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Silence in Social Media: A Multilevel Analysis of the Network Structure Effects on Participation Disparity in Facebook

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Abstract

Most messages on social media platforms are reportedly posted by a small number of active communicators, while the great majority of users remain silent as *lurkers* who read but seldom write. Despite extensive research to date, it remains unclear why such a disparity in individuals' participation in social media exists. Drawing on the behavioral data of 15,633 *Facebook* users nested in 73 local networks, this study attempted to examine how the structural properties of networks give rise to the highly skewed distribution of message contributions between individual users. Multilevel statistical analyses of the data revealed that the participation disparity among individuals might be in part a function of the structural characteristics of networks in which they are embedded, suggesting that being active or silent in the social media environment is largely conditional on the surrounding network structures.

Keywords

cooperation, lurking behavior, network structure, participation disparity, social media

Social media is the global aggregation of numerous local social networks that are self-organized through the voluntary efforts of individuals. However, the individual degrees of communication through message posting and/or photo sharing exhibit significant disparities (Ebner et al., 2005; Edelmann, 2013; Na et al., 2014; Rafaeli & Raban, 2005). Studies have found that the top 1% of social media users produce more than 70% of all posts, while over 90% only occasionally write or read (Heil & Piskorski, 2009; van Mierlo, 2014). Likewise, it has also been reported that less than 1% of *Wikipedia* users perform more than half of all edits (Swartz, 2006). Not surprisingly, the vast

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majority of social media users (i.e., ≥80%) view themselves as idle rather than active in posting messages and content (Williams et al., 2012).

This silent majority, classified as *lurkers*, has received considerable scholarly attention (Edelmann, 2013; Leshed, 2005; Neelen & Fetter, 2010; Nonnecke et al., 2006; Rau et al., 2008). However, singling out lurkers as a discrete category of Internet users may be misleading as most social media users are de facto occasional lurkers. That is, lurking without active participation is considered a universal behavior differentiated only by frequency rather than something special conducted only by certain individuals. Therefore, rather than attempting to separate them, it seems more appropriate to view lurking as a context-dependent behavior and ask why the disparities in individuals' communication are so prevalent. While prior studies have identified diverse psychological factors affecting individual lurking tendencies (for a review, see Na et al., 2014), fewer efforts have been devoted to clarifying contextual factors, more specifically, particular social settings in which participation disparities become more or less prevalent (Sohn & Leckenby, 2007).

In a socially networked environment, the incentive structure underlying voluntary participation in communication may be in part a function of the patterns of social relationships (Bonacich, 1990; Centola, 2010; Gould, 1993; Sohn & Leckenby, 2007). To illustrate, imagine a network of N individuals in which a person at the center is tethered with $N - 1$ others, none of whom are tied to anyone other than the central person (commonly referred to as a *star network*). Your likelihood to post messages would presumably be higher if you are the person at the center (i.e., everyone else is supposed to be your audience) rather than on the periphery (Huberman et al., 2009). As the $N - 1$ others can communicate only through you as the person at the center of the star network, you may feel either more obligation or more control over the communication processes. Though oversimplified, this example sheds light on the roles of *network structure*—the arrangement of nodes and relations in a network. That is, the skewed distributions of participation among individuals might be in part a function of the structural characteristics of networks in which they are embedded (Bonacich, 1990; Sohn & Leckenby, 2007).

Extensive studies have identified various factors affecting online information and knowledge sharing, including the psychological characteristics of participants (e.g., Cheshire & Antin, 2010; Kimmerle & Cress, 2008), communication structures (e.g., Caimo & Lomi, 2015; Liang & Fu, 2016; Sohn & Leckenby, 2007), temporal extensions and group size (e.g., Cress et al., 2009), and the technological characteristics of the platforms (e.g., Majchrzak et al., 2013). Despite many important findings, it still remains unclear whether and how the structural properties of networks give rise to the participation disparity in social media. The current study examines how network structural factors along with personal attributes affect the volume of cumulative messages posted by individuals. Drawing on the behavioral data of *Facebook* users nested in diverse local networks using a *multilevel mixed modeling* approach (Raudenbush & Bryk, 2002), the respective influences of actor-level and network-level characteristics are examined, as well as the cross-level interactions on the degree of message posting behavior.

The Role of Network Structures in Collective Communication

It has been extensively documented in social science literature that cooperation among autonomous actors is often subject to a particular incentive structure called *social dilemma* or *N-person prisoners' dilemma* (Kollock, 1998). Both suggest that the self-interested actions of individuals may lead to a collectively irrational or suboptimal consequence as exemplified in a situation referred to as the *tragedy of the commons* (Hardin, 1968). Allowing actors to communicate with one another has been repeatedly confirmed as an effective solution to these dilemmas (for a review, see Balliet, 2010; Fehr & Gintis, 2007). This, however, leads to a second-order problem called the *communication dilemma* (Bonacich, 1990) in which the interests of individuals may be best served by not communicating (e.g., to save time or hoard information) while benefitting from the contributions of others. If all individuals behaved in this manner, everyone would receive fewer benefits as less information would be shared, eventually making collective communication unsustainable (Kalman et al., 2002).

In recent years, scholars have tried to determine what drives individuals to participate voluntarily in online communication. In a comprehensive review of the relevant literature, Na et al. (2014) summarized the factors into four categories: (1) *community characteristics* (e.g., identity or sense of community, usability, norms, reputation), (2) *individual characteristics* (e.g., goals, needs, self-efficacy), (3) *commitment factors* (e.g., affective, normative relations within the community), and (4) *quality requirement* (e.g., security and privacy concerns). Overall, it is widely understood that the stronger the community identity with which the individual's goals are well-aligned, the stronger the individual's affective/normative relations with the community, and vice versa, which would increase the likelihood of communication behaviors (Hogg & Reid, 2006; Kalman et al., 2002; Ling et al., 2005).

Evidently missing from the categories above is what lies between individuals and the community as a whole, namely, the intermediate patterns of relations and communication. An implicit assumption underlying most previous studies is that many-to-many online communication occurs in largely structureless forms, such as *pooling*, thus neglecting many other possible network configurations and their implications (Sohn & Leckenby, 2007). It is conceivable that a person's cooperative behavior in a *dyadic* relationship in which one person is obliged to reciprocate with the other may be quite different from those in *triadic* relationships where brokerage or *generalized exchange* becomes possible. Since human behaviors are inseparable from the constraints and opportunities imposed by the immediate social environment, it is of crucial importance to attend to the conjunctions between individual behavior and the incentive structures realized through relationship networks (Cook & Whitmeyer, 1992; Emerson, 1976).

