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To Retweet or Not to Retweet: Understanding What Features of Cardiovascular Tweets Influence their Retransmission

Qinghua Yang[1], **Christopher Tufts**[2], **Lyle Ungar**[2,3], **Sharath Guntuku**[2], and **Raina Merchant**[2]

[1]Bob Schieffer College of Communication, Texas Christian University, Fort Worth, TX

[2]Perelman School of Medicine, University of Pennsylvania, Philadelphia, PA

[3]School of Engineering and Applied Science, University of Pennsylvania, Philadelphia, PA

Abstract

Twitter is one of the largest social networking sites (SNSs) in the world, yet little is known about what cardiovascular health related tweets go viral and what characteristics are associated with retransmission. The current study aims to identify a function of the observable characteristics of cardiovascular tweets, including characteristics of the source, content, and style that predict the retransmission of these tweets. We identified a random sample of 1,251 tweets associated with CVD originating from the United States between 2009 and 2015. Automated coding was conducted on the affect values of the tweets as well as the presence/absence of any URL, mention of another user, question mark, exclamation mark, and hashtag. We hand-coded the tweets' novelty, utility, theme and source. The count of retweets was positively predicted by message utility, health organization source, and mention of user handle, but negatively predicted by the presence of URL and non-health organization source. Regarding theme, compared to the tweets focusing on risk factor, tweets on treatment and management predicted fewer retweets while supportive tweets predicted more retweets. These findings suggest opportunities for harnessing Twitter to better disseminate cardiovascular educational and supportive information on SNSs.

Keywords

Twitter; cardiovascular disease; retransmission; content analysis

Cardiovascular disease (CVD) affects more than 80 million adults in the United States, (Benjamin et al., 2017). Previous research has demonstrated that disseminating CVD-related information, raising awareness about the disease, and receiving social support could be potential strategies for reducing disease risk and improving treatment and management (Lockwood & Yoshimura, 2014; Long, Taubenheim, Wayman, Temple, & Ruoff, 2008).

Enabled by new media and technology, the Internet has become a primary venue for acquiring and disseminating health information (Fox & Jones, 2009; Kommalage & Thabrew, 2008). A national survey shows that 72% of Internet users searched for online

Contact of corresponding author: Qinghua Yang, Ph.D., Assistant Professor, Department of Communication Studies, Bob Schieffer College of Commuication, Texas Christian University, TCU Box 298045, Fort Worth, TX 76244, q.yang@tcu.edu.

health information within the past year (Fox & Duggan, 2013). Internet and online health communities have also become a source of support for patients with chronic medical problems and other health concerns (Wright, Johnson, Bernard, & Averbeck, 2011). Individuals seek information from health professionals online when they have technical, detailed questions related to health issues (e.g., “Is hypothyroidism a risk factor for heart disease”, “What is the normal range for the hemoglobin A1c level”, but often seek information from peers and online communities when they have “personal” questions or questions about how to cope or manage a particular health issue (e.g., “What can *I* do to deal with *my* high/low blood pressure”, “Do *I* have diabetes if *my* feet are always freezing; Ruppel & Rains, 2012). Despite the burden of disease, the latter conversation of health-related information seeking has been understudied for CVD.

Having emerged as increasingly popular online platforms for health information, communication and interventions, social media exert higher impact on people’s health-related perceptions, attitudes and behaviors in recent years. One-third of U.S. individuals are using social media to find health information, share their symptoms and offer opinions about doctors, drugs, and treatments. Besides information acquisition and sharing, a recent meta-analytic review of 21 social-networking-site-based health interventions found a significant overall effect indicating the effectiveness of using social media to conduct health interventions (Yang, 2017). Despite previous content analyses analyzing the characteristics of health (re)tweets (e.g., Chung, 2017; Kim, Hou, Han, & Himelboim, 2016; Guntuku, Ramsay, Merchant, & Ungar 2017; Jaidka, Guntuku, Buffone, Schwartz, & Ungar, 2017; Guntuku, Yaden, Kern, Ungar & Eichstaedt, 2017), to the best of our knowledge, no one has focused on CVD specifically, leaving what content (e.g., theme of Twitter messages, presence of novel or efficacy information) and features (e.g., presence of URL/hashtag, valence, source of Twitter messages, etc.) of CVD tweets drive their virality remain unclear. The lack of such knowledge provides health communication researchers and professionals with little direction to design effective Twitter messages for cardiovascular health education and promotion. Therefore, the current study aims to fill the gap in the literature and practice by examining the content and characteristics of CVD tweets as well as their influence on Twitter message propagation.

Social Media Use in Cardiovascular (CV) Health Communication

Social media has been playing an increasingly important role in individuals’ health. For instance, 90% of the young adults between 18 to 24 years engaging in health activities or obtaining the medical information shared in their social media networks (PwC Health Research Institute, 2012), and 30% of adults share information about their health on social networking sites (SNSs) with other patients, 47% with doctors, and 43% with hospitals (ReferalMD, 2017). Twitter, one of the top four SNSs, has 328 million average monthly active users and received increasing attention from health consumers, scholars and practitioners. The dynamic conversations on Twitter provides an opportunity to study which messages are most disseminated, who are disseminating messages, and what factors drive and increase certain dissemination. Answering these questions becomes a new field of study for scholars and enables researchers and practitioners to using Twitter as a platform to effectively promote health benefits.

Twitter was found as a particularly beneficial tool for cardiovascular health (Wildmer, Engler, Kiarich, & Timimi, 2016) and holds promise as a research tool for studying CV health (Sinnenberg et al., 2016). With more CV health information accessible on social media, these platforms are becoming more prominent not only for individuals to share and learn information, but also for health professionals to disseminate and engage users in emerging areas in CVD. By categorizing 62,163 tweets, Bosley and colleagues (2013) documented that Twitter Users are utilizing this social networking platform to discuss cardiovascular health issues. It has also been found that it is crucial for health professionals to establish credibility on Twitter when discussing health issues by establishing authority and attracting followers to their accounts (Lee & Sundar, 2013). When appropriately applied, Twitter can serve as a powerful tool for health professionals to raise awareness and discuss cardiovascular-related health issues.

