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Status and Expertise in the Structuring of Reciprocal Exchanges on Twitter: Replies, Retweets, and Mentions During National Diabetes Awareness Month

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Social media play an important role in health campaigns. Extending social exchange theory to online contexts, this study examines the structure of communicative exchanges among health organizations and a broader set of Twitter users, with a particular focus on how users' status and expertise explain the likelihood of reciprocal communication in dyads. Results based on network analysis of users engaged in replies, retweets, and mentions during National Diabetes Awareness Month reveal (1) a tendency for homophily in which communication among users of differing status and expertise levels is unlikely to exist, and (2) a concentration of reciprocal exchanges in communication among high-status users and non–topic expert users. Implications of the patterns of hierarchy are discussed in relation to social exchange theory and health campaign practices.

Keywords: social exchange theory, reciprocity, health campaign, Twitter, exponential random graph modeling

The mechanisms of social exchange, or reciprocal exchange in dyadic relationships, have been an ongoing inquiry in network research. Since Blau's (1964) initial formulation of social exchange as an essential principle guiding human relations, numerous investigations have been conducted into the processes and determinants of reciprocal exchanges (e.g., Emerson, 1976). Much research focused on the

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exchange of resources, such as advice in organizational settings (e.g., Agneessens & Wittek, 2012) and monetary rewards in experimental settings (e.g., Thye, 2000). In the past decade, the reciprocity patterns of communicative messages on social media have gained increasing attention (Cheng, Romero, Meeder, & Kleinberg, 2011; Hayes & Scott, 2018; Surma, 2016).

Reciprocity as an endogenous structural mechanism—the tendency for *i* to connect to *j* and for *j* to connect to *i* without regard to other attributes of *i* and *j*—has been found to be prevalent in human interactions. With the goal of theorizing the conditions that influence the likelihood of reciprocal exchanges, studies have incorporated the effect of exogenous actor attributes (i.e., characteristics of *i* and *j*). The current study examines two pervasive aspects of social hierarchy—status and expertise—as attributes of users that influence reciprocal exchanges on social media. Social hierarchy impacts the exchange of attention (e.g., P. S. Park & Kim, 2017), flow of information and messages (Gatignon & Robertson, 1986), and coordination of activities (e.g., Magee & Galinsky, 2008), all of which constitute important functions of health campaigns. Accordingly, interrogating the ways in which user status and expertise shape reciprocal communicative exchanges contributes to (a) the important theoretical debate surrounding the structure of hierarchy on social media and its implications for broader public conversation (e.g., Ausserhofer & Maireder, 2013; Wu, Hofman, Mason, & Watts, 2011) and (b) the practical understanding of audience engagement and message sharing in health campaigns.

The context of this study involves a diabetes awareness health campaign on Twitter. The presence of reciprocity is particularly meaningful in health campaigns in that two-way interactions that include feedback and participation from users are important mechanisms for the sustainability of campaigns (Heldman, Schindelar, & Weaver, 2013). Twitter is used by a range of organizational and individual users for health-related information sharing, conversations, and campaigns. Much research has examined health-related communication on Twitter, with a particular focus on support networks and information diffusion (e.g., H. Park, Reber, & Chon, 2016). A large stream of research has highlighted message content, such as various themes (e.g., provision and request of support) in the messages (e.g., Ure, Galpin, Cooper-Ryan, & Condie, 2017) and the motivations behind posting messages (e.g., Berry et al., 2017). A few recent studies have examined the structure of communication emphasizing who is communicating with whom (Himelboim, Smith, Rainie, Shneiderman, & Espina, 2017), providing insights as to how health information diffuses via social media.

This study builds on network theories and methods to examine the ways in which users engage in reciprocal communicative exchanges surrounding diabetes awareness campaigns, concentrating on the role of users' status and expertise. Further, we disentangle three micro-level communicative practices on Twitter—reply, retweet, and mention—and examine whether the characteristics of the three functionalities are reflected in the observed network structures.

Micro-Level Communicative Practices on Twitter

A significant body of literature has examined Twitter as a broadcast channel where information can be disseminated to large audiences through many-to-many conversations (e.g., Murthy, 2013). These studies have found that less than half of users' following is reciprocated (Myers, Sharma, Gupta, & Lin, 2014). In this case, communication takes the form of a one-way, asymmetrical channel, often with the existence of information hubs (Anger & Kittl, 2011). Yet, the extent to which reciprocal exchanges, or dialogues, are formed in the actual *communicative activities*—reply, retweet, and mention—is not well known. Ties formed by reply, retweet, and mention constitute the micro-level layer of communicative activities (Bruns & Moe, 2014). These micro-level ties represent the interaction among users that cannot be captured by follower–followee relationships (e.g., Anger & Kittl, 2011).

The three communicative practices have unique functionalities. First, the reply feature involves communication directed at a specific user, including sending a targeted message (e.g., thanking, asking a question, or responding to a user). Replies can be an initiation or continuation of a conversation among two users and can facilitate personalized relationships (boyd, Golder, & Lotan, 2010). Second, the retweet feature facilitates information diffusion. Retweets serve several goals, including sharing information with a new audience, starting a conversation about the content of a tweet, and making the original tweeters aware that they are being listened to (McNeill & Briggs, 2014). Retweets are a form of public recognition or acknowledgement of others' comments (Pelaprat & Brown, 2012). Third, the mention feature is used as a mechanism for endorsement, such as by bringing attention to a user, promoting visibility, and raising awareness of others' activity. In cases, it can also bring attention to disagreements between users or criticisms that one may have toward another user. The mention feature indicates that a user pays attention to the other user's comments or activity (Honeycutt & Herring, 2009).