Along with evidence that individual behaviors are conjoined with those of social neighbors (e.g., Christakis & Fowler, 2007, 2008), DiMaggio and Garip (2012) emphasize that individual-level advantages or disadvantages incurred through actions can be compounded through social networks. That is, peers of those benefited or harmed by an action are more likely to access the benefit or avoid the loss, thereby widening the gap between those in better and worse situations over time, also known as the *Matthew effect* (Merton, 1968). As such, network structures as "interstitial coordinating mechanisms" (Erikson & Occhiuto, 2017, p. 230) may be transformative with the potential to regulate individual actions toward certain macro-social consequences, including information inequality (DiMaggio & Garip, 2012) or opinion polarization (Sohn, 2022; Sohn & Geidner, 2016; Song & Boomgaarden, 2017).

This *path-dependent* process may be observed in any domain in which individuals base their behaviors on those of others (Page, 2015). The more (or less) observable some behaviors or outcomes become, the more (or less) individuals will follow them, thus making them even more (or less) observable and popular. With such a positive feedback loop along the path, a highly skewed distribution of outcomes emerges.[1] Note that the entire process hinges on the extent to which individuals observe or influence the actions of others, which is largely dependent on the structures of social networks—what you can see and do in social media is delimited by your location in the network (Sohn & Choi, 2019). In the current context, this suggests that the highly skewed distribution of message contributions we see throughout social media might have emerged through path-dependent processes based on certain network structures that serve as mechanisms through which individual actions (e.g., lurking or posting messages) are reinforced or hindered.

Network Effects on Participation in Communication

Verifying the existence of such a path-dependent process requires examining the statistical associations between various structural properties of networks and the cumulative message counts of individuals. Among many indicators of network structural properties, network centrality has arguably received the most scholarly attention regarding its role in determining actor popularity, power, and performance (Borgatti et al., 2009; Burt, 1995). Holding abundant social connections, which translates to greater *degree centrality*, leads naturally to a broader window of opportunities to reach audiences. Further, being capable of reaching greater audiences may elicit feelings of empowerment and/or additional obligations, thus increasing the individual's likelihood to participate compared to those with fewer associations (Faust, 1997; Huberman et al., 2009; Lee et al., 2010; Polonski & Hogan, 2015).

However, by no means does this suggest that well-connected individuals should always post voluntarily more messages than others. Instead, it is also possible that having more social relations makes coordination between them more difficult as heterogeneity in many respects could also increase (Dunbar, 2008). The person may, in turn, become reluctant to communicate based on an increased degree of self-censorship, thus making stagnant the increase in the cumulative message volume. This suggests that the effects of degree centrality on an individual's cumulative message volume should be an empirical question rather than a presumption.

H1. The higher the degree (i.e., first-order) centrality, the more messages social media users post.

While degree centrality counts only a person's direct social connections, ample evidence suggests that individual behaviors can be shaped substantially by indirect social relations and structural positions in networks (Bond et al., 2012; Christakis & Fowler, 2007, 2008). It is already broadly accepted that the mere occupation of a bridging or brokerage position, namely, a *structural hole* (Burt, 1995), endows one with substantial bargaining power and leverage in various social processes. However, the two most popular measures of positional advantage, *closeness* and *betweenness centrality*, cannot be assessed properly with local networks (e.g., egocentric networks) examined here (Perry et al., 2018).

As an alternative, we may consider *eigenvector centrality* or its variants that indicate the extent to which one is tethered to well-connected others (Newman, 2002).[2] It is generally true that the more socially prominent one becomes, the more friends that person is likely to have, a relationship that is not always the other way around. Having a friend who is well-connected with a few important persons (e.g., politicians or celebrities) may turn out to be better than to befriend numerous social isolates. A person's prominence or importance in a network depends not merely on the quantity but also the quality of relationships. Thus, if indirectly associated with influential others, even the person with a low degree centrality may be in an advantageous position to gain access to useful and novel information, thereby broadening the windows of opportunity for communication (Polonski & Hogan, 2015). Taken together, the hypothesis is stated as follows:

H2. The higher the indirect (i.e., higher-order) centrality, the more messages social media users post.

In addition to actor-level positional characteristics, the structural properties of the local network as a whole may influence the behaviors of the individuals nested within. It has been found that highly clustered networks tend to contain redundant social ties (i.e., friends of friends are friends themselves; Granovetter, 1973; Watts & Strogatz, 1998) that increase the frequency of contacts, and hence the volume of messages communicated in general (Bond et al., 2012; Centola, 2010). Some studies have indeed found that local community structures, such as network redundancy or clustering affect the probability of message diffusion (Liang, 2018; Liang & Fu, 2016; Harrigan et al., 2012; Centola, 2010). This suggests that being part of highly clustered networks, as redundant ties increase the chances of message exposure, may induce individuals to post more messages than those in less clustered networks. Therefore, the next hypothesis can be stated as follows:

H3. Social media users nested in highly clustered networks tend to post more messages over time than those in networks with lower degrees of clustering.

On the other side of network redundancy or clustering, we need to consider the possibility of whether a network comprises a single cluster or component in which all constituents are reachable through any number of paths or connections. If a network can be decomposed into multiple components or islands separated from one another (i.e., connected only via the ego), messages communicated in one cluster can seldom reach those in other components, presumably lowering the network-wide frequency of communication (Centola, 2010; Perry et al., 2018).

Consider an extreme case in which the number of subcomponents reaches its maximum (i.e., $N - 1$)—everyone else but one at the center lacks connections with one another (i.e., star network). This naturally reduces the overall chances to communicate as each person, except the one at the center, has an audience of only one, thus diminishing the total volume of messages communicated throughout the network. Although it remains possible that a smaller close-knit network might facilitate frequent communication (Centola, 2010; Liang & Fu, 2016), such local increases might not be sufficient to overcome the blocking effects of network compartmentalization. Therefore, we posit the following:

H4. Social media users tend to post fewer messages over time as the networks in which they are nested are subdivided into smaller clusters or subcomponents.

Lastly, the effects of individual-level structural properties on communication behaviors may be intertwined with the community-level structures. Being central in a network of others with fewer connections—figuratively speaking you are the only sun in the solar system—may be significantly different than being the central person in a network populated by well-connected individuals (Bonacich, 1991). Further, being central in a highly clustered network may have a very different impact on an individual's message posting behaviors than in an open-radial network (Valente, 1995). Since network clustering is positively associated with tie strength and homophily (Burt, 1995; Granovetter, 1973; Watts & Strogatz, 1998), the occupation of a central position in a clustered network translates to having more of a *bonding* type of social capital. On the other hand, the same position leads to a *bridging* type of social capital in a less clustered, radial network that facilitates the exposure to more diverse information and opinions (Huckfeldt et al., 2004; Song & Eveland, 2015). On the basis of the paucity of relevant evidence, it is difficult to postulate whether such a network-level context facilitates or hinders the effects of individual-level network centrality on cumulative message contribution. For now, we state this as an exploratory research question rather than as a specific hypothesis:

RQ1. Are there significant cross-level interactions between the effects of individual- and network-level structural properties on the cumulative message counts contributed by social media users?

