International Journal of Communication 13(2019), 3802–3825 1932–8036/20190005

Unpacking the Influence of Informational, Organizational, and Structural Factors on the Longitudinal Change of the NPO Follower-Followee Network on Twitter

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A growing body of research has treated interorganizational networks as dynamic systems of communication. However, most longitudinal network studies have confounded the processes of new tie formation and old tie maintenance, resulting in an incomplete understanding of the processes of network change. Based on the multitheoretical multilevel framework, this study examines how different factors shape new tie formation and existing tie maintenance of a follower-followee network among 184 environmental nonprofit organizations on Twitter from 2014 to 2017. Actor-oriented modeling results demonstrated that organizations were more likely to form new ties with other organizations that more actively tweeted, shared similar organizational age and geographic location, and were already popular in the network. However, tie maintenance only correlated with geographic location and popularity. Organizations were particularly likely to dissolve existing ties with organizations of the same age. This study advances research on interorganizational communication, social networks, collective action, and networked relationship management.

Keywords: interorganizational communication, social networks, nonprofit organization, social media, collective action, strategic communication, social network analysis (SNA), actor-oriented modeling (SIENA), longitudinal research, Twitter, affordance

Organizational communication and public relations scholarship has increasingly recognized that organizations' relationship building involves not only strategically managing organization–public relationships but also organization–organization relationships (Shumate, Atouba, Cooper, & Pilny, 2017; Yang & Taylor, 2015). The success of collective action depends on the ability of participating organizations to change their network ties and adapt to the ever-changing environment (Diani, 2004). Hence, examining how the interorganizational network connecting nonprofit organizations (NPOs) unfolds over time is valuable to advance their missions (Lai, She, & Ye, 2019). Moreover, studying network change sheds light on how

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Date submitted: 2019–01–14

[1] I would like to thank Michelle Shumate, Noshir Contractor, Darren Gergle, Aaron Shaw, Katherine Ognyanova, Yu Xu, and three anonymous reviewers for their constructive feedback to the earlier drafts of this article.

organizations select partners to achieve organizational objectives (Sommerfeldt & Yang, 2017). In light of these insights, a growing body of scholarship has treated interorganizational networks as dynamic systems of communication to understand how organizations (re)configure their relationships to achieve organizational and network goals over time (e.g., Bryant & Monge, 2008; Doerfel & Taylor, 2017; Lee & Monge, 2011; Margolin et al., 2015; O'Brien et al., 2019; Weber, Ognyanova, & Kosterich, 2017).

However, research to date often confounds new tie formation (i.e., selection) and old tie maintenance (i.e., retention), examining the factors that predict the presence or absence of ties, irrespective of their prior status (for a notable exception, see Shumate, 2012). In fact, retention is conditional on selection and occurs only after a tie has been created (Monge & Contractor, 2003). Mixing the two processes together obscures the distinct factors that might shape selection and retention processes (Cheadle, Stevens, Williams, & Goosby, 2013). Without distinguishing selection from retention, researchers are limited in their ability to ascertain whether, and how, different factors are related to selection, retention, both, or neither of the two processes.

To address this gap, this research seeks to ascertain the factors that influence the two fundamental processes—selection and retention (Kleinbaum, 2018; Monge, Heiss, & Margolin, 2008)—in the longitudinal change of interorganizational communication networks. It does so using the multitheoretical multilevel (MTML) framework, which emphasizes the need to gain better understanding of social networks from multiple levels of analyses and varied theoretical lenses (Monge & Contractor, 2003). The network examined in this study is a Twitter follower-followee network among 184 environmental NPOs (ENPOs). I selected this network for four reasons. The first three do not relate to the organization's missions. They are (1) NPOs rely on social media (e.g., Facebook, Twitter) for relationship building and stakeholder engagement in a digital age (Briones, Kuch, Liu, & Jin, 2011); (2) Twitter offers an ideal platform to examine the two fundamental processes in longitudinal network change (Kwak, Moon, & Lee, 2012); and (3) interorganizational follower-followee networks are fundamental to information diffusion on social media and are critical to collective action online (Huang & Sun, 2014).