Theory of Social Exchange and the Structure of Communicative Exchanges on Twitter

The theory of social exchange (Emerson, 1976) suggests that reciprocal exchanges are the basis of a trusting relationship as well as cohesive and interdependent networks. The theory views complex social structures as composed of microstructures, or the relationships between individuals. In this sense, reciprocal communication on Twitter at the dyadic level can be a foundation for building one-to-one, interpersonal relationships on which communities can be formed (Kwak, Lee, Park, & Moon, 2010).

The present study examines the patterns and determinants of these microstructures on Twitter. Social media present a unique venue where the tenets of social exchange theory can be tested in a naturalistic setting (Faraj & Johnson, 2011). In contrast to offline contexts, exchanges on social media tend to involve nonmaterial and symbolic resources (e.g., P. S. Park & Kim, 2017). The norm of reciprocity is common in many online communities (Aggarwal, Rai, Jaiswal, & Sorensen, 2016). For example, a study of Facebook found that posting content or "liking" another's post attracted reciprocal reactions of "likes" (Surma, 2016).

Social exchange involves costs and benefits, and actors are more likely to engage in an exchange relationship when benefits outweigh costs (Homans, 1958). One motivation behind such social exchange is approval and recognition (Hemetsberger, 2002). The benefits may also include gains in social support and companionship. Costs, given the nature of the Twitter platform, would be relatively low and could include time and effort devoted to interacting with another user. People have an innate tendency to reciprocate when they feel indebted. Because of the quasipublic and symbolic nature of social exchanges on Twitter, the pressure or incentive to reciprocate communication can be strong (Lee, Antoniadis, & Salamatian, 2010).

Reciprocated messages on Twitter indicate that a user directly engages with another user (Sutton et al., 2012). In the case of organizations, reciprocity can indicate efforts to engage with the public by sharing information and responding to questions.

Status and Expertise in the Structuring of Reciprocal Exchanges on Twitter

The present study focuses on assessing attribute-based reciprocity, in which organizations or individuals with certain levels of status and expertise may be more likely to reciprocate. First, status forms a basis for hierarchy in that actors tend to communicate with and adopt the behaviors of others who hold privileged social status (Valente & Rogers, 1995), sometimes with the goal of improving their own status and position (Loch, Yaziji, & Langen, 2001). Forming ties with high-status actors, including the case of negative ties such as rivalry, can benefit the reputation of low-status actors (Halgin, Borgatti, & Huang, 2020). High-status individuals act as opinion leaders because their messages can spread rapidly and widely (Rogers, 2003). In addition, unlike offline counterparts, where high-status actors tend to be costly to approach, social media pose little limit on access to such users. Another unique aspect of social media is the visibility of status or popularity, where user profiles show the number of followers and followees.

The link between status and reciprocity on social media platforms has been examined. For example, status differences in dyads affect the likelihood and timing of reciprocal exchanges. Higher status users delay reciprocation longer than their lower status counterparts (P. S. Park & Kim, 2017). People also associate the value of communicated messages with the status of the communicator; messages sent by higher status users are regarded more highly (Berger & Fişek, 2006). Further, Seinen and Schram (2001) found that the behaviors of individuals with high social status are more likely to be reciprocated. Individuals reciprocate behaviors and participate in online spaces when they believe it will improve their reputation (Wasko & Faraj, 2005).

While studies mainly examined reciprocity in the context of status *differences,* the ways in which reciprocal exchanges might take place among those of *similar* status in social media are yet to be examined. Individuals with similar status often reciprocate, while people with disparate status do not (Cheng et al., 2011). In online health communities, higher status individuals are more inclined to reciprocate (Oh, 2012). For example, Hua and Haughton (2012) found that higher status physicians on a professional networking site answered the questions of lower status users. Furthermore, individuals with higher status in the form of online connections were more likely to engage in reciprocal behaviors (Wasko & Faraj, 2005).

Given these findings on status, combined with the nature of social media platforms, it is predicted that the incentive to reciprocate messages among higher status users, who have high visibility, would be stronger than that among lower status users. The gains in reputation and visibility will drive the tendency to reciprocate messages, particularly among higher status users:

H1: *Reciprocity in tweets is more likely to be observed among users of higher status than among users of lower status in (a) reply, (b) retweet, and (c) mention networks.*

Second, the expertise of individuals affects the structure of reciprocal relationships (Agneessens & Wittek, 2012). The theory of social exchange has been applied to understand sharing and transfer of knowledge between experts and nonexperts (H. K. Wang, Yen, & Tseng, 2015). According to Rogers, Daley, and Wu (1982), the most likely influencers in the diffusion of a new idea are the experts with a greater level of knowledge. Expertise is considered a form of online social currency; experts are often the main contributors to online communities and may be rewarded through gains in social reputation and prestige (Hemetsberger, 2002).

On the other hand, some users share their expertise with no expectation of rewards (C. Wang & Lai, 2006). Propositions of social exchange theory suggest that the motivation for social exchange is formed when users have differing levels of resources (Faraj & Johnson, 2011). In this sense, reciprocal exchanges among users who possess common expertise may not be encouraged. Further, because users with topic expertise are more likely to have an established network of communication surrounding the specific topic of relevance, their inclination to strengthen relational ties through reciprocation is expected to be lower than that of nonexpert users.

H2: Reciprocity in tweets is less likely to be observed among users with topic expertise than among users without topic expertise in (a) reply, (b) retweet, and (c) mention networks.