Methods

Data Employed and Measures

The data employed here were part of the graph data of Facebook users' (*egos* hereafter) personal networks, collected in 2014 using an application named *Netvizz*[3] for a research project that studied the news consumption of college students in South Korea. From the 167 network graphs originally collected, this study analyzed 73 networks that had a complete set of variables for the attributes of network members (*alters* hereafter), including gender, the active age of the account, locale and the cumulative count of messages posted, within which 15,633 individuals in total were nested.[4] Apart from being used as a grouping variable for identifying local networks, the ties and personal attributes of the *egos* were not included for the analysis in this study.[5] The sizes of the 73 local networks ranged from 29 to 510 with a mean of 291 (SD = 126.77), and the network density varied widely from 3.18% to 55.62% with a mean of 9.1% (SD = 6.45%).

The data employed primarily contained two levels of information, the individual level for *alters* nested within each network (i.e., level-1) and the level for each network provided by the *ego* (i.e., level-2). The cumulative count of wall posts, the main dependent variable for this study, is the total number of messages accumulated for each alter, starting from the date the account was first created until the data were collected. Only the messages the account owners themselves posted on the wall or timeline were counted, while those ancillary messages, such as likings, comments, and replies, were excluded. Although some exceptions (e.g., birthday wishes posted by friends) might exist, the wall posts tend to be the ones initiated primarily by account owners, which makes them more relevant for the focal issue here: how individuals' message contributions are conditional on the properties of surrounding social structures.

Notice that the network structural variables at both levels were derived from the connection patterns *within* the local networks observed, thus possibly excluding any external relations that might have existed. This issue previously noted as "partial system fallacy" (Laumann et al., 1983) might, however, be more problematic when dealing with a single network rather than multiple networks for identifying statistical regularities as done here (Perry et al., 2018), unless the structures of those multiple networks were substantially distorted. As for egocentric networks, further, it has been found that increasing their sizes could alleviate this boundary specification problem to some extent (McCarty et al., 2007).[6] If we would view each alter and its surrounding ties as constituting an alter-wise network, such networks employed here would turn out mostly larger (i.e., 41° in average with the maximum of 414) than many egocentric networks reported previously, thus suggesting that the key structural properties of interest might have been captured.

Actor-Level Predictors

The individual-level variables include personal attributes, including gender and the elapsed age of the active Facebook account indicating the length of use, as well as network positional characteristics. The length of use (UL hereafter) was originally measured as an ordinal variable that ranked the members of a network in descending order, thus indicating that the larger the value, the longer the person had been using Facebook. In a network of 100 members, for example, the earliest account holder was assigned 100, followed by the second who was assigned 99. The most recent user was assigned a value of 1. As the values of the variable could vary widely depending on the network size, we normalized the variable as follows: $UL_{norm} = (R_i - 1)/(N - 1)$, where R_i was the rank given to a person i belonging to a network of size N, ranging from 0 to 1. UL was included in the statistical models as a control variable because the cumulative count of posted messages tends to be proportional to the length of use.

Of the network structural variables, degree (first-order) centrality indicating the number of direct ties an alter holds is often used to reflect the person's interconnectedness or sociability. Along with degree centrality, sociologists, and network scientists have long explored the possibility of developing alternative centrality measures, especially for indirect (higher-order) relations (Freeman, 1979; Kiss & Bichler, 2008). Among many others, eigenvector and Katz centrality have been widely used, but known to have a potential problem, in that, a well-connected node passes centrality to all of its contacts, thereby artificially inflating the centrality of even those at marginal positions (i.e., not everyone connected to a well-known person is also well-known).

Page-Rank centrality (PRC hereafter), a variant of Katz centrality, alleviates this problem by dividing a node j's centrality diffused to all other contacts including a node i, denoted by CP_j, by its degree, d_j, as follows

$$PRC_i = \alpha \sum_{j}^{n} A_j \frac{CP_j}{d_j} + \beta \tag{1}$$

where α is an attenuation factor, A_j is an adjacency matrix, and β is a bias term. With PRC, the centrality passed to a node i from a node j is diluted depending on the number of connections of the node j. This means that being tied or merely following a prominent node with many connections would not significantly increase one's PRC (Kiss & Bichler, 2008). This also suggests that when an alter is tied to some well-connected others outside of a local network, excluding such external ties might not yield substantial changes in the person's PRC, which is beneficial for the studies dealing with partial networks. Therefore, while degree centrality shows a node's direct or first-order connectedness, PRC complements degree centrality by reflecting the value of the higher-order connections into which the node is embedded.[7]

Network-Level Predictors

Network-level variables were incorporated to reflect various characteristics of each network as a whole that might affect or interact with all of the individuals nested within. For example, the role of a person's gender during communication might be dependent on the gender distribution within the given network and whether gender proportions were similar or disparate. To consider this network-level information, the Blau's diversity index (BDI; also known as the Gini-Simpson index) was calculated as follows for gender composition

$$BDI = 1 - \sum_{k} p_k^2 \tag{2}$$

where k denotes the number of categories or classes and p is the proportion or probability of each category in the population of interest. As for gender (i.e., $k = 2$ categories), BDI is one minus the sum of squared category proportions, which reaches its maximum, 0.5, when the gender composition is maximally heterogeneous (i.e., equal gender proportions) while 0 at maximum homogeneity.

In network-related terms, *component* refers to a maximal subnetwork in which any pair of nodes can be connected via a path of any length, meaning that a node belongs to a component if a path exists connecting the node to another belonging to the same component. Since no *between path* should exist for any two components—otherwise they should merge into a single component—the presence of multiple components means that the network is compartmentalized. One example is an egocentric network in which the ego has distinct groups of friends that are separate from one another, and the groups of friends would be similar to multiple disconnected islands without the presence of the ego. Such a fragmented environment could constrain the communicative motivation and behaviors of individuals, and even those in the same network would not be able to reach others in separate components. *Component Ratio* (*CR*) represents this degree of compartmentalization of a network as follows: $CR = (C - 1)/(N - 1)$, where C denotes the number of components present in a network while N is the network size (Perry et al., 2018). *CR* becomes 1 when every alter in a network is disconnected from everyone except the ego so that the number of components is identical to the network size; conversely, it approaches 0 as alters are connected to form bigger components.

Further, another network-level variable included was the degree of transitivity in a network. This refers to the extent to which members of a local network are tied to themselves (i.e., the proportion of friends who are also friends themselves; Watts & Strogatz, 1998). Formally, the global transitivity of a network (T_G) is calculated as the proportion of complete or closed triads in a whole network, $T_G = N_{triad}/N_{triple}$, where the numerator is the number of closed triads and the denominator is the number of *triples*, a set of three nodes connected with two (i.e., open triad) or three ties (i.e., closed triad). Along with the aforementioned network-level variables, the group or cluster average of individual-level structural indicators, *group-mean degree* and *group-mean PRC*, was included to avoid *cluster confounding* in a multilevel analysis (Perry et al., 2018) (Table 1).

Lastly, for reasonable interpretations, all individual-level (i.e., level-1) predictors were centered using the cluster means (i.e., local network averages), while all network-level (i.e., level-2) predictors were centered around the grand mean following the suggestion of Enders and Tofighi (2007).