The fourth reason is that ENPOs are at the forefront of the activism to influence environmental governance. A large number of ENPOs have formed alliance networks to fight against climate change (Greenpeace, 2017). However, findings on the effectiveness of these interorganizational networks are mixed. On the one hand, research suggests that environmental groups have successfully used social media and deployed communication strategies to mobilize broad public participation, such as the People's Climate March in 2017 (Hestres & Nisbet, 2018). But more lofty goals remain out of reach (Ackland & O'Neil, 2011; Gunther, 2018). Given that interorganizational networks can help NPOs achieve their goals (Diani, 2004), studying interorganizational networks among ENPOs may illuminate why they have not generated greater success, and how they could in the future.

This study makes four theoretical contributions. First, it reveals that different factors influence tie selection and retention in unique ways, highlighting the need for further studies that distinguish selection from retention. Second, it unpacks the influence of informational, organizational, and structural factors on the longitudinal change of NPO follower-followee networks, contributing to a growing body of research on interorganizational networks as dynamic systems of communication. Third, this study highlights the utility

of theories of socioevolution, homophily, preferential attachment, and research on information diffusion on social media in jointly predicting follower-followee networks. Hence, it contributes to the refinement of the MTML framework and the extension of research in collective action. Finally, this study sheds light on how organizations should dynamically configure their networks for relationship management.

The rest of the article is organized as follows: The next section reviews literature on interorganizational networks, highlighting the significance of follower-followee networks in facilitating collective action and relationship building for NPOs. Next, building on the MTML framework, I present a set of hypotheses to assess how various factors influence the evolution of follower-followee networks. Descriptions of the methods and the findings follow. The conclusion discusses the theoretical contributions and practical implications of this study.

Conceptualizing NPO Follower–Followee Networks

Research on interorganizational communication—"the structures, forms, and processes created by the exchange of messages and the co-creation of meaning among organizations and their stakeholders" (Shumate et al., 2017, p. 1)—has increased significantly in recent years. In this line of research, scholars often take a social network perspective to understand the antecedents, structures, processes, and outcomes of interorganizational communication. Studies have shown that virtual interorganizational communication networks among NPOs (e.g., hyperlink and retweet networks) facilitate online collective action (Ackland & O'Neil, 2011; Huang & Sun, 2014) and are critical for the success of social movements (Yang & Saffer, 2018) and off-line collaborative networks that provide tangible public goods (Lai et al., 2019; Pilny & Shumate, 2012).

Follower-followee networks allow users to consume and share information. Evidence of reciprocity (i.e., two actors mutually connect with one another) and transitivity (i.e., three actors having ties to one another) in follower-followee networks (Liang & Fu, 2017; Peng, Liu, Wu, & Liu, 2016; Xu, Huang, Kwak, & Contractor, 2013) suggests that social actors are aware of others' following and unfollowing behavior and tend to reciprocate and balance relationships on Twitter. Further, NPOs prefer to follow organizations that are more active in tweeting, located in the same geographic region as they, and have higher status (Huang, Gui, & Sun, 2015; Huang & Sun, 2014). Taken together, these findings suggest that follow relations are NPO actors' intentional communication choices and fundamental to online community building and collective action (Shumate, 2012).

Scholars typically conceptualize interorganizational follower-followee networks among NPOs and civil actors as facilitators of collective action (Huang et al., 2015; Huang & Sun, 2014). In a follower-followee network, organizations can intentionally select accounts to follow and make visible these affiliations to other organizations in the network or the general public. Following the logic of connective collective action (Monge et al., 1998; Shumate & Lipp, 2008) and representational communication (Shumate, 2012), these interorganizational linkages enable members and nonmembers to purposefully connect with like-minded actors working on similar issues and make the social issue advocated visible to the public. The connections established among NPOs through follower-followee ties can facilitate information diffusion, help advance network goals, and enhance the collective visibility of a common social issue to the public. Essentially,

