to address an issue, those users may not engage in any subsequent actions" (p. 579). These individuals may very well be Slacktivists who do not engage in any type of face-to-face organizing. On the contrary, a post-election poll found that Millennials who voted for Hillary Clinton are likely to engage in protests, volunteer, and attend public meetings (CIRCLE, 2017). Whether Social Action associated with growing awareness that government policies impact the daily lives of Americans remains online or expands into the real world is ultimately inconsequential because both are valid forms of civic engagement that provide people the opportunity to negotiate their identities. This process of negotiation and dialogue will facilitate concientization and eventually redefine the boundaries between nationalistic Imagined Communities leading to new digital citizenship practices.

Implications

The findings of this study inform digital citizenship education in two ways: (1) concientization provides a framework for generating productive dialogue by avoiding dehumanizing actions and (2) network structure elements provide context which contributes to appropriate message interpretation. Concientization should be a vital element of digital citizenship education because it lays the foundation for people with very different viewpoints to learn about one another by identifying, removing, and avoiding dehumanizing actions. In this study dehumanizing comments were common especially among those in the Intransitive stage. For example, when a Republican calls a Democrat a "Libtard" or a Democrat calls a Republican a "TrumPet," dehumanization is taking place because the human qualities of the individual are subjugated to a derogatory label that enforces the existence of a disempowered "other." Neither deserves such treatment for even trolls negotiate identity and present their ideal self as they harass others online (Buckels, Trapnell, & Paulhus, 2014). People who operate from a Transitive consciousness are most likely to engage in productive dialogue with people who hold different opinions. The finding regarding the influence of network structure informs digital citizenship education because the information source and the size of the community need to be considered to correctly interpret messages. For example, comments made to #NotMyPresident and #PresidentCuck share a negative sentiment of President Trump. However, messages on #PresidentCuck (cuck is short for cuckold) would be more graphic than those posted to #NotMyPresident. In addition, in a cohesive community the larger the network the more likely it is for message sentiment to be highly polarized based on community values. An awareness of the network structure makes a meaningful contribution to digital citizenship education because it provides an appropriate context for interpreting online comments. Including concientization in digital citizenship education provides a framework to help avoid dehumanizing behaviors which impede understanding and collaboration between people with differing viewpoints while awareness of network influences can help people contextualize and therefore interpret the messages they consume.

Conclusion

This study examined how concientization of tweets influenced the likelihood of a tweet being Retweeted among people on the far right and far left of the American political spectrum. Findings indicate that concientization and network structure elements of Twitter have a positive influence on the likelihood of being Retweeted. In their report on civic renewal, Levine and Liu (2015) challenge readers to engage people in trans-political dialogue in order to solve problems collectively as a nation instead of as partisan groups who fight tooth and nail over the boundaries of their Imagined Communities. Establishing a common understanding between polarized parties, via their online interactions is a productive first step to achieve this end. Indeed, the high negative sentiment among

Trump supporters can be used as a foundation to build this common understanding. Wojcieszak (2009) notes that participation in online extremist groups, like the anarchists and racists in this study's dataset, "might increase the visibility of extreme groups, assure members' representation in the political process, and ultimately reshape the political agenda" (p. 580). Dialogue is a critical element in this scenario because meaningful change does not result from unilateral communication (Freire, 1970). Holland et al. (1998) provides some useful guidance to establish such dialogue writing that behaviour is a sign of self-in practice rather than the essence of someone's being. As groups and individuals, we must separate ideology from humanity if we are to engage in dialogue that will result in the genesis of meaningful social change.

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