Results

To test the proposed hypotheses, a series of generalized multilevel linear models were constructed for the dependent variable—the cumulative count of wall posts. Count data are normally

Table 1. Descriptive Statistics of Individual and Network-Level Characteristics.

	N	Mean	SD	Max	Min
Individual-level					
Cum. message	15,633	123.9	236.13	8500	0
Degree	15,633	41.22	44.91	414	0
PRC	15,633	0.0047	0.0047	0.0662	0.0003
Network-level					
Gender-BDI[a]	73	0.46	0.061	0.50	0.096
Size	73	291	126.77	510	29
Degree (Group Mean)	73	41.22	12.43	77.14	6.04
PRC (Group Mean)	73	0.0047	0.0036	0.0345	0.0020
Transitivity (%)	73	52.66	14.07	87.34	27.78
Component Ratio (%)	73	6.76	3.77	27.69	0.68
Density (%)	73	9.1	6.45	55.62	3.18
Diameter	73	8.04	2.30	14	2

Note. Shown above are the descriptive statistics of the key variables prior to normalization.
PRC = PageRank centrality; BDI = Blau's diversity index.
[a]The maximum value of Gender-BDI is 0.5, indicating that the gender distribution is maximally heterogeneous.

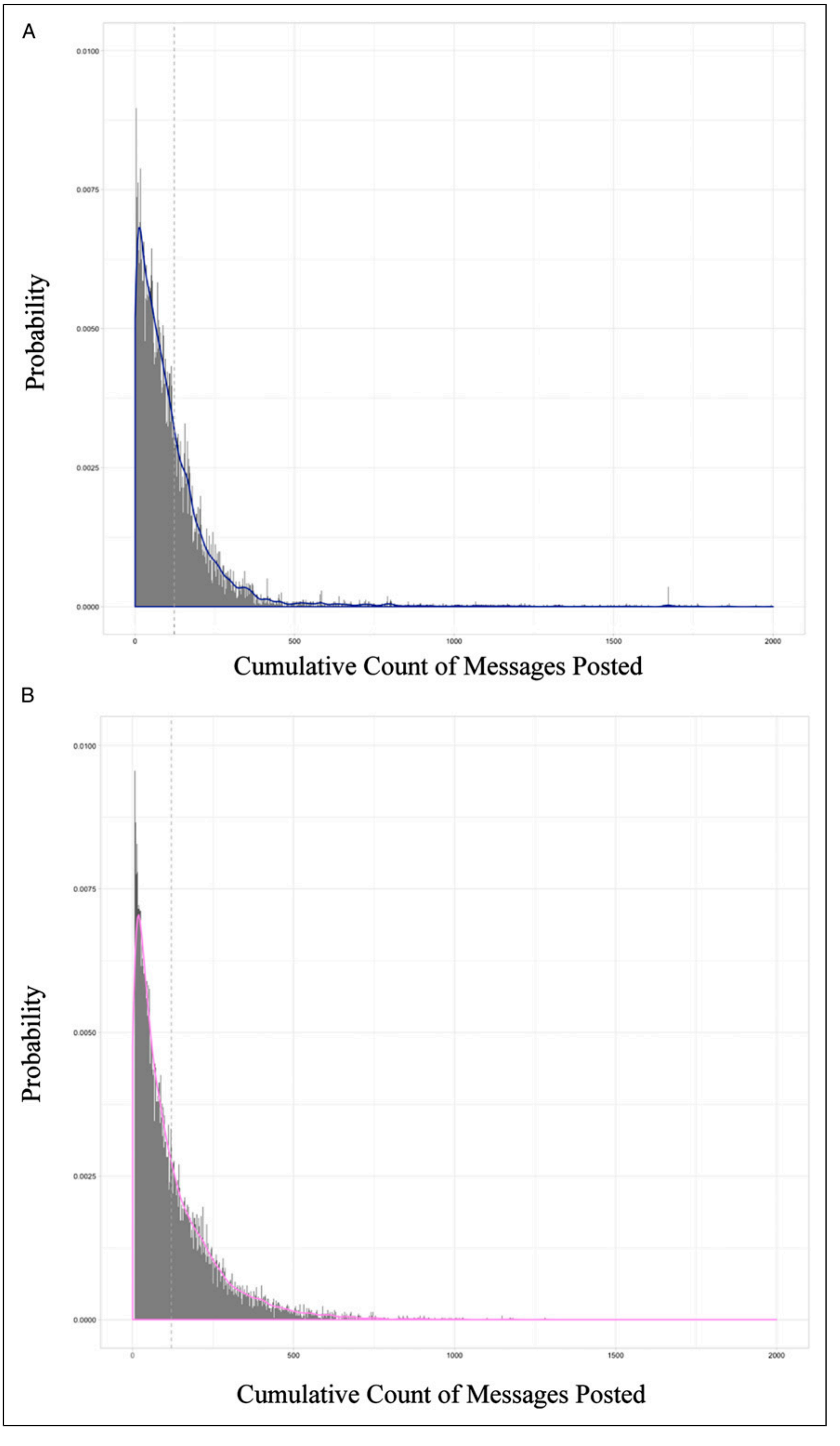

Figure 1. Actual and simulated distributions of message contributions. (a) Actual distribution of message contributions (b) Simulated distribution of message contributions.

approximated by the *Poisson* distribution, for which the mean is equal to its variance. However, as illustrated in Figure 1(a), the distribution of the current dependent variable had a very long tail to the right, thereby illustrating that there was a small number of users who had posted far more messages than the overwhelming majority. This visually confirmed the disparity in communication among individuals. To incorporate this *overdispersion* characteristic (i.e., the variance of the distribution is much larger than the mean), we assumed the dependent variable would follow a *negative binomial* (NB) distribution, thus allowing an extra variation of the variance with θ parameter, $\text{NB}_{\text{var}} = \lambda + \lambda^2/\theta$, where λ is the mean.

Besides visual inspection, we calculated the dispersion statistics for both distributions, Pearson's χ^2/df, known to increase with overdispersion but otherwise converge to 1.0. Consistent with our expectation, the dispersion parameter soared to 12.17 for the models with the Poisson distribution assumed, confirming the presence of overdispersion. However, the negative binomial distribution assumed the parameter reverted to 1.06, meaning that the models assuming the negative binomial distribution indeed fit well with the data. Figure 1(b) illustrates a simulated distribution with $\theta = 0.85$, closely approximating the actual distribution shown in Figure 1(a).

Multilevel models are needed when meaningful differences exist among the groups or categories (i.e., between-group variance), such as local networks, and must be accounted for. To check whether the non-negligible between-network variance was existent, we first conducted a likelihood ratio test to compare two models—one with a fixed intercept and the other with a random intercept—and found a statistically significant difference, χ^2 (2) = 1715.29, $p < .001$. The intraclass correlation (ICC) that indicates the proportion of the between-network variance to the existing total variance was 0.1451, that is, the between-network variance accounted for 14.51% of the total variance present in the data. The initial test results suggested that the differences among the local networks were meaningfully large and they justified the multilevel analyses.