Diffusion of Health Messages on Social Media

Diffusion of Innovation (DOI), proposed by Everett Rogers (1983), is a “process by which an innovation is communicated through certain channels over time among the members of a social system” (p. 5). The theory was originally conceived to explain the process of new ideas or technology being adopted, but has been widely applied to a variety of areas, such as marketing, health communication, and sociology. An *innovation* could be “an idea, practice, or object that is perceived as new by an individuals or other unit of adoption” (p.35), and are technological in nature (Rogers, 1983). The two components of most technologies are *hardware* (the tool that embodies the technology as physical objects) and *software* (the information or knowledge base of the technology, such as health-related tweets). Although the adoption of information is not easily observable, which makes information-only technologies hard to study, SNSs enable studying the adoption of information-only innovations by making communication process more visible, which is impossible for other media (Vos, 2016).

DOI as a theoretical framework helps explain what message characteristics influence the propagation of health messages on SNSs. Rogers (1983) identified the following five characteristics of innovations that affect diffusion.

Relative advantage.

An innovation will more easily be adopted if it is “perceived as being better than the idea it supersedes” (p.213), such as CVD tweets with novelty and/or utility. *Novelty* is hypothesized to increase virality since unusual or surprising content contains high social currency and is good for conversation (Berger, 2014). Therefore, novel or surprising messages are more likely to gain virality (Berger & Milkman, 2012; Kim et al., 2013). Messages with information *utility*, conceptualized in health contexts as presence of efficacy information, provide effective means to increase perceived capability to produce valued outcomes and/or to prevent undesired ones (Cappella, Kim, & Albarracín, 2015; Knobloch-Westerwick & Sarge, 2015), and therefore are more likely to be shared.

Compatibility.

Innovations compatible with the users' values, norms, and past experiences are more ready for adoption. Given that social media users tend to maintain positive images and look good (Barasch & Berger, 2014; Berger, 2013), *positivity bias*, that positive messages receive more retransmission than negative ones, was found driving shares (Berger & Milkman, 2012; Kim et al., 2013), and can be explained by the compatibility characteristic.

Complexity.

The likelihood of being retransmitted decreases if the innovation is perceived as difficulty to understand or use. For instance, a tweet that contains URLs requires extra effort and time from the users, such as clicking and downloading the link, which may also be subject to the Internet speed, was found less likely to be retweeted (Sutton et al., 2015).

Trialability.

Trialability is referred to as the "degree to which an innovation may be experimented with on a limited basis" (p.239). The Elaboration Likelihood Model (ELM; Petty & Cacioppo, 1981, 1986) suggests that the individuals could process information through central or peripheral route, and those with less motivation and/or capability of information processing tend to be convinced by the messages through mental shortcuts and make the judgements of experimentation based on peripheral cues, such as source credibility. Since health organizations are perceived as more credible than individuals (Hovland, Janis, & Kelley, 1953), the tweets by health organizations could be more persuasive and likely to be retweeted especially by less motivated and/or capable users.

Observability.

If the results of an innovation are visible and easily identifiable, it will be more readily adopted. In the Twitter context, when a tweet contains hashtags (#), interrogative (?) or exclamatory (!) linguistic feature, they would make the message more attention-catching and consequently more likely to be retransmitted. On the contrary, a direct mention (a message begins with @) makes the tweet less visible to all users, but only the followers of the sender and receiver, which will reduce the retweets.

Hypotheses and Research Questions

Highly retransmitted tweets are more likely to reach a larger audience, as retransmission provides an indicator of public attention to tweets (Sutton et al., 2015). Despite the ubiquity of Twitter and the potentials of applying Twitter to improving cardiovascular health, there is scarcity of literature examining the features of CVD tweets and how they influence number of retweets, which gives great difficulty to design the most influential and effective campaign messages to reduce CVD, the leading cause of death and major causes of disability (CDC, 2017). Thus, the current study sought to generate knowledge of predicting the retransmission of the CVD tweets by their content and structural features.

Under the DOI framework, it is possible to optimize the characteristics that influence the adoption of innovations to increase the reach and influence of information (Haider & Krep,

2004) – the “software” of technology (Rogers, 1983; Vos, 2016). Drawing on DOI and previous studies that examined the retransmission of tweets (Kim, 2015; Kim, Lee, Cappella, Vera, & Emery, 2013; Sutton et al., 2014, 2015), we proposed the following hypotheses and research question delving into the message content and structural features of CVD Twitter messages that influence their diffusion (or retransmission).

In terms of the message content, previous research demonstrated that novel or surprising messages, as well as messages with higher informational utility, are more likely to be retransmitted (Berger & Milkman, 2012; Kim et al., 2013). Utility was found as a positive predictor for message retransmission since efficacy information focuses on effective means to achieve health-related goals such as promoting health and reducing health risks (Bandura, 2004; Moriarty & Stryker, 2008) and is effective in shaping health behaviors (Witte & Allen, 2000). Therefore, we hypothesize that tweets with novelty (H1) and utility information (H2) will receive more number of retweets. In addition, due to positivity bias, positive messages were found to be more likely to be shared, which boost the good feeling of the recipients and the public images of the sharers (Berger, 2014; Berger & Milkman, 2012; Kim et al., 2013). Thus, H3 was proposed in line with the positivity bias. Although themes were found to influence retransmission (Sutton, et al., 2014, 2015), little evidence exists regarding the effects of themes specific to cardiovascular health. Therefore, our study will be answering the research question (RQ) about how the themes of CVD tweets influence their retransmission.

Regarding the structural features, previous research found that messages including a URL or directed to another user (individual or organization) are less likely to be retweeted among the online public because users appear to prefer brief and broadly targeted messages that are easily transmitted across the network (Sutton et al., 2015). On the contrary, tweets’ presence of certain linguistic features (e.g., exclamatory, interrogative) or hashtag(s) are likely to have more predicted retweets, which draw the audience’s attention and reduce ambiguity about the content of the message (Sutton et al., 2014, 2015). Following the logics of previous studies, we hypothesize that containing a URL (H4) or a directed mention (H5) will decrease the number of retweets, while the presence of an interrogative or exclamatory linguistic feature (H6), or a hashtag (H7) will increase the number of retweets. In addition, since formal and credible sources have positive effects on retransmission (Lee & Sunder, 2013), we hypothesize that tweets posted by an organization are more likely to be retweeted compared to those by an individual (H8). These message content and structural features of CVD tweets are theoretically and practically important to examine, by adding empirical evidence to the applicability of DOI on social media under the health context, and informing scholars and practitioners of CV message design.