These hypotheses were tested in the context of a diabetes campaign. Diabetes affects approximately 9.4% of the United States population and was the seventh leading cause of the death in 2015 (Centers for Disease Control and Prevention [CDC], 2017). The Diabetes Awareness Campaign is of particular value because, in addition to the prevalence of diabetes, a large majority of U.S. prediabetic adults are not aware of their condition (CDC, 2017). Thus, how organizational and individual users interact with other users during the campaign has significant implications for public health.

Method

Data Collection

Tweets were collected using the GNIP firehose through DiscoverText (Shulman, 2011), which guarantees the harvest of all tweets. Tweets posted by a set of seed organizations and the tweets that retweeted, mentioned, or replied to these organizations during National Diabetes Awareness Month (November) in 2014 were collected. Thus, the universe of tweets examined in the present study involved a much larger set of both organizational and individual users beyond the seed organizations.

A list of seed organizations was formed based on the National Institutes of Health's (2014) directory, which includes organizations that address diabetes or relevant diseases. All organizations with active Twitter accounts were selected, which led to nine governmental organizations (e.g., National Diabetes Education Program, @NDEP; Healthy Moments, run by National Institute of Diabetes and Digestive and Kidney diseases, @HealthyMoments; National Kidney Disease Education Program, @NarvaNKDEP) and 14 nonprofit organizations (e.g., Joslin Diabetes Center, @JoslinDiabetes; Eat Right, run by the Academy of Nutrition and Dietetics, @eatright; Endocrine Society, @TheEndoSociety). Similar to Sutton and colleagues' (2012) approach, using organizations as a starting point for data collection helps examine the communicative behaviors surrounding organizations engaged in a health issue. In addition, as opposed to a search using keywords or hashtags, this approach allowed us to limit the size of data while capturing communicative exchanges involving major organizations. Tweets from the first week of data collection revealed that the majority of tweets from non-diabetes-focused organizations were not related to diabetes. Thus, tweets from these organizations were included only if they contained keywords of "diabetes" or "diabetic." A total of 17,659 tweets were collected, together with data on follower and followee counts for each user.

Coding of Tweets and Attribute Variables

Type of Tweet

Collected tweets were categorized into one or more of the three types: (a) reply, (b) retweet, and (c) mention. A codebook was established through an iterative process. First, an undergraduate coder determined the type of tweet and recorded the recipient of the tweets (users being replied to, mentioned, and retweeted). After the first 200 tweets were coded, the first and second authors reviewed and refined the codebook. Subsequently, the undergraduate coder marked all ambiguous cases to be reviewed until there were no more cases to be discussed. The final codebook defined various conventions used in Twitter, as follows: Tweets starting with @username were categorized as a reply; retweets included tweets that started with RT@username, MT@username, or mRT@username (modified retweet) or that contained via@username in the middle of tweets; and tweets that included @username in the middle of tweet, began with a quotation mark followed by @username, or included cc: @username were coded as a mention. Because reply tweets are shown only to the recipient, users established practices to make reply tweets visible to everyone by including "." before @username. Such tweets were coded as both reply and mention. Table 1 illustrates examples of tweets of each type.

Table 1. Examples of Tweets by Type.

Type	Tweet Poster	Tweets
Reply	@MilfordRegional	@AmDiabetesAssn #Diabetes causes more deaths yearly than breast cancer/AIDS combined. 2/3 ppl w/diabetes die from hrt disease/stroke. #MRMC
Retweet	@theovertime1410	RT @eatright: Tips for those with #diabetes to fuel up and train for endurance sports: http://t.co/z4zpo7cRmI #eatright #DiabetesMonth
Retweet	@AmDiabetesAssn	RT @NDEP: If you have #diabetes, @AmDiabetesAssn has tips to help you plan for the #Thanksgiving holiday and stay on track: http://t.co/nq…
Mention	@pfizer	Pfizer & @AmDiabetesAssn collaborated on #StepOnUp w @CedEntertainer to raise awareness of #diabeticnervepain! http://t.co/Ymd1PRPmbu
Mention	@coad4kids	November is American #Diabetes Month. @AmDiabetesAssn states "Nearly 30 million children & adults in the US have diabetes."

Status

Status was measured with the ratio of followers to followees (Anger & Kittl, 2011). In line with previous studies (Xu, Huang, & Contractor, 2013), the measure was calculated by the number of users following i divided by the number of users i is following. To be able to estimate a parameter assessing reciprocity among users of similar status levels, users were divided into three groups: high status (67th percentile and up), medium status (between the 34th and 66th percentile), and low status (up to the 33rd percentile).

Expertise and User Types

The coding of expertise and user types was conducted by the authors and two trained undergraduate coders. Initial reliability, assessed after coding the first 50 users in the data set, ranged from 93% to 96% in the three networks. After discussing the discrepancies, they reached a level of agreement of 98%–100%. The undergraduate coders proceeded with coding users of degree 3 (i.e., users who have three connected nodes) or higher in the three networks. Disagreements were resolved through discussion with the authors.

Topic expertise was coded into a binary variable of users who are diabetes focused (1) or not (2), adapting the coding scheme from Harris and associates (2014). To determine whether a user is an expert on the topic of diabetes, the user's profile (biography narrative) and the 10 most recent tweets were reviewed. If the user's Twitter profile included links to external sources, the content of those sources (e.g., Web pages) was also examined for a more informed decision.