The generalized multilevel linear models constructed shared the following basic form in common

$$\log(Y_{ij}) = \beta_0 + \zeta_{0j} + (\beta_1 + \zeta_{1j})x_{1ij} + \beta_2 x_{2j} + \beta_3 x_{1ij}x_{2j} + \varepsilon_{ij} \tag{3}$$

where Y_{ij} was the cumulative count of messages contributed by a person i nested in a jth network, and x_1 and x_2 were individual-level and a network-level predictor, respectively. Model I was constructed as the baseline *random intercept* model that allowed only the intercept, $\beta_0 + \zeta_{0j}$, to vary across the local networks along with four individual-level predictors for fixed effects. Model II comprised the same individual-level predictors as Model I, with the exception that the coefficients of the predictors were allowed to vary across the networks, $\beta_1 + \zeta_{1j}$, commonly called a *random-coefficient* model. A series of likelihood ratio tests confirmed that allowing random effects would cause statistically significant differences for the length of use, (χ^2 (2) = 273.38, $p <$ .001), gender (χ^2 (2) = 28.01, $p < .001$), degree centrality (χ^2 (2) = 105.98, $p < .001$), and PRC (χ^2 (2) = 36.27, $p < .001$).

Overall, Model II outperformed Model I as the chi-square deviance was significantly large (χ^2 (2) = 405.07, $p < .000$). The between-network variances for the respective terms are shown in the bottom section of Table 2. All Models II through V had random-coefficient terms of which covariance structures were unconstrained. Model III had only the individual-level predictors and the within-level interaction terms, while both the individual- and network-level predictors were included in Model IV and the cross-interaction terms in Model V.

Since the negative binomial distribution was assumed for the dependent variable, it was necessary to exponentiate each coefficient to form an incidence matrix before interpretation.[8]

Table 2. Generalized Multilevel Linear Regression Models.

	Model I	Model II	Model III	Model IV	Model V
Individual-level predictors					
Length of Use (UL)	1.41 (0.03)***	1.46 (0.10)***	1.41 (0.10)***	1.42 (0.10)***	1.42 (0.10)***
Gender (male)	−0.18 (0.02)***	−0.20 (0.03)***	−0.20 (0.03)***	−0.20 (0.03)***	−0.20 (0.03)***
Degree	0.12 (0.01)***	0.08 (0.03)**	0.21 (0.05)***	0.21 (0.05)***	0.22 (0.05)***
PRC	−0.01 (0.01)	0.04 (0.02)	0.14 (0.04)***	0.14 (0.04)***	0.12 (0.04)***
Individual-level interaction					
Gender × Degree			−0.06 (0.02)**	−0.06 (0.02)**	−0.06 (0.02)**
UL × Degree			−0.17 (0.06)**	−0.15 (0.06)**	−0.16 (0.06)**
UL × PRC			−0.15 (0.06)**	−0.16 (0.06)**	−0.14 (0.06)*
Network-level predictors					
Gender-BDI				−0.24 (0.53)	−0.14 (0.50)
Degree (Group Mean)				0.13 (0.04)**	0.14 (0.05)**
PRC (Group Mean)				−0.08 (0.03)*	−0.22 (0.06)***
Transitivity				−0.05 (0.05)	−0.04 (0.05)
Component Ratio				0.02 (0.04)	−0.01 (0.05)
Cross-level interaction					
Degree × Transitivity					−0.04 (0.03)
Degree (Group) × Transitivity					−0.03 (0.05)
PRC × Transitivity					0.04 (0.02)*
PRC (Group) × Transitivity					0.09 (0.03)**
Degree × Component Ratio					0.05 (0.03)*
Degree (Group) × Component Ratio					−0.01 (0.03)
PRC × Component Ratio					−0.03 (0.02)
PRC (Group) × Component Ratio					0.03 (0.02)
Intercept	3.95 (0.05)***	3.89 (0.06)***	3.93 (0.06)***	4.13 (0.25)***	4.04 (0.24)***
Variance of random components					
Intercept	0.16	0.22	0.24	0.12	0.09

(continued)

Table 2. (continued)

	Model I	Model II	Model III	Model IV	Model V
Length of Use		0.55	0.56	0.58	0.58
Gender		0.02	0.02	0.02	0.03
Degree		0.04	0.04	0.04	0.03
PRC		0.02	0.02	0.02	0.01
Model summary					
Akaike-Information Criterion (AIC)	177,053.72	176,676.65	176,611.10	176,592.60	176,591.77
Log-Likelihood	−88,519.86	−88,317.32	−88,281.55	−88,267.30	−88,258.88
χ^2 Deviance	—	405.07***	71.55***	28.50***	16.84*

Note. Model I is a baseline model with only a random intercept, to be compared with the others having random coefficients.
PRC = PageRank centrality; BDI = Blau's diversity index.
*$p \le .05$, **$p \le .01$, ***$p \le .00$.

Looking at the results of Model II, the simplest random-coefficient model, the length of social media use had a substantial impact on the cumulative count of contributed messages; a one standard deviation increase of the length of use increased the amount of message contribution approximately 4.3 times (i.e., $e^{1.46} = 4.306,\ R_p^2 = 0.10$) more than the benchmark case at the mean. With the length of use and other predictors held constant, male users were found to contribute messages approximately 18% less (i.e., $e^{-.20} = 0.819,\ R_p^2 = 0.007$) than their female counterparts. With the personal attributes controlled, the degree centrality or connectedness was found to cause a modest increase in message contribution of around 8% (i.e., $e^{.08} = 1.083,\ R_p^2 = 0.002$) per one standard deviation increase in degree. Thus, H1 was supported.

However, when the within-level interaction terms were included, as in Model III, the effects of degree centrality escalated to around 23% (i.e., $e^{.21} = 1.234,\ R_p^2 = 0.002$). Further, individuals' PRC scores that were insignificant in Models I and II were statistically significant in Model III; a one standard deviation increase of PRC elevated the message contribution by around 15% (i.e., $e^{.14} = 1.15,\ R_p^2 = 0.001$) more than those with the average PRC, thereby largely supporting H2. Notice the negative two-way interaction effects of degree centrality (i.e., $e^{-.17} = 0.84,\ R_p^2 = 0.001$) and PRC (i.e., $e^{-.15} = 0.86,\ R_p^2 = 0.001$), respectively, with the length of use, which means that the positional effects on participation were diluted as the account got older. This implies that individuals' positional advantages or disadvantages concerning the degree of participation might be more pronounced with the newer than older accounts. Other influences, such as the account holders' personalities (e.g., extroversion vs. introversion) and lifestyles, could be blended.