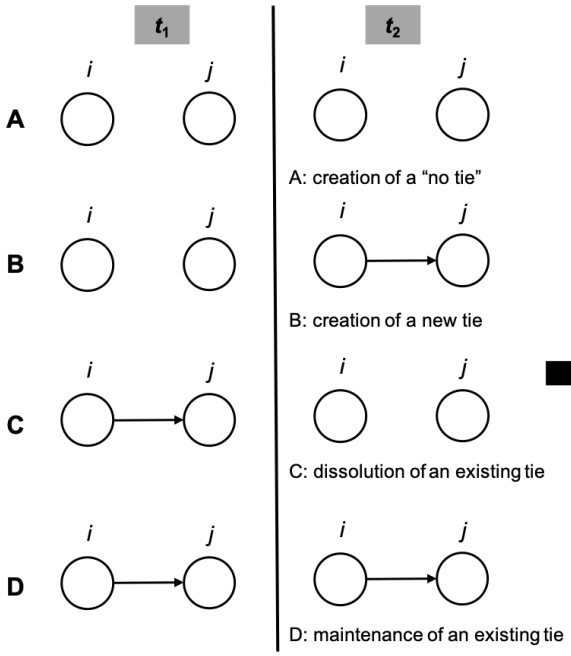
follower-followee networks, as facilitating structure for online collective action (Huang & Sun, 2014), break assumptions about membership and formal organization in traditional hierarchical models of collective action organizing (Bimber, Flanagin, & Stohl, 2005), which offer more opportunities for enhancing mobilization capacity and higher levels of public engagement (Bennett & Segerberg, 2011).

Beyond network-level outcomes, interorganizational communication networks on social media also have important consequences for organizations at the meso level. The central tenet of networked relationship management research posits that interorganizational network is a communication strategy for organizations to build relationships with others and therefore enhance social capital (Yang & Saffer, 2018) and organizational reputation (Lai, She, & Tao, 2017; Yang & Taylor, 2015). Recently, Sommerfeldt and Yang (2017) theorized a dynamic model of interorganizational relationship building, highlighting the necessity for organizations to devise differential network strategies based on the stage of development of the issue in question. Building on such insights, the next section introduces the socioevolutionary approach to the study of longitudinal network change.

An Evolutionary Approach to Longitudinal Network Change: New Tie Formation (Selection) and Old Tie Maintenance (Retention)

Grounded in socioevolutionary theory (Aldrich & Ruef, 2006; Campbell, 1965), the evolutionary perspective to social networks denotes two fundamental processes in longitudinal network change: selection and retention (Kleinbaum, 2018; Monge & Contractor, 2003; Monge et al., 2008; Shen, Monge, & Williams, 2014; Snijders, 2001). In this research, selection[2] describes an actor's choice to select new alternative partners over others to optimize benefit and minimize harm (Campbell, 1965; Monge & Contractor, 2003). In a follower-followee network, selection describes an NPO's choice to start following (or not to follow) an organization (i.e., Scenarios A and B in Figure 1). Retention refers to the act of persistent following behavior (i.e., Scenario D in Figure 1) or unfollowing behavior (i.e., Scenario C in Figure 1) when a tie has been created in a prior period.

[2] For forced selection, see Aldrich (2008).



Note. Four possible scenarios of tie changes for a dyad. Adapted from Ripley et al. (2019).

Tie Change Scenarios Covered by Each of the Three Functions in Stochastic Actor-Oriented Modeling

	Evaluation (A + B + C + D)	Creation (A + B)	Endowment (C+D)
A	negative	negative	
B	positive	positive	
C	negative		negative
D	positive		positive
		Selection	Retention

Note. This table illustrates the tie change scenarios covered by each of the three functions, and if covered by that function, the expected sign of coefficients.

Figure 1. Possible tie changes and modeling of these scenarios using longitudinal network functions. Note. See Snijders (2017) for why Scenarios A and B represent selection and Scenarios C and D represent retention.

Creating and keeping/removing a communication relation should be understood as different evolutionary processes (Monge et al., 2008; Shen et al., 2014; Shumate, 2012). And there has been increasing attention to the longitudinal change of interorganizational networks generally (e.g., Bryant & Monge, 2008; Lee & Monge, 2011; Margolin et al., 2015; O'Brien et al., 2019; Weber, 2012), and follower-followee networks more specifically (e.g., Liang & Fu, 2017; Xu et al., 2013). However, most research has failed to distinguish new tie formation from old tie maintenance. Studies often mix the two processes together (see the Evaluation function in Figure 1) and predict the factors that shape the presence (i.e., Scenarios B and D) versus absence (i.e., Scenarios A and C) of ties in a network, irrespective of their status in a prior time period (e.g., Choi, Yang, & Chen, 2018; Margolin et al., 2015; Weber, 2012). However, without separating the two processes, researchers cannot determine if the coefficients of these factors are insignificant or opposite to their effect on each individual process. Thus, mixing the two processes together leads to an incomplete understanding of the different factors that shape them (Cheadle et al., 2013; Shumate, 2012). Similarly, studies that examine either selection (i.e., Scenario A vs. B; e.g., Huang & Sun, 2014; Peng et al., 2016) or retention (i.e., Scenario C vs. D; e.g., Kwak et al., 2012; Liang & Fu, 2017; Shen et al., 2014; Xu et al., 2013) obscure the fact that tie maintenance is conditional on prior formation of these ties.