To control for a key attribute of the users—the type of organizations or individuals—we included a categorical variable of user type. Coding category for user types was adapted from Beguerisse-Díaz, McLennan, Garduño-Hernández, Barahona, and Ulijaszek (2017). Seven categories were defined: governmental, nonprofit, commercial, media, individuals, online community, and others. Like expertise, users' profile (biography narrative and Web links) and the 10 most recent tweets were the basis for coding. Table 2 includes descriptions and examples of each of the seven user types, and Table 3 presents the breakdown of user types in each of the three networks. Although the seed organizations were limited to governmental and nonprofit organizations, a large number of individual users, as well as commercial and media organizations, were represented in the data set.

Table 2. Categories of User Types.

Type	Criteria	Examples
Governmental	Government, governmental agencies, federal, city/local governments and municipal organizations	@NarvaNKDEP @NDEP @NatEyeInstitute
Nonprofit	Professional associations, community service/nonprofit organizations, research centers, and organizations	@AmDiabetesAssn @UrologyCareFdn @JoslinDiabetes
Commercial	Commercial/for-profit organizations	@Amazonsmile @Bayer
Media	Media/news organizations, tweet feed for specific magazines, newspapers, etc.	@ARISEtv @BBCCiN
Individuals	Individuals not representing any organizations, individual-run blogs or websites	@Alan_motaguense @danrundan
Online community	Online community, online advocacy community	@DiabeticConnect
Others	Not belonging to above categories (Examples: sports teams, education organizations that are not research institutions)	@D2SDiabetes @NHLFlyers

Table 3. Key Descriptive Statistics of the Reply, Retweet, and Mention Networks.

	Reply	Retweet	Mention
Number of nodes	1,541	6,439	6,066
Number of ties	3,147	12,313	18,005
Network density	0.00132	0.00030	0.00046
Top 3 degree nodes	@AmDiabetesAssn (876) @JDRF (399) @JoslinDiabetes (163)	@AmDiabetesAssn (2,537) @JDRF (1,749) @nkf (578)	@AmDiabetesAssn (5,348) @JDRF (2,913) @JoslinDiabetes (575)
Top 3 indegree nodes	@AmDiabetesAssn (657) @JDRF (390) @bretmichaels (124)	@AmDiabetesAssn (2,176) @JDRF (1,707) @nkf (557)	@AmDiabetesAssn (4,794) @JDRF (2,725) @NDEP (513)
Top 3 outdegree nodes	@AmDiabetesAssn (219) @*individual (119) @*individual (78)	@AmDiabetesAssn (361) @theovertime1410 (136) @NDEP (94)	@AmDiabetesAssn (554) @JDRF (188) @*individual (129)
Number of Users			
Governmental	30	30	34
Nonprofit	176	408	418
Commercial	159	209	230
Media	112	99	125
Individual	1,002	1,683	1,630
Online community	25	23	34
Others	37	68	89

Note. Measures of users' degree in parentheses. For retweet network, user type was coded for a total of 2,520 users (degree > 2 nodes). For mention network, user type was coded for a total of 2,560 users (degree > 2 nodes). *individual: individual user account names are omitted for anonymity.

Network Construction and Analysis

For each of the three tweet categories, directed networks were derived. A reply tie (i to j) was formed when i replied to j. For the retweet network, a tie (i to j) was created when i retweeted j's original tweet. A mention tie (i to j) was formed when i mentioned j in the tweet. Based on the data collection criteria, all nodes were involved in one or more of the three network types. This approach helped us identify key users involved in diabetes-related tweets, because it is not possible to define a boundary or community of relevant Twitter users a priori. For descriptive measures, a full data set of 1,541 nodes in the reply network, 6,439 nodes in the retweet network, and 6,066 nodes in the mention network was examined (see Table 3).

The analysis was performed using the exponential random graph models (ERGM) approach (Robins, Pattison, Kalish, & Lusher, 2007) with the Statnet package in R (Handcock, Hunter, Butts, Goodreau, &

Morris, 2008). ERGM allows an understanding of the structural patterns of an observed network through investigation the local configuration of relations. For parameter specification, mutuality was the key parameter of interest capturing reciprocal exchange in communication. To test the baseline structural reciprocity, mutual parameter was included. This parameter assesses whether an *i* to *j* tie is likely to coexist with a *j* to *i* tie without considering any exogenous nodal attributes.

Attribute-based reciprocity for status and expertise, which underlies H1 and H2, was estimated with the *mutual same* parameter. A categorical breakdown (low, middle, and high) for status was used to assess the structural tendency for reciprocity within each group, because the parameter only allows categorical measures within the Statnet package. The parameter assesses whether there is a higher likelihood of reciprocated ties among nodes of the same attribute, which is an extension of the basic homophily principle.