Model IV had additional predictors regarding the effects of network-level characteristics, including gender distribution (i.e., gender-BDI), group-mean degree and PRC, global transitivity (T_G), and component ratio (CR). With all individual-level predictors controlled, the effects of the group-mean degree and PRC were found to be statistically significant, thus indicating that there were environmental or contextual influences at work apart from the individual-level characteristics. Respectively, the message contribution of individuals was found to increase around 14% per one standard deviation increase in the group-mean degree (i.e., $e^{.13} = 1.139,\ R_p^2 = 0.009$), while it decreased 7.7% for every one standard deviation increase of group-mean PRC (i.e., $e^{-.08} = 0.923,\ R_p^2 = 0.002$). This suggests that the individuals' degree of message contribution is partly a function of the overall characteristics of the networks to which they belong. Merely being part of a network in which the members contribute more messages on average might entice a person to also increase participation. However, the opposite occurred when the members' PRCs were higher on average.

In Model V that included the cross-level interaction terms, the effects of the group-mean degree and PRC became more pronounced. The increase of the group-mean degree raised the amount of message contribution to 15% (i.e., $e^{.14} = 1.15,\ R_p^2 = 0.007$), while the increase of the group-mean PRC lowered the message contribution by up to 20% (i.e., $e^{-.22} = 0.803,\ R_p^2 = 0.002$). The negative main effects of group-mean PRC can be explained in light of the well-known *friendship paradox* that refers to a phenomenon that most people have fewer friends than others do on average (Feld, 1991; Hodas et al., 2013). In a star network consisting of N individuals, as a canonical example, everyone but the one at the center has fewer friends (i.e., one friend) than the average in the network (i.e., $2(N-1)/N$). This is because the $N-1$ members of the network share a disproportionately well-connected neighbor at the center, which elevates the average PRC. In other words, belonging to a network with higher average PRC could imply that there might be better-connected neighbors than yourself, and thus make you more dependent on them in a relative sense unless you had other positional advantages.

However, this should not be the case if the network is internally clustered. As the $N-1$ members are tied to one another, the number of friends people have is closer to the network average (i.e., you have as many friends as others on average). With the structural asymmetry being lessened (i.e., less structural dependency on the central one), the disparity in social prominence may be diminished, hence encouraging individuals to be more proactive in communication. Consistent with this speculation, the effects of the interaction between (both individual and group-mean) PRC and the global transitivity was positive. As illustrated in Figure 2(a), while the effects of individual-level PRC on communication were slightly negative to almost negligible when the network's degree of transitivity was very low, they became positive as the network was more clustered (i.e., $e^{.03} = 1.03,\ R_p^2 = 0.001$). While no main effects of global transitivity were found, these results suggest that the overall effects of individual and group-level PRC on voluntary participation were a function of the degree of network clustering, thereby partially supporting H3.

Further, the cross-level interaction between the individual-level degree centrality and the network-level component ratio (CR) was also statistically significant, while the hypothesized negative main effects (i.e., H4) were not found. The positive interaction effects indicate that the more fragmented the network, the more prominent or important the role of individuals' connectedness or degree in determining the extent of message contribution (Figure 2(b)). More specifically, the effects of degree centrality on message contribution tended to increase around 5% more per one standard deviation increase of the component ratio of the network (i.e., $e^{.05} = 1.051,\ R_p^2 = 0.001$). Together, the results suggest that the effects of individual-level positional characteristics like degree centrality or PRC on the extent of voluntary participation in communication may vary to some extent on the network's structural properties as a whole.

Discussion and Implications

Social scientists for many years have posited that the behavior of individuals—whether joining a riot (Granovetter, 1978), voting (Bond et al., 2012), adopting a technology (Valente, 1995), or endorsing a product (Salganik et al., 2006)—is in large part a function of their peers who have already manifested similar behavior. This study's findings suggest that similar mechanisms might also be at work in the context of collective communication on social media. Individuals

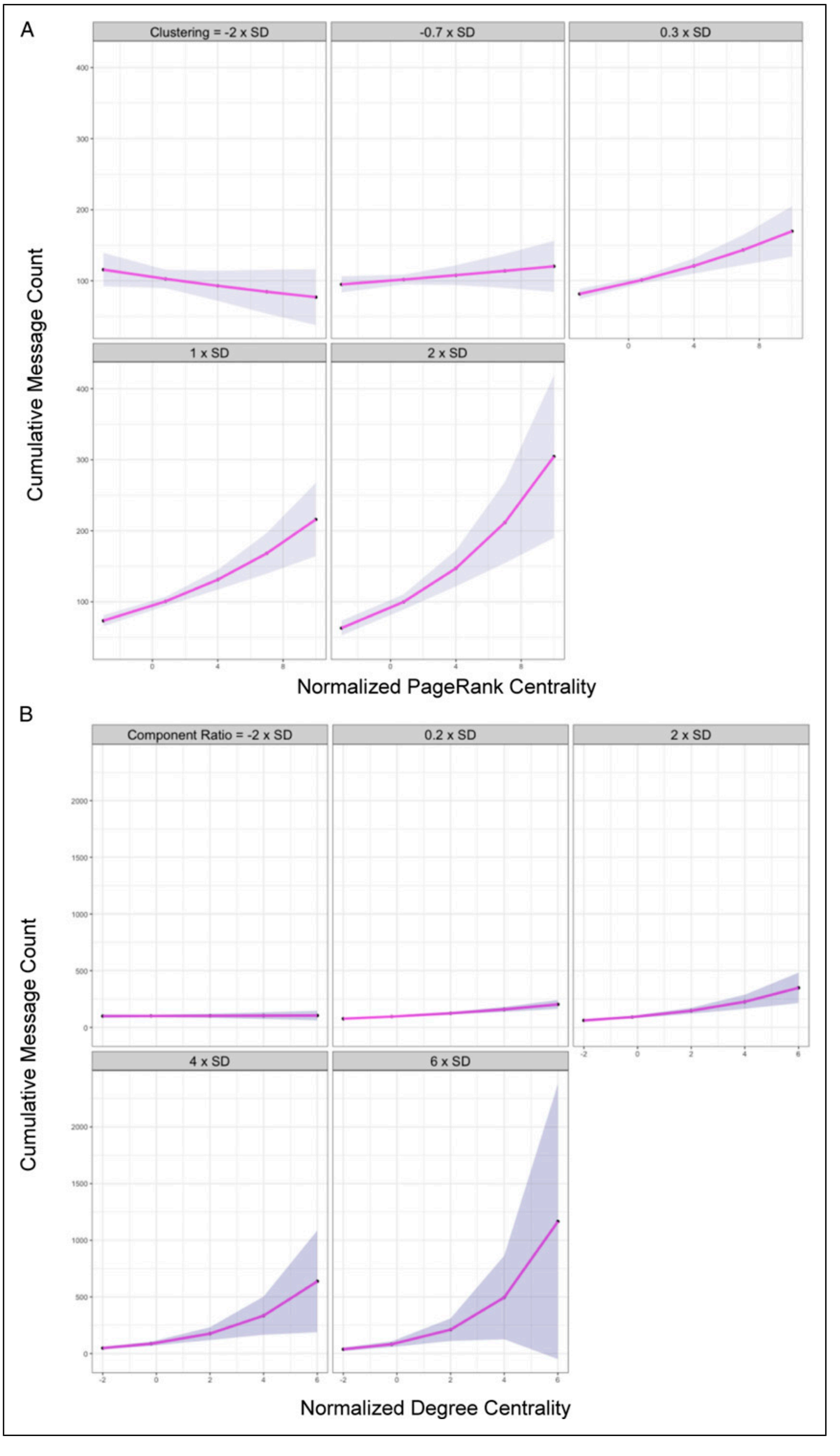

Figure 2. Visual Plots for Cross-Level Interaction Effects. (a) Actor-level PageRank centrality x network clustering (b) Actor-level degree x network component ratio.