Methods

Twitter Data Collection

Tweets were collected from Twitter, a social media platform allowing users to send and receive messages no longer than 140 characters. A random 10% sample of tweets from July 23, 2009 to October 1, 2015 was extracted as described in previous studies (Preotiuc-Pietro, Samangooei, Cohn, Gibbins, & Niranjan, 2012). The sample was then filtered for tweets containing language related to cardiovascular disease as outlined in Sinneberg and colleagues' previous work (Sinnenberg et al., 2016).

The CVD sample was then filtered based on keywords referencing two primary cardiovascular diseases: *hypertension* and *diabetes*. We identified the following keywords as a set of search terms: *hypertension* (*high blood pressure*), *diabetes* (*blood glucose and mellitus*) (Sinnenberg et al., 2016). An English-language classifier was applied to the sample to ensure that Tweets with these keywords were in English. A sample of 1251 tweets (hypertension n = 663, diabetes n = 588) were randomly selected from the collected dataset and included in the data analyses. This study was approved by the Institutional Review Board of the authors' institute.

Coding Scheme

Both machine- and hand-coding were applied in the current study. The basic information that was collected for each tweet includes *message content*, *number of retweets*, *number of followers* using Twitter Application Program Interface (API). *URLs* and *user handles* were identified and retweets (starting with an 'RT:') were removed using the Differential Language Analysis Toolkit (DLATK; Schwartz et al., 2017). *Direct mentions* (*@*), *question marks*, *exclamation marks*, and *hashtags* were identified using MySQL and DLATK. URLs, direction mentions, question marks, exclamation marks, and hashtags were coded dichotomously (0 = absent, 1 = present). Tweets' affect score (i.e., valence) was estimated by a machine learning model developed by in Preotiuc-Pietro et.al (2016). The data for the valence model was obtained through annotations on messages by two independent raters with a training in psychology. The raters annotated each message by rating every tweet on a nine-point scale (1 = very negative, 5 = neutral/objective, 9 = very positive). A linear regression model was then developed to predict valence using bag-of-words features extracted from each tweet with a performance of Pearson r = .65 (See Preotiuc-Pietro et.al [2016] for details). The resulting model was applied on the dataset we collected to estimate valence score for each tweet.

Twitter's *utility*, *novelty*, *genre*, and *source* were hand-coded. *Novelty* was measured as being "surprise"," new", and "unusual" (Kim, 2015; Turner-McGrievy, Kalyanaraman, & Campbell, 2013), such as the tweets containing new information (e.g., "New Name for HFCS Hoodwinks Consumers"), new study (e.g., "New study: Diabetes drug could hold promise for lung cancer patients", or surprising news (e.g., "BBC News - Home: UK ranks fifth for child diabetes"). *Utility* contained in the messages conveys practically useful information and makes the messages more likely to be retransmitted (Berger & Milkman, 2012), and was operationalized as the efficacy information in tweets (Kim, 2015). *Novelty* and *utility* were coded into dichotomous variables (0 = absent, 1 = present). The operationlization of theme was adapted by a previous content analysis conducted by Sinnenberg and colleagues (2016), who categorized the semantic content of tweets into *risk factor*, *awareness*, *treatment and management*, *mechanism*, *outcomes*, *symptoms*, *prevention*, and *support* (see Table 2). The *source* was coded as individuals (e.g., John Moss; Michael), health-related organizations (e.g., U-M Health System), and non-health-related organizations (e.g., WiFi in Japan), which was adapted from previous content analytic health communication studies on social media (e.g., Stellefson et al., 2014; Yang et al., 2018).

Coding Procedure

The first author of the study, who formulated the research questions and designed the study, and one naïve coder, who was blind to the research objectives and questions, first independently coded 100 tweets for training purpose. After conducting thorough discussion to reconcile the discrepancies, the researcher and the naïve coder independently coded another 100 tweets until reaching acceptable reliability coefficients across all four variables (i.e., *utility*, *novelty*, *genre*, *source*). Inter-coder reliability was calculated using Krippendorff's alpha. The reliability coefficients of novelty (α= .86), utility (α= .75), theme (α= .70), and source (α= .80) were all satisfied according to Krippendorff (2012). After the reliability was established, the remaining tweets were coded by the naïve coder.

Data Analysis

Given that retweets are count data and the distribution of retweets (Min = 0, Max = 22880, M = 159.57, SD = 1379.00) is over-dispersed, the assumption of Poisson distribution (i.e., mean and variance are equal) was violated (Fox, 2015). Therefore, the negative binomial regression model, an alternative zero-inflated model, was applied in testing the hypotheses. All analyses were conducted using STATA version 14.0.

Results

Descriptive Statistics

The descriptive statistics and zero-order correlations between the key variables are shown in Table 1. Among the 1,251 tweets collected, novelty message was present in 72 (6%) tweets, utility message in 157 (13%) tweets, URL in 580 (46%) tweets, direction mention in 589 (47%) tweets, exclamation mark in 153 (12%) tweets, question mark in 193 (15%) tweets, and hashtag in 358 (29%) tweets. 976 (78%) tweets were from individuals, 197 (16%) from health-related organizations, and the other 78 (6%) from non-health-related organizations. The valence (affect value) of the tweets are neutral on average (M = 5.26, SD = .63). The most prevalent theme is awareness (35.74%), followed by risk factor (27.36%) and treatment and management (16.96%), which is generally consistent with prior work (Sinnenberg et al., 2016)[1] The frequency and examples of each theme are shown in Table 2.

The number of retweets as the outcome variable was zero-inflated, with 798 (63.79%) tweets having no retweet while six tweets being retweeted over 10 thousand times, which is consistent with the over-dispersion nature of the retweet variable (i.e., the variance is much larger than the mean). The average number of followers was 9,741 (SD = 46,162.54).

Inferential Statistics

A multivariate negative binominal regression model was implemented, with the number of retweets as the dependent variable. All the hypothesized independent variables were

[1]A full list of tweets under each theme are available upon request.

included in the regression model. The dispersion parameter (i.e., *alpha*) is 7.90 (95%CI = 7.02, 8.89) and significantly greater than 0, which indicates that the data are over-dispersed and should be estimated using a negative binominal model rather than a Poisson model. The results of the negative binominal regression are shown in Table 3.