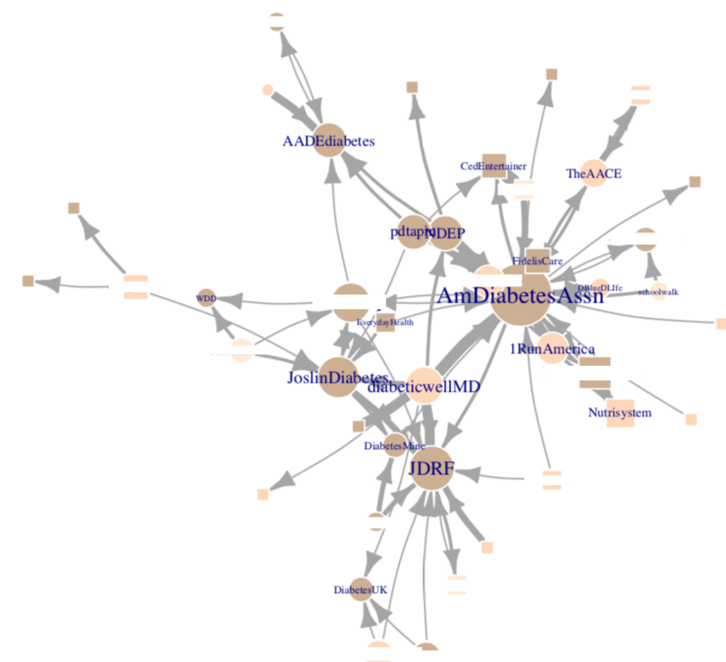
A set of parameters were included as control variables. First, baseline homophily effects (i.e., whether two nodes of similar values in the given attribute are more likely to form ties) were modeled with the *absdiff* parameter (for continuous variables) for status and the *nodematch* parameter (for categorical variables) for expertise and user types. Second, indegree effects (i.e., whether nodes possessing a certain attribute are more likely to receive ties, or get replies, retweeted, and mentioned: the *nodeicov* parameter for continuous and the *nodeifactor* parameter for categorical variables) and outdegree effects (i.e., whether nodes possessing a certain attribute are more likely to send ties, or reply, retweet, or mention: the *nodeocov* parameter for continuous and the *nodeofactor* parameter for categorical variables) were specified. Continuous measures of status were used for these homophily, alter, and ego effects. Further, *gwodegree* was included as an endogenous influence. To control for the effects of multiplexity (e.g., the presence of mention tie from *i* to *j* explaining the presence of reply tie from *i* to *j*), edge covariate parameters (*edgecov*) for the two other types of networks were included in all models.

Ties were dichotomized to allow the estimation of the key parameter (*mutual same*) in the Statnet package. In addition, a smaller subset of the networks was derived to (a) minimize randomness that can be caused by a large number of peripheral users who do not make active contributions and (b) reduce the size of data to be manageable for analysis given a large number of parameters, including the edge covariate parameters. To be able to capture an approximately comparable number of users, between 500 and 900 users were kept to be included in the analysis. The reply network was limited to degree > 1 users (501 nodes), the retweet network to degree > 4 users (854 nodes), and the mention network to degree > 5 users (814 nodes), respectively. These cutoff points gave the highest level of similarity across the three networks. After several model runs, MCMC burn-in (50,000), sample size (20,000), and interval (5,000) were increased to improve model convergence. Goodness-of-fit for the converged models was assessed by comparing network statistics of the simulated networks with those of the observed network.

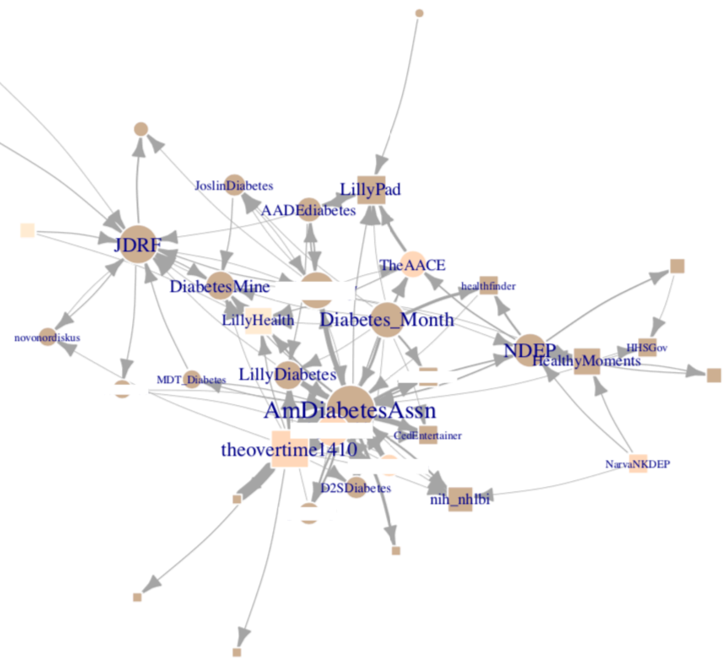
Results

Table 3 shows the key structural metrics of the three networks. The retweet network had the largest number of users involved. The reply network had the smallest number of users, yet showed the highest density. In all three networks, the American Diabetes Association and JDRF (formally known as the

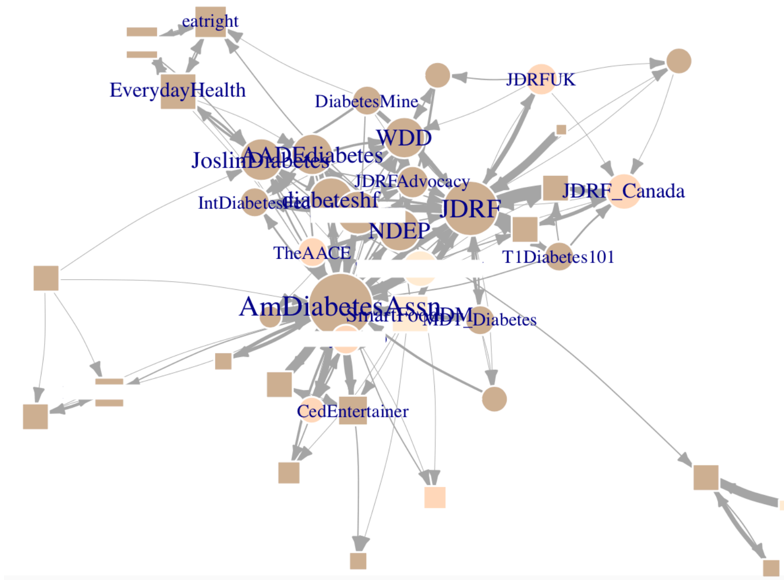
Juvenile Diabetes Research Foundation) were the most central users in terms of degree. In other words, these two organizations were involved in a large number of tweets by either tweeting or being the recipients of retweets, replies, or mentions. Figure 1 visualizes the patterns of communication, including the frequency of ties, among the key players. The reply network is the most decentralized, with many instances of one-way ties among high-status users, as is also found in the ERGM analysis. In contrast, the mention network is the most centralized around high-status and diabetes-focused organizational users, which shows their dominant role in the campaign and a large asymmetry between users. The four most central users mentioned included the American Diabetes Association and governmental diabetes research centers, showing the key role of governmental and research organizations. The retweet network was also highly centralized around key governmental organizations.