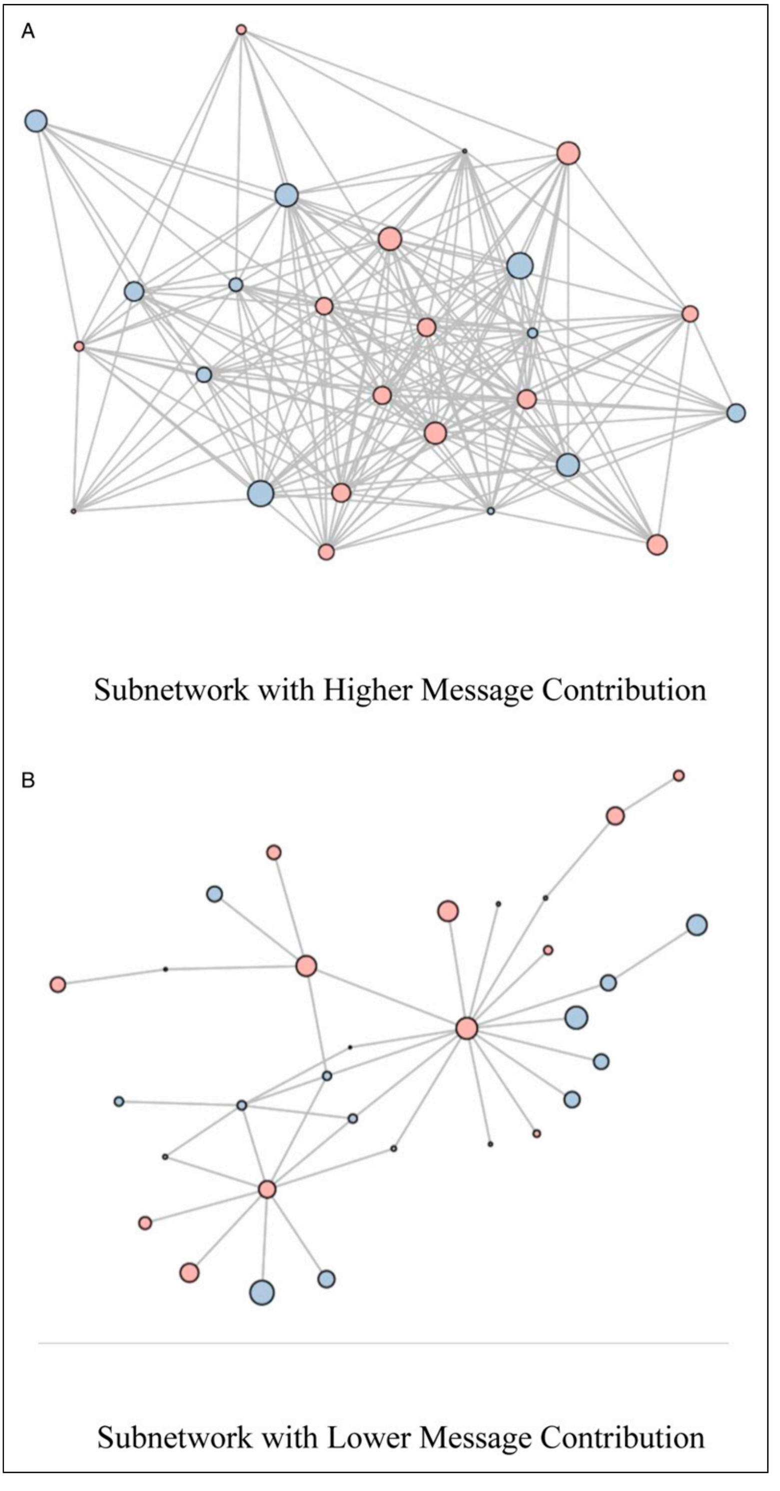

Figure 3. Examples of subnetwork structures. (a) Subnetwork with higher message contribution (b) Subnetwork with lower message contribution. Note. Subnetworks shown above (red = female, blue = male) are extracted from the same network.

who are well-connected directly or indirectly with others, and/or merely belong to well-connected local communities (e.g., networks with higher average degree) are likely to post more messages. This also implies that, in the long run, idle communicators or lurkers will more likely be those deprived relatively of social ties, or they will be embedded in loosely connected communities (e.g., networks with lower clustering degree), thus enticing them to remain relatively inactive.

Figure 3 shows two exemplary subnetworks extracted from one of the local networks examined here, respectively, with the cumulative message posts above or below two standard deviations from the local mean. It seems clear that the subnetwork with higher levels of message contribution (3a) is more densely connected and internally clustered than the other with lower contributions (3b) in which multiple radial structures (i.e., star networks) appear. The presence of radial structures means that most individuals, while lacking ties with one another, are tethered to, hence dependent on a few well-connected individuals. Even within the same local network, therefore, this suggests that active communicators are more likely to form or be embedded in a clustered region than their counterparts.

Neither this suggests that active communicators prefer being in a clustered region nor that network structures can exclusively determine the extent to which anyone would engage on social media platforms. The interaction effects found at a cross-level rather indicate that it should be viewed as an emergent outcome generated through *the agency-structure interactions*, that is, the path-dependent processes in which final outcomes are contingent on prior outcomes along the way (Lazer et al., 2010; Slater, 2007; Sohn, 2022; Song & Boomgaarden, 2017). Path dependence is a key characteristic of a networked environment in which the constituents (e.g., individuals) are interdependent (Page, 2015). The skewed distribution of cumulative messages (i.e., longer tail to the right) as seen here might not have emerged if the actors were mostly independent of one another, in which encountering a normal distribution instead should be more likely. This suggests that things we observe at any moment in social media should be understood as a multilevel phenomenon that is constrained by the participants' attributes as well as the connection patterns among them.