Regarding the categorical variable, *risk factor* was treated as the reference group for theme and *individual users* as the reference group for message source. Under the negative binomial regression model, utility (H2; $b = 1.48$, $p < .01$), support theme (RQ; $b = 3.77$, $p < .001$), health organization source (H8; $b = 1.40$, $p < .001$) and mention (H5; $b = 5.38$, $p < .001$) positively predicted the retweet volume, while treatment and management theme (RQ; $b = -1.02$, $p < .01$), non-health organization source (H8; $b = -1.37$, $p < .05$), and containing URL (H4; $b = -.75$, $p < .01$) negatively predicted the number of retweets[2]. Other variables were not significant in the model. Therefore, H2 and H4 were fully supported, H8 was partially supported, while other hypotheses were not supported.

Discussion

Given that Twitter has become a major channel for people to learn and share health information (Bosley et al., 2013; Park, Rodgers, & Stemmle, 2013), and a potential platform to deliver health interventions (Yang, 2017), there is an opportunity for researchers and professionals to identify the content and features that drive CVD tweet's social epidemics. Such understanding can enable the design of interventions and public health messaging. Despite pioneering efforts in describing the volume and content of Tweets associated with CVD as well as the characteristics of Twitter users (Sinnenberg et al., 2016), what characteristics of tweets are more likely to be retransmitted remains unknown, hindering the message design endeavor on SNSs to improve CV health. By examining behavioral data on the retransmission of CVD tweets related to their content and features, we identified the CVD tweets' message-level predictors of audience' sharing behavior, shedding light on what CVD tweets are likely to be propagated.

The descriptive results indicated that a large share (63.79%) of the CVD tweets in this analysis were not retweeted, which is consistent with (non)retweeting of tweets in general. Many tweets are personal and not related to anyone else (e.g., "<USER> <USER> have a lovely time", "Think I have high blood pressure") or do not convey a clear meaning (e.g., "<USER> diabetes"," aka diabetes"), and hence perhaps less suitable for retweeting. Among the themes of the CVD tweets, *raising awareness* was found as the most prominent one, for which there are two plausible explanations. The broadcasting nature of social media a) requires posting content with broader appeal and b) leads people to share self-presentational content to make them look good (Barasch & Berger, 2014; Berger & Milkman, 2012). Therefore, since awareness-raising are usually information-laden messages, individuals are more likely to take advantage of this channel to retweet such messages to a) share

[2]Given that the number of retweets could also be influenced by the number of followers of the tweeter, we fitted an alternative model with the current predictors and also controlling for the number of followers. The natural log transformation was performed on the number of followers, which was originally zero-inflated and highly skewed, to make the data normally distributed. Most of the results obtained by the alternative model remained similar with the model reported in the main text, with only the *treatment and management* theme being non-significant in the alternative model.

information efficiently to a relatively large audience, and b) to present themselves as well-informed and knowledgeable.

H2 hypothesizing the predictive effect of utility was supported by the results that CVD tweets containing informational utility are more likely to be shared by the audience compared to those without utility (Berger & Milkman, 2012; Knobloch-Westerwick, 2015), which is in line with the previous study of online health news retransmission (Kim, 2015). Efficacy information contained in CVD tweets could enhance the confidence of patients and vulnerable population in their ability to take action in improving their health status (Rosenstock, 1974). These tweets present very practical tips and suggestions (e.g., “Walking to Work Tied to Lower Diabetes Risk”), which can be easily adopted by patients or risky population to control their blood sugar levels and calories. Although such efficacy information may not necessarily be accurate, they are more likely to be shared by the users in their online social networks to people who may need such information.

The results also supported the notion (H4) that a URL link negatively drives people’s retweeting behavior, which is consistent with previous studies of tweets retransmission (Sutton et al., 2014, 2015). Since one of the key features for Twitter as a primary social media platform is communicating using succinct messages no longer than 140 characters, which are easily retweeted in the social network, messages including a link requires an extra step (i.e., click and download the link) to access the actual information. According to Sutton and colleagues (2015), such extra steps could be perceived as time-consuming and resource-intensive compared to those self-explanatory 140-character tweets, and some original readers of the message involving an URL could be distracted by the information on that website and forgot to come back and retweet.

The H8 that the likelihood of tweets posted by an organization being retransmitted is higher than that of tweets by individuals was partially supported; health organization as the source positively drives while non-health organization negatively drives the number of retweets. According to the ELM (Petty & Cacioppo, 1981, 1986), people may go through central or peripheral route to judge the information depending on their motivation and ability to process the information, with source credibility serving as a peripheral cue that facilitates mindless acceptance. For those who are less motivated and/or capable to process the CVD tweet messages, they tend to process the messages peripherally through mental shortcuts and make the judgements based on peripheral cues, such as source credibility. As people tend to perceive a health organization as a high-authority source and therefore more credible compared to individuals, the messages posted by a health organization are more persuasive and therefore more likely to be retweeted (Lee & Sundar, 2013), especially by those who are incapable and/or unmotivated to process the messages using cognitive efforts and evaluate the messages through peripheral route (Petty & Cacioppo, 1981, 1986). Similarly, non-health organizations could be perceived as less credible, given that they are not related to health and may have self-interests involved in posting the tweets, resulting in less retransmission.

In answer to the RQ, we also observed that supportive tweets are well-retweeted, compared to those of other themes, which is similar to previous literature demonstrating that Twitter could be used to provide social support (Lockwood & Yoshimura, 2014; Wright et al., 2011). Many supportive messages are very warm and encouraging (e.g., "Diabetes Doesn't Have to Control Your Life <URL>", "Show your Support for Diabetes Awareness with this FREE Wristband! <URL>"). According to the buffering hypothesis, which suggests that social support is most important when individuals encounter stressful experiences, and the effect "occurs through its influence on feelings of self-esteem and self-efficacy" (p.329; for a review, see Cohen & Wills, 1985), such supportive CVD tweets are expected to enhance the patients' self-efficacy, alleviate their negative emotions (e.g., depression, anxiety, loneliness) commonly experienced by CVD patients (Lund, Utz, Caserta, & de Vries, 2009; Taylor et al., 2005), and consequently more likely to be disseminated on Twitter. The less retransmission of treatment and management tweets, although not robust when controlling for the number of followers, could be attributed to the concern of credibility, given that most of those messages were posted by individuals. Tweeters may be hesitant to retweet these messages if unsubstantiated, which may cause mismanagement or mistreatment.