Previous longitudinal network research has most frequently referenced the influence of informational, organizational, and structural factors on the formation and dissolution of ties in online social networks (Huang & Sun, 2014; Kwak et al., 2012; Liang & Fu, 2017; Peng et al., 2016; Shumate, 2012; Weber, 2012). Based on the MTML framework that emphasizes the need to understand social networks from multiple theoretical lenses and from multiple levels of analyses (Monge & Contractor, 2003; see also Brass, Galaskiewicz, Greve, & Tsai, 2004), this article will integrate theories of information diffusion on social media, homophily, and preferential attachment to understand network selection and retention as evolutionary processes and the factors shaping the formation and maintenance of interorganizational relationships.

New Tie Formation (Selection)

Information Diffusion on Social Media

Liang and Fu (2017) conceptualized followees as information repertoire on social media. According to the authors, social media users' following patterns determine their information access and consumption. Information diffusion via tweets and retweets within issue-specific networks facilitates the formation of follower relations (Chen & Fu, 2016; Xu et al., 2013). Previous research reveals that NPOs were more likely to follow alters (i.e., other organizations in a network) who were more active in posting messages on microblogs (Huang et al., 2015; Huang & Sun, 2014). The more frequently an organization tweets, the more likely they are to have tweets that are diffused across a social network and gain the attention of other organizations in the ecology (Guo & Saxton, 2018). As such, frequent tweeting generates social influence and cumulative visibility to attract followers to organizations. Based on previous research, I hypothesize the following:

H1: Organizations are more likely to follow NPO alters who tweet more frequently.

Age Similarity

Research on nonsocial media networks posits that there are cohort effects in that organizations prefer to connect with others of a similar age. Those who subscribe to the notion of organizational births in evolutionary theory theorize that organizations tend to connect with others of the same tenure group in the organizational ecology (Shen et al., 2014; Shumate, Fulk, & Monge, 2005). Those who draw on homophily theory (McPherson, Smith-Lovin, & Cook, 2001) attribute cohort effects to shared experiences and commonality, which contribute to enhanced trust, identification, and ease of communication (Atouba & Shumate, 2015). Organizational ecology researchers have made similar observations from the perspective of organizational imprinting effects (Marquis, 2003; Stinchcombe, 1965). The age-based homophily hypothesis has received strong empirical support from studies of off-line NPO networks (Atouba & Shumate, 2015; Shumate et al., 2005). Based on the existing evidence, I posit that cohort effects persist as organizations attempt to connect with their peers in the social media space. Therefore, I hypothesize the following:

H2: Organizations are more likely to follow NPO alters of similar organizational age.

Geographic Similarity

Scholars have found that geography shapes network evolution (Shen et al., 2014; Shumate et al., 2005). From the perspective of organizational ecology, Lee and Monge (2011) suggest that organizations occupying similar spaces for environmental resources, such as being embedded in the same geographic location, show greater levels of interdependence, so they are more likely to build linkages with each other. Geography-based homophily also posits that NPOs embedded in a common political, socioeconomic, and cultural environment are more likely to encounter similar problems and form connections around those problems (Atouba & Shumate, 2015). Geographic similarity promotes a sense of compatibility for organizations facing similar social issues in a common region (e.g., the same state) to advance collective action (Ackland & O'Neil, 2011; Huang & Sun, 2014; Shumate et al., 2005). Building on these two lines of research, I hypothesize the following:

H3: Organizations are more likely to follow NPO alters headquartered in the same state.