Reply network



Retweet network



Mention network

Figure 1. Visualization of three network types. The visualization shows the frequency of tweets in each network, as reflected in the weight of edges. For the purpose of readability, in Figure 1a, users with degree 7 or greater are only displayed. In Figures 1b and 1c, users with degree greater than 30 are displayed. Node and label sizes indicate the degree centrality of nodes. Shade of nodes indicates status: Darker color indicates higher status, and lighter color indicates lower status. Shape of nodes indicates expertise (circle for diabetes-focused users and square for non-diabetes-focused users). Individual user account names are omitted for anonymity.

The results of ERGM analysis are presented in Table 4. Findings common to all three networks are explained, followed by the explanation of structural tendencies that were specific to each network type. Several common structural tendencies were observed. First, an overall significant tendency for ties to be reciprocated was present in all three networks (*mutual*). The tendency for sending ties to multiple alters (*gwodegree*) was negative.

Table 4. Structural Characteristics of Reply, Retweet, and Mention Networks.

	Reply	Retweet	Mention
edges	−5.28 (0.10)***	−5.72 (0.05)***	−4.84 (0.05)***
mutual	5.38 (0.25)***	3.88 (0.20)***	3.68 (0.19)***
gwodegree	−0.48 (0.15)**	−1.75 (0.10) ***	−1.41 (0.12) ***
Status			
absdiff	−0.10 (0.03)***	−0.07 (0.02)***	−0.25 (0.02)***
nodeicov	0.64 (0.03)***	0.46 (0.02)***	0.50 (0.02)***
nodeocov	−0.26 (0.03)***	−0.09 (0.01)***	−0.16 (0.01)***
mutual			

low status	−0.31 (0.54)	0.16 (1.01)	−0.93 (0.46)*
medium status	0.17(0.28)	0.67 (0.51)	−0.58 (0.30)
high status	−0.87 (0.33)**	1.43 (0.22)***	0.43 (0.18)*
Expertise			
nodematch	0.34(0.09)***	0.70 (0.05)***	0.38 (0.05)***
nodeifactor (diabetes-non-focus)	−2.25(0.09)***	−1.68 (0.06)***	−2.08 (0.05)***
nodeofactor (diabetes-non-focus)	0.08(0.08)	−0.23 (0.04)***	−0.12 (0.04)**
mutual			
diabetes-focus	−1.69(0.31)***	−1.18 (0.26)***	−1.27 (0.21)***
diabetes-non-focus	0.69(0.30)*	0.11 (0.28)	0.92 (0.22)***
User type			
nodematch	−0.86(0.08)***	−0.01 (0.05)	−0.38 (0.04) ***
mutual			
governmental	5.57(1.11)***	2.25 (0.51)***	2.72 (1.06)*
nonprofit	1.96(0.48)***	0.82 (0.35)*	1.73 (0.22)***
commercial	*-Inf*	*-Inf*	0.20 (1.00)
media	*-Inf*	*-Inf*	
individual	0.88(0.27)**	−0.62 (0.35)	0.76 (0.22)***
online community	*-Inf*	*-Inf*	
others	*-Inf*	*-Inf*	2.83 (0.80)***
edgecov			
	[Retweet]	[Reply]	[Reply]
network1	0.89(0.23)***	1.32 (0.32)***	1.66 (0.14)***
	[Mention]	[Mention]	[Retweet]
network2	2.26(0.12)***	1.16 (0.23)***	0.59 (0.22)**

Note. Standard errors in parentheses. Parameter estimates noted with *-Inf* indicate empty cells where there is no observed statistics. Each parameter represents network structure; *mutual* assesses reciprocity; *gwodegree* assesses the tendency to send ties to multiple alters; *absdiff* and *nodematch* assess whether two nodes of similar values in the given attribute are more likely to form ties; *nodeicov* (or *nodeifactor*) assesses whether nodes with higher values (or of a particular category) in a given attribute are more likely to receive ties; *nodeocov* (or *nodeofactor*) assesses whether nodes with higher values (or of a particular category) in a given attribute are more likely to send ties; and *edgecov* assesses multiplexity, that is, the effects of other network types.
*$p < .05$. **$p < .01$. ***$p < .001$.

In terms of status, higher status contributed positively to incoming ties (*nodeicov*) and negatively to outgoing ties (*nodeocov*). Difference in status was negatively associated with the likelihood of ties (*absdiff*), indicating the existence of status homophily. This finding provides the foundation for examining reciprocity among users of the same status levels rather than between users who differ in their status levels. Findings regarding expertise were fairly similar. A baseline homophily for expertise was observed in all three networks (*nodematch*), indicating that those with expertise communicated more with other experts, and nonexpert users communicated with other nonexperts. The results regarding indegree and outdegree varied for the attribute of expertise. Those without expertise had fewer incoming ties in all three network types (*nodeifactor*), and fewer outgoing ties (*nodeofactor*) in retweet and mention networks.