There are several results that are inconsistent with our hypotheses. First, novelty did not turn to be a driver of retransmission on Twitter, which differs from H1 and previous literature (Berger & Milkman, 2012; Berger, 2013; Kim et al., 2013). However, that we failed to support the positive novelty-retransmission relationship hypothesis shows consistency with previous study that analyzed mainly diabetes and health-related tweets (Kim, 2015). The mixed results could be attributed to the retransmission channels. On the broadcasting channels, such as social media, people tend to avoid content that might make them look bad (Barasch & Berger, 2014). Since novel information is usually unproven, people may be concerned about the credibility and persuasiveness of the content. Instead, individuals could feel more comfortable propagating certain and familiar messages to prevent disseminating misinformation or misleading information, which undermines their self-image on broadcasting channels. Second, positivity bias was not observed in the study, which is different from H3 and previous studies (Kim, 2015; Kim et al., 2013). The current finding could be CVD-specific. Some messages emphasizing the negative effects of CVD were well-retweeted (e.g., "If you have diabetes & are experiencing nerve pain or nerve damage, you need to start treatment ASAP before symptoms worsen") probably because these consequences are important to know for patients or susceptible population to prevent the deterioration of their situation.

Also, besides URL, no other structural factors were found affecting retransmission rates. The null results of exclamatory and interrogative sentences (H6) are consistent with previous studies; although the sentence type was identified as a potential predictor, this feature may not be powerful enough to influence retweet count of a message (Sutton et al., 2014, 2015). Since clear and specific messages were found to most strongly influence retweeting behaviors, exclamatory (expressing strong feelings or emotions) and interrogative sentences (bringing up a question) do not help clarifying the messages, if not adding more confusion. Although the presence of a hashtag keyword was found as a significant predictor in previous studies (e.g., Sutton et al., 2014), it was nonsignificant in the current study, which did not support H7. Different from the tweets posted by organizations or public officials, where the hashtag keywords were well-crafted and helped clarifying the content, some hashtags in the user-generated tweets collected in the current study were either irrelevant to the content or confusing by themselves (e.g., "#oomf", "#endo", "#diabetesbitches", "#bisu", "#fools"). Thus, such hashtags increasing the ambiguity and confusion did not contribute to more retransmission of the tweets.

Finally, the direct mention of a user was found to positively drive the tweet propagation in this study, which is at odds with H5 and existing studies (Sutton et al., 2014, 2015). One plausible explanation could be that mentioning a name could indicate higher social presence (Short, Williams, & Christie, 1976), and be perceived as more "real" compared to those without mentioning a name (Gunawardena, 1995), which may motivate users to retransmit. The results could be specific to the cardiovascular health context, and future examination in a variety of contexts is needed to generate a better understanding of the relationship between direct mention and the number of retweets.

Implications

The present investigation examined the content and features present on Twitter about CVD and how they influence the diffusion of CVD tweets through user-generated data (i.e., number of retweets). Though several recent studies have examined retweeting behavior of obesity messages (So et al., 2016) and hazard events (Sutton et al., 2014, 2015), to the best of our knowledge, there has not yet been an investigation of tweets about hypertension and diabetes. This study empirically investigated the potential reach of CVD tweets, as well as some understanding into uses' tweet sharing behavior. We believe this study offers theoretical and practical insights into the diffusion of health information on social networking channels. Given the significance of the health risk, we hope the study draws attention to the urgency for examining more discourse in the communication environment surrounding heart health.

The theoretical implications of the findings for DOI are two folds. First, the study shed lights on the utility and heurism criteria in evaluating DOI as a theoretical framework, by filling the gap in the DOI literature with empirical evidence of CVD tweets. The results indicated that the virality of health-related messages on social media, which could be conceptualized as software innovations, is predictable by the general attributes proposed by Rogers (1983). In addition, by collecting and analyzing large-scale observational data using machine-assisted approaches, we tested DOI with an innovative method, which overcomes the *recall problem* criticism (Haider & Kreps, 2004). Given that the diffusion is a longitudinal process, traditional DOI research has relied on participants' retrospective memory, which inevitably incurs noise and inaccuracy in empirical data (Rogers, 1983). However, the collection of large-scale behavioral data could reduce such limitation to a large extent, which enables researchers to provide a more objective and generalizable picture of the theory.

The findings of the current study provided empirical support for conceptualizing health message on SNSs as innovations to study how their propagation is driven by message characteristics. This study echoes to previous studies and adds to the existing literature by identifying diffusion of innovations as the theoretical basis to examine message design on SNSs. Furthermore, the results of this study also provide evidence for the supportive function of SNSs and the buffering hypothesis of social support, which posits that "support 'buffers' (protects) persons from the potentially pathogenic influence of stressful events" (Cohen & Wills, 1985, p. 310). The sharing behavior of Twitter users indicates their endorsement to these supportive and encouraging messages in alleviating the psychological stress of CVD patients, which could be translated into better health condition. The findings also highlight the pivotal role of self-efficacy, one of the most widely applied constructs in health behavior theories. Since the likelihood of individuals' conducting health behavior will be higher if they know what to do and believe that they are capable of taking action (Bandura, 1997), tweets containing utility information have better persuasive effects and wider reach.

The present study also has several practical implications. First, in order to reach more audiences, it is suggested to include efficacy information in the social media messages by giving concrete and easy-to-implement tips (e.g., "To avoid diabetes, eat fruit, don't drink fruit juice", "Walking to Work Tied to Lower Diabetes Risk"). Furthermore, including supportive and encouraging information in the Twitter messages could improve the receivers' psychological well-being and message propagation while external links (i.e., URL) could negatively impact virality and should be used with caution. Finally, messages posted by health organizations may also result in more dissemination and therefore should be well-conceived. As an authority cue enhances persuasive effects (Maddux & Rogers, 1980), well-designed accurate messages could have far-reaching positive effects, but misleading information or weak arguments could cause detrimental or boomerang effects.

Limitations and Future Research

This study has several limitations. First, the data are not representative of the entirety of CVD messages on Twitter. Since our results are anchored to keywords, future research could replicate the current study with a different random sample and with expanded search terms to test the robustness of the results. Second, there are other features enabled by Twitter (e.g., framing of the message, containing pictures and/or videos) that might impact retransmission but were not evaluated to keep a parsimonious model. Finally, although content analyses are often limited in the ability to inform conclusions about message effects, we were still able to make inferences on user-generated outcomes. The current findings provide insight for future experimental work, which is warranted to test the psychological mechanism underlying the retransmission. Even so, the relationships between features and behavioral meta-data reported in the current study may also provide more robust external validity than manipulated experimental studies.