Beyond exogenous factors, the choice to create or remove a communication relation should be understood in relation to network embeddedness. Prior literature has uncovered three relational factors that most significantly structure the patterns of follower-followee networks and interorganizational networks: reciprocity, transitivity, and indegree popularity. However, research has consistently found that actors are more likely to form and maintain reciprocated and transitive ties (Kwak et al., 2012; Liang & Fu, 2017; Shumate, 2012; Weber, 2012). In contrast, findings on whether actors tend to dissolve ties to popular actors with high indegree centrality are mixed. This study further interrogates the influence of indegree popularity on tie formation and maintenance in an effort to clarify these findings.

Preferential Attachment

Preferential attachment describes organizations' preference to build connections with popular actors in a network (Barabasi & Albert, 1999; Merton, 1968). Organizations tend to affiliate with popular actors in an interorganizational network because of their credibility, social influence, and perceived legitimacy (Lai et al., 2019; Pennock, Flake, Lawrence, Glover, & Giles, 2002; Shumate, 2012). Following popular organizations that have many followers not only enhances a focal organization's status but also "enhance(s) the visibility of the network's goals" (Shumate & Lipp, 2008, p. 178); the resulting issue-specific network thus demonstrates coordinated behaviors among a set of civil actors, placing the most influential actors in the center to further collective action (Ackland & O'Neil, 2011; Huang & Sun, 2014). In sum, following organization alters with high indegree popularity has positive organizational and network benefits. Therefore, I hypothesize the following:

H4: Organizations are more likely to follow NPO alters with high indegree popularity.

Old Tie Maintenance/Dissolution (Retention)

The second fundamental process in network evolution is retention, or maintenance (Scenario D) or dissolution (Scenario C) of existing ties after a tie has been created in previous time periods. Retention is only meaningful after ties have been established, which makes it conditional on the processes of selection

(see Figure 1; Kleinbaum, 2018; Monge et al., 2008; Snijders, 2001). As reviewed earlier, previous longitudinal network research largely fails to distinguish selection from retention processes. Although a few studies have examined the factors shaping tie dissolution (e.g., Shen et al., 2014), findings are mixed. For example, Shumate (2012) found that organizations tend to dissolve ties with organizations with high indegree centrality and similar website communication. In contrast, Liang and Fu (2017) found that actors tend to maintain reciprocated ties as well as ties to popular users, users who post similar hashtags, and users who share followees. Similarly, Xu and colleagues (2013) and Kwak and colleagues (2012) found that users tend to maintain their ties to users who shared common followees and who used common hashtags. In light of these mixed findings in a paucity of extant research on tie decay, and given the conditional nature of retention on selection, this research examines if and how the four hypothesized factors that influence selection also influence retention by asking the following:

RQ1: To what extent do (a) active tweeting, (b) similar organizational age, (c) similar geographic location, and (d) high indegree popularity influence existing tie maintenance?

Method

Sample

This study used a purposive sample of ENPOs (National Taxonomy of Exempt Entities [NTEE], Category C) from the 2014 Urban Institute National Nonprofit Research Database of all registered NPOs in the United States. Although social media allows smaller organizations to have larger audiences in the digital age, research suggests that deficient organizational resources make it difficult for small ENPOs to use Twitter effectively for relationship building (Hou & Lampe, 2015). Therefore, I selected ENPOs with revenue of $5 million or more ($N$ = 271) because these organizations are more likely to have dedicated staff members to manage their Twitter profiles and negotiate network affiliations (Briones et al., 2011). Among these ENPOs, 201 organizations had Twitter profiles. After tracking three years of activity for these 201 organizations, I removed 17 inactive accounts, indicated by zero change in the number of tweets. As such, 184 ENPOs comprised the final sample.

Procedure

To construct a follower-followee network matrix, I recorded the follow relations among 184 ENPOs from April 2014 to April 2017. The procedure was as follows. First, I created a Twitter account following only the 201 ENPOs with Twitter profiles. Through the "Followers You Know" function, I determined each focal organization's ENPO followers from the sample of 201 organizations. I then repeated this procedure for all organizations in the sample for every three-month interval in the three years. After I deleted the 17 inactive ENPOs, each network became a 184 × 184 asymmetric directional matrix, with "0" indicating the absence of a follow relation and "1" representing the presence of a follow relation.