Salganik et al. (2006), for instance, conducted an experiment where subjects downloaded music online. They found that people tended to choose the same music that others had already downloaded. When they were allowed to observe the choices of others, popularity begat further popularity. Neglecting the path-dependent nature of the process, one may be tempted to attribute the most successful music to its intrinsic qualities, such as style, lyrics, and tempo. Coupled with our inherent psychological bias toward intrinsic (i.e., dispositional) rather than extrinsic (i.e., situational) factors—also known as *fundamental attribution error* (Ross, 1977)—this often leads scholars to either disregard or underemphasize the roles of the collective social processes underlying. In a similar vein, it may be misleading to view communicative actions like lurking or free riding as behavioral outcomes of selfish desires, lack of motivation/ability, or some other intrinsic attributes alone. Instead, silent social media users might be reluctant to post messages partly because the surrounding social fabrics and dynamics have not encouraged them to participate.

It has been reported repeatedly that social media usage is declining worldwide. One survey shows that over 40% of Facebook users in the United States alone stated that they had reduced their engagement (Perrin, 2018). Many factors may contribute to this trending global decline, including social media fatigue, growing privacy concerns, and media competition/diversification (Bright et al., 2015; Dhir et al., 2018). We believe that the disparity in voluntary participation, exacerbated through the path-dependent processes in networks, might also play an important role. The results of this study imply that once you become a lurker it becomes increasingly difficult to reactivate, partly because the gap between you and the active communicators in terms of message volume and friend connections has become wider than ever. Reversing this process requires far more motivation and effort than previously required, thereby discouraging many from renewing their engagement.

As the process goes on, in the long run, a relatively small number of individuals might become excessively dominant while the vast majority continue to lurk. This can eventually depress a network's vitality and long-term sustainability. The rise of *influencers* in social media (also known as Power Twitterians or Power YouTubers) demonstrates how online social networks have become unfair playing fields where the vast majority of users passively consume the messages and information fed by a small number of influencers, not unlike the previous eras of traditional mass media. In order to weaken the structural inertia and foster voluntary contributions of more individuals, it is important to recognize the contingency of individual behaviors on the underlying network structures and develop contextual settings (Sohn & Leckenby, 2007) or algorithmic interventions (Malik & Pfeffer, 2016) that might possibly motivate diverse users to participate voluntarily, thereby making the collective online communication processes more robust and stable.

Limitations

This study is subject to some limitations. First, the inferences made were drawn from a snapshot of local network structures of individuals rather than from an actual examination of longitudinal changes. While this may not necessarily keep us from concluding that the cumulative distribution of messages posted should be conditional on networks' structural properties, the mechanism of *social selection* or *homophily* may also be at work in the process of social networking such that individuals selectively form ties with similar others over time (McPherson et al., 2001). Evidence suggests that individuals' personalities (e.g., extroversion vs. introversion) might play an important role in forming social networks (e.g., Quercia et al., 2012). For studying the dynamic agency-structure interactions, longitudinal multilevel modeling or dynamic network modeling (e.g., Braha & Bar-Yam, 2006) and agent-based simulation (e.g., Sohn, 2022; Song & Boomgaarden, 2017) may be utilized.

Second, local networks entail the issues of boundary specification. Trying to determine which relations or ties are included in a network depends on how the network boundaries are specified, and this might alter important structural properties like centrality for some individuals (Perry et al., 2018). To alleviate this potential problem, one might attempt to capture extended ego networks with wider boundaries that could possibly contain more distant relations (McCarty et al., 2007) or multiple small networks that share common connections (Lowell et al., 2018).

Third, not all lurking behaviors stem from the same reason—there may be various psychological motivations underlying, including social comparisons (Burnell et al., 2019), anxiety and loneliness (O'Day & Heimberg, 2021), social media fatigue (Liu & He, 2021), fear of isolation and perceived affordances (Fox & Holt, 2018), and privacy concerns (Osatuyi, 2015), among many others. Different motives may lead to different patterns of silence—for instance, anxiety or social comparisons are associated with temporary and repeated silence, whereas social media fatigue or privacy concerns can lead to long-term silence. Detailing all the reasons behind the lurking behavior is beyond the scope of this study, but for further research, a mixed-methods approach combining computational and qualitative text analysis (Andreotta et al., 2019) along with in-depth interviews of social media users may be applied. Illuminating not only social contextual influences, but also diverse psychological motives would help us understand being silent in social media as a more nuanced behavior.

Fourth, the data used here might not accurately reflect the current state of network structures on the platform as they were collected a few years ago before the blocking of Facebook APIs, unfortunate for research communities (Hogan, 2018). Although there is little doubt that the current state of disparity in voluntary communication might not differ greatly from what was found in this study, confirmation with more recent data would be beneficial. Lastly, the findings of this study may be platform-specific (i.e., Facebook) and not generalizable to other networks or platforms. Malik and Pfeffer (2016) already found that social media's behaviors might be significantly varied by the platform-specific features, such as recommendation algorithms. For more generalized results, further research is required using other types of social media settings with different algorithmic features as well as structural characteristics.

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Notes

1. Path dependence is often modeled as the *Polya process* in which at each period a ball is randomly drawn from an urn filled with balls of different colors and returned along with an additional one of the same color as the one drawn, and this is repeated many times. An interesting property of this process is that every distribution of outcomes (e.g., balls of different colors) has an equal probability, meaning that anything extreme (e.g., 98% balls of the same color) is as likely as more moderate distributions. When outcomes are extremely path dependent, highly skewed outcome distributions become far more likely than when outcomes are probabilistically independent.
2. This by no means implies that eigenvector centrality and its variants should be free from the boundary specification problems of local networks, but rather suggests that eigenvector centrality can at least be calculated from an actor's point of view, while a whole-network approach is required for both closeness and betweenness centrality.
3. It was once possible for users to extract the graph data of their complete Facebook networks for the purposes of visualization and analysis. This is no longer available because of restrictions imposed by Facebook.
4. While egocentric networks typically refer to the networks reported and (subjectively) defined by egos, note that the network data collected and analyzed here were actual connection patterns recorded, thus free from the possible errors or biases associated with the egos' memory or perspective.
5. With the ego included in an egocentric network, the maximum distance between any two alters should be limited to two as they are tied via the ego, which may greatly underestimate the distances among alters in the real sense. Particularly in social media, any two alters sharing no other friend than the ego are likely more distant than similar cases in an offline context.
6. While egocentric networks measured using surveys typically consist of less than 10 alters due primarily to the respondent burdens, McCarty and colleagues found through the simulations of randomly dropping

alters that some important structural patterns (e.g., density, centrality, clustering) could be captured if the networks had around 25 alters or sometimes less.

7. It is often argued that PRC, originally developed for directed graphs, would not be applicable to undirected networks as it is proportional to degree centrality. However, Grolmusz (2015) confirmed through simulations that PRC is not proportional to degree centrality. PRC becomes identical to degree centrality if and only if the network graph is regular, meaning that every node has the same degree.
8. There are no agreed upon ways to calculate standard effect sizes for individual terms in generalized multilevel linear models due mainly to the partitioned variances. We nevertheless calculated semi-partial R^2, following the suggestion of Nakagawa and Schielzeth (2012), as a measure of effect sizes for the fixed terms.

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