Conclusion

Because of its powerful dissemination capability, Twitter has been used widely by numerous health organizations in conducting health campaigns or interventions. By examining the retransmission of health messages on Twitter with the case of CVD, this study contributes to our understanding of online health message diffusion in the social media environment and provides guidance for SNS-based message design.

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References

Bandura A (1997). Self-Efficacy: The Exercise of Control. New York, NY: W.H. Freeman and Company.

Bandura A (2004). Health promotion by social cognitive means. Health Education & Behavior, 31, 143–164. doi:10.1177/1090198104263660. [PubMed: 15090118]

Barasch A, & Berger J (2014). Broadcasting and narrowcasting: How audience size affects what people share. Journal of Marketing Research, 51(3), 286–299. doi: 10.1509/jmr.13.0238

Benjamin EJ, Blaha MJ, Chiuve SE, Cushman M, Das SR, Deo R, … & Isasi CR (2017). Heart disease and stroke statistics—2017 update: A report from the American Heart Association. Circulation, 135(10), e146–e603. doi: 10.1161/CIR.0000000000000485 [PubMed: 28122885]

Berger J (2014). Word of mouth and interpersonal communication: A review and directions for future research. Journal of Consumer Psychology, 24, 586–607. doi:10.1016/j.jcps.2014.05.002

Berger J, & Milkman KL (2012). What makes online content viral? Journal of Marketing Research, 49(2), 192–205. doi:10.1509/jmr.10.0353.

Bosley JC, Zhao NW, Hill S, Shofer FS, Asch DA, Becker LB, & Merchant RM (2013). Decoding twitter: Surveillance and trends for cardiac arrest and resuscitation communication. Resuscitation, 84(2), 206–212. doi: 10.1016/j.resuscitation.2012.10.017 [PubMed: 23108239]

Cappella JN, Kim HS, & Albarracín D (2015). Selection and transmission processes for information in the emerging media environment: Psychological motives and message characteristics. Media psychology, 18(3), 396–424. doi:10.1080/15213269.2014.941112. [PubMed: 26190944]

CDC. (2017). Cardiovascular health. Retrieved from https://www.cdc.gov/healthcommunication/toolstemplates/entertainmented/tips/CardiovascularHealth.html

Chung JE (2017). Retweeting in health promotion: Analysis of tweets about Breast Cancer Awareness Month. Computers in Human Behavior, 74, 112–119. doi: 10.1016/j.chb.2017.04.025

Cohen S, & Wills TA (1985). Stress, social support, and the buffering hypothesis. Psychological Bulletin, 98, 310–357. doi:10.1037/0033-2909.98.2.310 [PubMed: 3901065]

ConsumerHealthVocab.org. (2017). Open-access and collaborative consumer health vocabulary (OAC CHV). Retrieved from http://consumerhealthvocab.org.

Fox J (2015). Applied regression analysis and generalized linear models. Thousand Oaks, CA: Sage Publications.

Fox S, & Duggan M (2009). Health online 2013. Washington, DC: Pew Internet & American Life Project Retrieved from http://www.pewinternet.org/2013/01/15/health-online-2013/

Fox S, & Jones S (2009). The social life of health information. Washington, DC: Pew Internet & American Life Project Retrieved from http://www.pewinternet.org/Reports/2009/8-The-Social-Life-of-Health-Information.aspx?r=1

Gunawardena CN (1995). Social presence theory and implications for interaction collaborative learning in computer conferences. International Journal of Educational Telecommunications, 1(2/3), 147–166

Guntuku SC, Ramsay JR, Merchant RM, & Ungar LH (2017). Language of ADHD in adults on social media. Journal of attention disorders, 1087054717738083.

Guntuku SC, Yaden DB, Kern ML, Ungar LH, & Eichstaedt JC (2017). Detecting depression and mental illness on social media: an integrative review. Current Opinion in Behavioral Sciences, 18, 43–49.

Haider M, & Kreps GL (2004). Forty years of diffusion of innovations: Utility and value in public health. Journal of Health Communication, 9(S1), 3–11. doi:10.1080/10810730490271430

Hovland CI, Janis IL, & Kelley HH (1953). Communication and persuasion: Psychological studies of opinion change. New Haven, CT: Yale University Press.

Jaidka K, Guntuku SC, Buffone A, Schwartz HA, & Ungar L (2018). Facebook vs. twitter: Differences in self-disclosure and trait prediction. In Proceedings of the International AAAI Conference on Web and Social Media.

Kim HS (2015). Attracting views and going viral: How message features and news-sharing channels affect health news diffusion. Journal of Communication, 65(3), 512–534. doi: 10.1111/jcom.12160 [PubMed: 26441472]

Kim E, Hou J, Han JY, & Himelboim I (2016). Predicting retweeting behavior on breast cancer social networks: Network and content characteristics. Journal of Health Communication, 21(4), 479–486. doi: 10.1080/10810730.2015.1103326 [PubMed: 27007166]

Kim HS, Lee S, Cappella JN, Vera L, & Emery S (2013). Content characteristics driving the diffusion of antismoking messages: Implications for cancer prevention in the emerging public communication environment. Journal of the National Cancer Institute Monographs, 2013(47), 182–187. doi:10.1093/jncimonographs/lgt018. [PubMed: 24395989]

Knobloch-Westerwick S, & Sarge MA (2015). Impacts of exemplification and efficacy as characteristics of an online weight-loss message on selective exposure and subsequent weight-loss behavior. Communication Research, 42(4), 547–568. doi:10.1177/0093650213478440

Kommalage M, & Thabrew A (2008). The use of websites for disseminating health information in developing countries: An experience from Sri Lanka. International Journal of Electronic Healthcare, 4, 327–338. doi:10.1504/IJEH.2008.022669 [PubMed: 19174367]

Krippendorff K (2012). Content analysis: An introduction to its methodology. Thousand Oak, CA: Sage.