Key findings are shown in the tendency of mutuality in terms of status and expertise. First, as to status (H1), in the reply network, a significant negative tendency of mutuality within high-status users existed, thus, H1a was not supported. In the retweet network, mutuality was positive and significant among high-status users, supporting H1b. In the mention network, there was positive mutuality within the high-status group and a negative mutuality within the low-status group, supporting H1c. In terms of expertise (H2), those with expertise were unlikely to reciprocate ties among each other in all three networks, supporting H2a through H2c. Those without expertise had a significantly higher tendency to reciprocate in reply and mention networks, but not in the retweet network.

User types were controlled for in the models. In terms of the baseline homophily in tie formation (*nodematch*), there was a negative tendency of ties to exist among similar types of users in the reply and mention networks, but not in the retweet network. In terms of reciprocity, governmental organizations were more likely to form reciprocal ties among themselves in all three network types. The same tendency was observed for nonprofit organizations. Individuals were more likely to show reciprocity among themselves in the reply and mention networks. In addition, to account for the effect of multiplexity for each network type, the other two network types were included in the estimation. In all three network types, ties in the other two networks significantly explained a tie being observed, indicating a correlation between all three networks.

Discussion

The findings show the intersection of two fundamental properties of network structure—homophily and reciprocity—in extending theories of social exchange to the context of communicative exchanges on Twitter. Homophily of status levels and expertise was common to all three networks, indicating the presence of clusters of similar users, and at the same time, the infrequency of communicative ties that bridge these clusters. Further, reciprocal ties among users who are similar in status, particularly among high-status users, reflect hierarchies that exist in tweet practices. Overall, these findings refine the recent theoretical developments on the structure of hierarchies and authorities in online knowledge production and social network communities (e.g., Panzarasa, Opsahl, & Carley, 2009).

Overall Patterns of Communication and Reciprocal Exchanges

The network structure exhibited a combination of hierarchy and potential for interactive dialogues in each communication practice: Reply involved the fewest number of users, serving as a channel for intimate communication among a small set of users who were not necessarily of high status, whereas mention was employed to acknowledge several prominent figures of the campaign. In many cases, a high-status user was mentioned to bolster the trustworthiness of one's own messages (e.g., November is American #Diabetes Month. @AmDiabetesAssn states "Nearly 30 million children & adults in the US have diabetes"). Despite the high centralization in the retweet network, there were instances of a more diverse set of non-diabetes-focused users retweeting the messages of diabetes-focused users, indicating the possibility of a wider diffusion of campaign messages beyond a selected set of diabetes-focused users.

A significant baseline tendency of reciprocity supports the promise of Twitter allowing conversational interactions (Honeycutt & Herring, 2009), with unique implications in each network. In the reply network, reciprocity indicates mutual exchanges of targeted messages, which may reflect a close relationship among users. Both parties are willing to engage in one-on-one conversations and respond to the other's attention. Reciprocity in the retweet network signals that both parties publicly recognize and value each other's tweets. Such recognition will provide practical benefits of facilitating the spread of messages. In the mention network, when involving positive communication, reciprocity reflects mutual endorsement. A reciprocated mention can signify the expression of gratitude for such public acknowledgement or approval. Yet, a user may also mention another user to get that user's attention for negative purposes.

Status and Expertise as Predictors of Communication Ties

In addition to the tendency for a general conversational practice, the incorporation of status and expertise as explanatory variables allows a more nuanced understanding of the theoretical mechanisms of social exchange. First, an overall presence of status homophily (*absdiff* parameter) indicates a low likelihood of ties bridging users of differing status. Such hierarchy was demonstrated in the discrepancy between incoming (*nodeicov* parameter) and outgoing (*nodeocov* parameter) ties as well. It is not surprising that higher status users were frequently retweeted, given the wide exposure of their message to followers. Noticeably, higher status, compared with lower status, also encouraged personalized communication of being replied to, and furthermore, of other users mentioning them, which could eventually lead to enhanced visibility and reinforcement of higher status. On the other hand, higher status did not translate into higher levels of activity in any of the three practices. High-status users, of whom many are organizational users, might be more selective in their tweets in terms of replying to and mentioning other users. Also, these users were not the most active in diffusing messages through retweets, although their reach can be wide given the large number of followers they have. Interestingly, those who are relatively lower in status appeared to have a greater tendency to engage with other users by replying to, retweeting, and mentioning them.

Some findings regarding expertise are noteworthy. Users with topic expertise were more likely to receive replies, be retweeted, and be mentioned (*nodeifactor* parameter), reflecting their role as a central source of information or attention. This result aligns with the argument that the expertise level of the source is a major criterion to assess source credibility, which is important in campaigns (e.g., Gatignon & Robertson, 1986). Given that diabetes is a chronic illness that requires active everyday self-care, the role of organizations or individuals with knowledge and expertise in empowering and supporting lay expertise is even more critical (Storni, 2015). Replying to, retweeting, and mentioning a user with expertise in the topic can increase the possibility of sharing and promoting relevant information. Users with topic expertise also played a role in diffusing or promoting information, because they had a higher likelihood of engaging in the activities of retweeting and mentioning, though not in terms of replying to others. However, most importantly, a baseline homophily of expertise was observed in all three networks (*nodematch* parameter), indicating that topic experts and nonexperts were less likely to send tweets to each other. This result is partly in contrast to the arguments of social learning theory, in which unexperienced users choose to communicate with users who are already well-connected or experienced (Wenger, 2010).