Measures

Following Liang and Fu (2017), posting frequency (H1) describes the average number of tweets across different waves of data. Organizational age (H2) describes the longevity of an organization since its official establishment. Based on the Urban Institute data, geographic location (H3) describes the state in which an NPO was headquartered. I treated the District of Columbia as a state, and none of the organizations were headquarters in a U.S. territory (e.g., Guam). In total, the sample covered 38 states. The most popular states were the District of Columbia (n = 29, 15.76%), California (n = 21, 11.41%), and New York (n = 16, 8.70%). Indegree popularity (H4) refers to the number of organizations among the 184 ENPOs that were following the focal organization.

I included eight control variables that research shows shape the patterns of follower-followee networks (Huang & Sun, 2014; Liang & Fu, 2017; Xu et al., 2013). Revenue, collected from the Urban Institute database, describes the total amount of revenue in 2013. This amount was used to capture the time-lagged influence on network evolution in the following years. The number of followers and followees describe each organization's cumulative number of followers and the cumulative number of accounts it was following, respectively. Twitter longevity, retrieved from the home page of each organization's Twitter profile, describes the number of years an organization had been on Twitter. The longevity of two organizations in the sample was unavailable, and thus their longevity was coded as missing data.

The integrated media effects suggest that signals on one media system influence interlinking practices on another media system (Fu & Shumate, 2017). Therefore, I controlled for the news media visibility and website visibility of each NPO. News media visibility accounts for the amount of coverage in the news media that an NPO received in 2013. News media visibility in 2013 was used to capture the time-lagged influence on network evolution in the following years. Following Pilny and Shumate (2012), I searched for the full name of each organization in all news stories from the LexisNexis database, including wire services, magazines, and newspapers. Website visibility, collected using Issuecrawler (Rogers, 2009), refers to the number of times other NPOs linked the organization's website on their own websites.

Following Gonzalez-Bailon (2009), I controlled for each organization's social mission as indicated by their NTEE code. Previous research indicates that issue niche width may shape the structures of NPO networks (Lee & Monge, 2011; Shumate & Lipp, 2008; Yang, forthcoming). Based on their NTEE code, I assigned each ENPO according to issue width niche. The two niches were generalist (i.e., general environmental advocacy, etc., C1 to C19) and specialist (i.e., a more focused area such as pollution abatement or natural resources conservation). In this research, 50 organizations (27.17%) were generalist NPOs, and 134 (72.83%) were specialist NPOs. Table 1 presents the descriptive statistics of these variables.

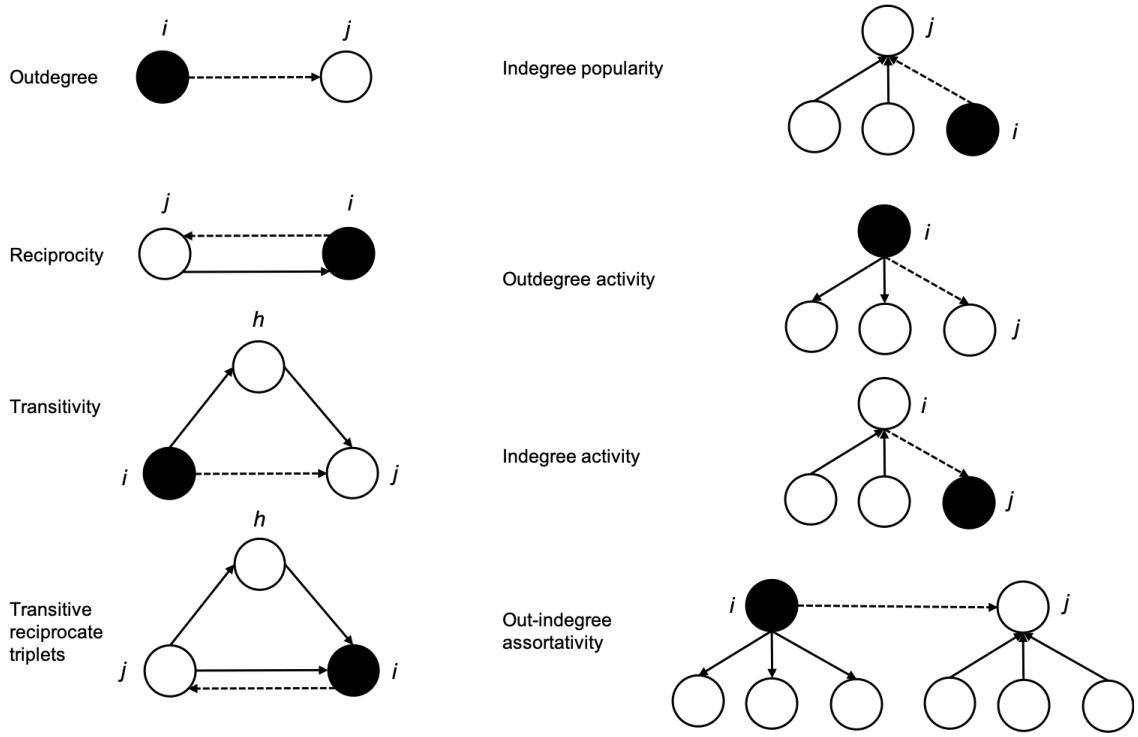
Table 1a. Descriptive Statistics of NPOs' Twitter Profiles, 2014–15.