Lee JY, & Sundar SS (2013). To tweet or to retweet? That is the question for health professionals on Twitter. Health Communication, 28(5), 509–524. doi: 10.1080/10410236.2012.700391 [PubMed: 22873787]

Lindberg DA, Humphreys BL, McCray AT (1993). The unified medical language system. Methods of Information in Medicine, 32(4):281–291. [PubMed: 8412823]

Lockwood NL, & Yoshimura SM (2014). The heart of the matter: The effects of humor on well-being during recovery from cardiovascular disease. Health Communication, 29(4), 410–420. doi: 10.1080/10410236.2012.762748 [PubMed: 23829386]

Long T, Taubenheim AM, Wayman J, Temple S, & Ruoff BA (2008). The Heart Truth: Using the power of branding and social marketing to increase awareness of heart disease in women. Social Marketing Quarterly, 14(3), 3–29. doi: 10.1080/15245000802279334 [PubMed: 19122892]

Lund DA, Utz R, Caserta MS, & de Vries B (2009). Humor, laughter, and happiness in the daily lives of recently bereaved spouses. Omega: Journal of Death and Dying, 52(2), 87–105. doi: 10.2190/OM.58.2.a

Maddux JE, & Rogers RW (1980). Effects of source expertness, physical attractiveness, and supporting arguments on persuasion: A case of brains over beauty. Journal of Personality and Social Psychology, 39(2), 235.doi: 10.1037/0022-3514.39.2.235

Moriarty CM, & Stryker JE (2008). Prevention and screening efficacy messages in newspaper accounts of cancer. Health Education Research, 23, 487–498. doi:10.1093/her/cyl163. [PubMed: 17289658]

Park H, Rodgers S, & Stemmle J (2013). Analyzing health organizations' use of Twitter for promoting health literacy. Journal of Health Communication, 18(4), 410–425. doi: 10.1080/10810730.2012.727956 [PubMed: 23294265]

Petty RE, & Cacioppo JT (1981). Attitudes and persuasion: Classic and contemporary approaches. Dubuque, IA: Wm. C. Brown.

Petty RE, & Cacioppo JT (1986). Communication and persuasion: Central and peripheral routes to attitude change. New York, NY: Springer-Verlag.

Preotiuc-Pietro D, Samangooei S, Cohn T, Gibbins N, & Niranjan M (2012). Trendminer: An architecture for real time analysis of social media text. AAAI Technical Report, WS-12-02, 38–42.

Preoţiuc-Pietro D, Schwartz HA, Park G, Eichstaedt J, Kern M, Ungar L, & Shulman E (2016). Modelling valence and arousal in Facebook posts. Proceedings of the 7th Workshop on Computational Approaches to Subjectivity, Sentiment and Social Media Analysis, 9–15.

PwC Health Research Institute. (2012). Social media "likes" healthcare from marketing to social business. Retrieved from http://www.pwc.com/us/en/health-industries/health-research-institute/publications/pdf/health-care-social-media-report.pdf

ReferalMD. (2017). 30 facts & statistics on social media and healthcare. Retrieved from https://getreferralmd.com/2017/01/30-facts-statistics-on-social-media-and-healthcare

Rogers E (1983). Diffusion of Innovations (3rd ed.). New York, NY: Free Press.

Rosenstock IM (1974). Historical origins of the health belief model. Health Education Monographs, 2(4), 328–335. doi: 10.1177/109019817400200403

Ruppel EK, & Rains SA (2012). Information sources and the health information-seeking process: An application and extension of channel complementarity theory. Communication Monographs, 79, 385–405. doi:10.1080/03637751.2012.697627

Schwartz HA, Giorgi S, Sap M, Crutchley P, Ungar L, & Eichstaedt J (2017). DLATK: Differential Language Analysis ToolKit. Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing: System Demonstrations, 55–60.

Short J, Williams E, & Christie B (1976). The social psychology of telecommunications. London: John Wiley & Sons.

Sinnenberg L, DiSilvestro CL, Mancheno C, Dailey K, Tufts C, Buttenheim AM, … & Merchant RM (2016). Twitter as a potential data source for cardiovascular disease research. JAMA cardiology, 1(9), 1032–1036. doi: 10.1001/jamacardio.2016.3029 [PubMed: 27680322]

So J, Prestin A, Lee L, Wang Y, Yen J, & Chou WYS (2016). What do people like to "share" about obesity? A content analysis of frequent retweets about obesity on Twitter. Health communication, 31(2), 193–206. doi:10.1080/10410236.2014.940675 [PubMed: 26086083]

Stellefson M, Chaney B, Ochipa K, Chaney D, Haider Z, Hanik B, … & Bernhardt JM (2014). YouTube as a source of chronic obstructive pulmonary disease patient education: A social media content analysis. Chronic respiratory disease, 11(2), 61–71. doi: 10.1177/1479972314525058 [PubMed: 24659212]

Sutton J, Gibson CB, Spiro ES, League C, Fitzhugh SM, & Butts CT (2015). What it takes to get passed on: Message content, style, and structure as predictors of retransmission in the Boston Marathon bombing response. PLoS One, 10(8), e0134452. doi: 10.1371/journal.pone.0134452 [PubMed: 26295584]

Sutton J, Spiro ES, Johnson B, Fitzhugh S, Gibson B, & Butts CT (2014). Warning tweets: Serial transmission of messages during the warning phase of a disaster event. Information, Communication & Society, 17(6), 765–787. doi: 10.1080/1369118X.2013.862561

Taylor CB, Youngblood ME, Catellier D, Veith RC, Carney RM, Burg MM, … Jaffe AS (2005). Effects of antidepressant medication on morbidity and mortality in depressed patients after myocardial infarction. Archives of General Psychiatry, 62, 792–798. doi:10.1001/archpsyc.62.7.792 [PubMed: 15997021]

Turner-McGrievy G, Kalyanaraman S, & Campbell MK (2013). Delivering health information via podcast or web: Media effects on psychosocial and physiological responses. Health Communication, 28, 101–109. doi:10.1080/10410236.2011.651709. [PubMed: 22420785]

Vos S (2016). Using social networking sites during public health crises: Theorizing the diffusion of effective messages (Doctoral dissertation). Retrieved from http://uknowledge.uky.edu/comm_etds/45/

Wildmer RJ, Engler NB, Kiarich KW, & Timimi FK (2016). An academic healthcare Twitter account: The mayo clinic experience. Cyberpsychology, Behavior & Social Networking, 19(6), 360–366. doi: 10.1089/cyber.2015.0607.