Status and Expertise as Predictors of Reciprocal Exchanges

Results demonstrate the role of status and expertise as factors explaining social exchange on Twitter. Overall, certain communication ties are more or less reciprocated partly because of the resources that certain users possess. On Twitter, one would become selective in his or her decisions to reciprocate based on considerations of potential gain or loss.

In the retweet network, users in the high-status group showed positive reciprocity. High-status users' activities are visible to a greater number of users compared with low-status users, and thus, the reputation benefits from reciprocal relationships are likely to be higher as well. The positive tendency of mutuality among high-status users observed in the mention network suggests that there is reciprocal endorsement among high-status users, likely resulting from motivations regarding increased visibility and enhancement of their status. In addition, because mentions involve attracting users' attention, high-status users are likely to mention each other so that a tweet will stand out among the many tweets they receive. Based on the theoretical arguments from Gould (2002) and Gouldner (1960), Panzarasa and colleagues (2009) suggest that users reciprocate others who pay attention to them, and such reciprocity strengthens social relationships. In sum, interactive communication in retweets and mentions occurs among users of higher status, which might lead to the reinforcement of cohesive circles of interaction.

Unlike retweet and mention networks, in the reply network, a negative tendency for reciprocity was observed among high-status users. This tendency may stem from the fact that replies are shown only on the receiver's feed, unlike retweets or mentions, which are shown publicly to all of one's followers. The lessened visibility and public recognition may discourage one from reciprocating the communication.

The results regarding expertise are worthy of attention. Those with expertise were less likely to reciprocate tweets in all three networks, which may be due to their established network of communication regarding diabetes. As users see that the other user is already knowledgeable about the topic, they may have a weaker motivation to engage in the campaign. The likely presence of information and communication overload and resulting fatigue for experts or professionals could be a reason for disengagement as well. In contrast, users without expertise may have a stronger motivation to engage in conversations because they see the need to expand their presence. Within the constraints of tie formation coming from observed baseline homophily, reciprocal communication is limited to nonexpert users. Because communication through social media conveys limited social cues regarding one's identity, individuals would try to emphasize their subject expertise or knowledge by frequently engaging in replies, retweets, or mentions.

Practical Implications

By adopting a national health event as the context, the present study examined the patterns of communication in goal-oriented organizational functions on social media and provided suggestions as to how health organizations can enhance public health promotion efforts. Overall, the findings show ways in which the platform can be used as an interactive communication channel. Campaign practitioners can tap into the three communicative features to better engage stakeholders, build trust, and eventually improve individual health (Sutton et al., 2012).

Importantly, the findings suggest a need to bridge the structural divide in communication that exists between high- and low-status users as well as between expert and nonexpert users. Reciprocity helps build continuing relationships, which enables a wider distribution of campaign messages to various types of stakeholders. An ecological model for health promotion (McLeroy, Bibeau, Steckler, & Glanz, 1988) emphasizes the participation from multiple parties, including individuals, communities, and institutions. This study shows that there is an untapped potential for engagement from individuals who tend to be of lower status. While communication in all three networks demonstrated general tendencies for reciprocity, there was a division in communication along the line of status: High-status users, such as large organizations, tended to reciprocate communication from other high-status users, missing the opportunity to engage individuals who are often the target of health messages. To broaden the reach of a health campaign, central organizations and users who have many followers and are reliable sources of health knowledge need to make efforts to communicate with lay users on Twitter.

The findings imply that high-status and expert users play a vital role in diffusing messages through retweets, or attracting the public's attention through reply and mention. Therefore, it is desirable to identify and involve popular individuals or organizations with respect to specific health topics when trying to increase the exposure of health campaigns. For example, a health campaign on diabetes may engage diabetes-related bloggers or health communities with many followers. In particular, engaging high-status users—such as key opinion leaders (e.g., health advocates, health community moderators) or media—can be helpful because the retweets and mentions from these users are more likely to be reciprocated by other major organizations.

Methodologically, the present study identified not only the users who are more or less involved in the campaign, but also the interaction patterns among the users. This type of analysis is particularly helpful when the campaign is a recurring one, because changes in the involvement of various users over time can be tracked in relation to other indicators of campaign efforts and performance. For instance, strong reciprocal communication involving a commercial sponsor of a campaign, compared with previous years, may be an evidence of the role the user played in campaign awareness. Further, network analysis is useful for a process evaluation of how campaign messages spread among various audiences and reach their intended target.

Limitations and Directions for Future Studies

First, the analysis of reciprocal exchanges was conducted not at the message level, but at the user level. Previous research on tweet messages can inspire an interesting extension. For example, Kim, Hou, Han, and Himelboim (2016) found that messages with positive emotions and assertive words were more likely to be retweeted. Future studies may examine how message characteristics interact with user attributes to encourage reciprocal exchanges, possibly over multiple chains of tweets. Second, because we used dichotomized data for the purpose of ERGM analysis, the structural patterns examined in the study do not specify the strength of connections. Future studies can incorporate communication frequencies in the analysis to investigate the extent to which users engage in repeated interactions with a given user, revealing a more accurate picture of reinforced relationships among users. Finally, examining the structures of embeddedness in the three types of communication practices, beyond the presence of correlations found in the present study, can reveal the patterns in which multiple types of communication may contribute to reciprocal exchanges (e.g., a mention from *i* to *j* being reciprocated by a retweet from *j* to *i*).

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