	M	*SD*	Min	Max
Number of tweets per 3 months	314.66	488.01	0.75	3047.50
Number of followees	2,359.28	6,429.76	0	63,140
Number of followers	65,938.55	652,920.93	49	8,859,011
Number of hyperlinks received	2.77	4.18	0	25
News media visibility	159.05	393.37	0	2,991
Twitter longevity (years)	4.32	1.33	0.42	7
Indegree centrality	17.30	21.26	0	110
Organizational age (years)	43.64	33.21	6	188
Revenue (millions)	23.82	43.47	5.01	456.08

Table 1b. Descriptive Statistics of NPOs' Twitter Profiles, 2014–17.

	M	*SD*	Min	Max
Number of tweets per year	1,332.32	2,138.96	3	15,388.33
Number of followees	2969.11	7604.54	0	69,773
Number of followers	116,973.08	1,229,979.58	78	16,691,856
Number of hyperlinks received	3.65	4.60	0	21
News media visibility	164.19	359.42	0	2,195
Twitter longevity (years)	7.32	1.33	3.42	10
Indegree centrality	19.09	23.26	0	120
Organizational age (years)	46.64	33.21	9	191
Revenue (millions)	23.82	43.47	5.01	456.08

Following Ripley, Snijders, Boda, Voros, and Preciado (2019), I included seven structural parameters required in longitudinal social network modeling. Outdegree describes the general tendency to follow other NPOs. Reciprocity occurs when organization *i* follows *j* and organization *j* also follows *i*. Transitivity estimates the formation of a follow relation between organization *i* and *j* when organization *I* follows organization *h* and organization *h* follows organization *j*. Additionally, I added interactions between transitivity and reciprocity. Outdegree popularity describes the tendency for NPOs that have many followees to receive more incoming links from other NPOs in the network. Outdegree activity represents the squared outdegree of an NPO because some NPOs follow significantly more accounts than others. Further, following Weber (2012), I included out-indegree assortativity, the differential tendency for NPOs that follow many organizations to follow NPOs that attract many NPO followers. Naturally, NPOs that actively follow others first select organizations that are most visible in the network (Fu & Shumate, 2017), particularly when Twitter makes these visibility cues available to the public by showing the number of followers of each account and recommending accounts to follow. Figure 2 shows these various structural parameters.



Note. Solid lines represent existing ties in the network; dashed lines represented predicted ties; dark circles represent the focal organizational actor.

Figure 2. Visualization of the network structural parameters in the models.

Analysis

Simulation Investigation for Empirical Network Analysis (SIENA) is an over-time repeated measures of social network analysis technique that uses stochastic actor-oriented modeling (Snijders, 2001; Snijders, van de Bunt, & Steglich, 2010). I used SIENA 4.0 within the R-project package to analyze a longitudinal model with four observations from 2014 to 2017 (April 2014, April 2015, April 2016, April 2017). Additionally, I validated the results using a longitudinal data set with five observations (every three months from April 2014 to April 2015) when new tie formation and old tie dissolution were more frequent than in subsequent years (see Table 2b). The average density of the network for the one-year and four-year data sets was 0.090 (*SD* = 0.004) and 0.095 (*SD* = 0.006), respectively.