Witte K, & Allen M (2000). A meta-analysis of fear appeals: Implications for effective public health campaigns. Health Education & Behavior, 27, 591–615. doi:10.1177/109019810002700506. [PubMed: 11009129]

Wright KB, Johnson AJ, Bernard DR, & Averbeck J (2011). Computer-mediated social support: Promises and pitfalls for individuals coping with health concerns In Thompson TL, Parrott R and Nussbaum JF (Eds.), The Routledge handbook of health communication (pp. 349–362). New York, NY: Routledge.

Yang Q (2017). Are social networking sites making health behavior change interventions more effective? A meta-analytic review. Journal of Health Communication, 22(3), 223–233. doi: 10.1080/10810730.2016.1271065 [PubMed: 28248623]

Yang Q, Sangalang A, Rooney M, Maloney E, Emery S, & Cappella JN (2018). How is marijuana vaping portrayed on YouTube? Content, features, popularity and retransmission of vaping marijuana YouTube videos. Journal of health communication, 23(4), 360–369. doi: 10.1080/10810730.2018.1448488 [PubMed: 29533139]

Table 1.

Descriptive Statistics and Zero-Order Correlation Matrix of Study Variables

Variable	1	2	3	4	5	6	7	8	9
1. # of Retweet	--								
2. Novelty	−.03	--							
3. Utility	.04	−.01	--						
4. URL	−.05†	.20***	.03	--					
5. Mention	.12***	−.01	.08**	−.27***	--				
6. Question Mark	−.04	−.08**	−.08**	−.04	.03	--			
7. Exclamation Mark	.05†	.01	−.06*	−.02	.09**	.06*	--		
8. Hashtag	−.00	.02	−.05†	.16***	−.04	−.07*	.07*	--	
9. Affect	.11***	.00	−.03	−.01	.09**	−.08**	.20***	.04	--
Mean or %	159.57	6.16	13.44	46.36	47.08	15.43	12.23	28.62	5.26
SD	1379.00								.63

Note. Continuous variables (i.e., number of retweet, affect) are presented in *Mean* and *Standard Deviation* (*SD*), while categorical variables (e.g., novelty, URL) are presented in percentage (%) only. Theme and organization as multi-category nominal variables are not included in the table, given that the correlations between them and other variables do not have conceptual meaning.

$^{†}p < .10$,

$^{*}p < .05$,

$^{**}p < .01$,

$^{***}p < .001$.

Table 2.

Definition, Frequency, and Examples of CVD Tweets Themes *(N* = 1,251)

Theme	Definition	*N* (%)	Examples
1. Risk Factor	The Tweet contains some factor that would increase likelihood of the disease, which has not been diagnosed. The connection can be a direct description of the risk factor or an indirect association to feelings such as stress.	284 (27.36)	“Zero-Calorie Artificial Sweetener Poses Very Real Diabetes Threat <URL>”
2. Awareness	The Tweet contains a statement or piece of advice that the writer is putting out to the world as sound direction or fact. The validity of the message of awareness may be undetermined.	371 (35.74)	“Today is World #Health Day! This year’s theme is high blood pressure. Learn more at <URL>
3. Treatment and Management	Treatment and management for those who already have diabetes. The Tweet contains some factor that would aid the treatment of the disease.	176 (16.96)	“Remedies For High Blood Pressure Patients <URL> via <USER>”
4. Mechanisms	The tweet contains a notion of how the body works, or how the tweeter is perceiving the workings of the body, whether that perception is correct or incorrect.	30 (2.89)	“So you were at the hospital for high blood pressure only to go home and eat a cheeseburger and fries? I’m sure he doesn’t wanna live. Right?”
5. Outcomes	The tweet discusses outcomes or results of the disease. These tweets would include death and complications from the disease.	37 (3.56)	“RT <USER>: High blood pressure and cholesterol levels can cause heart disease. Know your numbers: <URL> #hearthealth”; “Research: Lack of cardiovascular fitness kills more than diabetes, smoking and obesity combined <URL>”
6. Symptoms	The tweet pertains to specific corporeal symptoms secondary to the disease, such as palpitations, lightheadedness, chest pain, headache, etc.	16 (1.54)	“Diabetes <91>The Silent Epidemic<92>. Here you can see the signs and symptoms if you are having #diabetes <URL>
7. Prevention	The Tweet contains some factor that would aid in the prevention of the disease.	83 (8.00)	“RT <USER>: To avoid diabetes, eat fruit, don’t drink fruit juice <URL>“; “RT <USER>: Dancing helps protect you against heart disease and also prevents high blood pressure.”
8. Support	The Tweet reveals feelings of support and encouragement through positive and hopeful language.	41 (3.95)	“<USER> hope you’re feeling better xx!”; “RT <USER>: <USER> We’re raising $ for a little girl dealing with Type 1 diabetes. Help is a RT away. <URL>”

Note. There are 213 (17%) tweets that cannot be categorized in any of the theme (e.g., “<USER> Ready #dsma”, “aka diabetes”).

Table 3.

Negative binominal regression analyses predicting the number of retweets (N = 1,251)

Predictor	b (SE)	95%CI
Novelty	−.07 (.44)	(−.94, .81)
Utility	1.48 (.44) **	(.61, 2.35)
Theme (reference = risk factor)		
awareness	−.51(.33)	(=1.15, .13)
treatment and management	−1.02 (.38) **	(−1.77, −.26)
mechanism	.44 (.73)	(−.98, 1.86)
outcomes and symptoms	−.41 (.48)	(−1.34, .53)
prevention	−.18 (.55)	(−1.27, .91)
support	3.77 (.61) ***	(2.57, 4.98)
Source (reference = individual users)		
health organization source	1.40 (.34) ***	(.73, 2.06)
non-health organization source	−1.37 (.64) *	(−2.63, −.11)
URL	−.75 (.28) **	(−1.30, −.21)
Mention (@)	5.38 (.25) ***	(4.88, 5.88)
Question	−.39 (.30)	(−.98, .19)
Exclamation	−.09 (.38)	(−.84, .67)
Hashtag (#)	−.07 (.29)	(−.64, .50)
Affect value	−.32 (.26)	(−.82, .19)

Note.

* $p < .05$,

** $p < .01$,

*** $p < .001$.

The themes outcomes (N = 37) and symptoms (N = 16) were combined in the analysis given the small sample size in each category.