SIENA combined empirical estimations with simulations to understand longitudinal network change. Estimates were based on the network structure and changes across time periods (see Table 2a and 2b). Simulations were used to infer the process of change that occurred between time periods. Jaccard coefficients describe the variation and stability in adding and eliminating network ties between successive networks,

$$Jaccard\ index = \frac{N_{11}}{N_{01} + N_{10} + N_{11}}, \quad (1)$$

where N_{11} represents existing ties that are maintained; N_{01} represents new ties that are added; N_{10} represents existing ties that are removed. Jaccard indices less than 0.2 indicate strong network turnover, and coefficients larger than 0.3 are acceptable for SIENA modeling (Ripley et al., 2019). In this study, the Jaccard coefficients met the criteria for SIENA modeling.

Table 2a. Summary of Network Changes Across Five Time Periods, 2014–15.

Time period	0 → 0	0 → 1	1 → 0	1 → 1	Jaccard coefficient
$T_1 \rightarrow T_2$	30,674	118	93	2,787	0.930
$T_2 \rightarrow T_3$	30,655	112	0	2,905	0.963
$T_3 \rightarrow T_4$	30,583	72	25	2,992	0.969
$T_4 \rightarrow T_5$	30,474	134	15	3,049	0.953

Table 2b. Summary of Network Changes Across Four Time Periods, 2014–17.

Time period	0 → 0	0 → 1	1 → 0	1 → 1	Jaccard coefficient
$T_1 \rightarrow T_2$	30,365	427	124	2,756	0.833
$T_2 \rightarrow T_3$	30,246	243	99	3,084	0.900
$T_3 \rightarrow T_4$	30,163	182	72	3,255	0.928

Because of programming constraints, SIENA only allows the incorporation of one set of attributes into modeling. However, the correlations among the study variables (e.g., number of followings, hyperlinks, news mentions) across different periods were close to 1 (r ranged from 0.95 to 1.00). Therefore, using one set of time-invariant variables in SIENA modeling was acceptable.

Two factors jointly determined convergence: (1) t ratios of each parameter less than 0.1, and (2) overall model t ratio less than 0.25 (Ripley et al., 2019). All parameters converged in the three models. A parameter was considered significant when the estimate was at least 1.96 times the magnitude of the standard error (equivalent to $p < .05$).

Results

H1 suggested that organizations tend to follow NPO alters that are more active in tweeting. H1 was supported. Organizations that more actively tweeted were more likely to attract NPO followers (estimate = 0.39, SE = 0.13, $p < .01$). H2 stated that NPOs showed a preference to follow NPOs of a similar age. H2 was also supported; organizations were more likely to follow NPO alters in the same cohort group (estimate = 0.80, SE = 0.27, $p < .01$). H3 examined the effect of geography similarity on new tie formation. H3 was supported; NPOs tended to follow other NPOs located in the same state (estimate = 0.66, SE = 0.13, $p < .01$). According to H4, organizations tended to follow NPO alters that were already popular in the network. The results supported H4. Organizations with high indegree popularity were more likely to attract NPO followers (estimate = 0.03, SE = 0.00, $p < .01$).

RQ1 asked how the parameters that shape new tie formation were related to the maintenance or dissolution of existing ties. Of the four parameters, only active tweeting was not significant in the four-year model. Ties to NPOs from the same state were more likely to be maintained (estimate = 1.09, *SE* = 0.25, $p < .01$). Thus, geographic similarity was positively related to tie maintenance. Similarly, ties to popular NPOs tended to be retained (estimate = 0.01, *SE* = 0.00, $p < .05$). However, the results suggested that organizations tended to dissolve ties to organizations in the same cohort group (estimate = −0.87, *SE* = 0.43, $p < .05$).

Model Fit

To evaluate the general appropriateness of the model fit, collinearity of parameters was assessed based on the covariance matrix of each model. In addition, using the SIENA test, the goodness of fit for the model was assessed by generating simulated networks based on estimated parameters and comparing the observed values with the simulated values. Four auxiliary parameters were modeled in the goodness of fit test to compare the macrocharacteristics of the simulated and actual networks: indegree, outdegree, geodesic distance, and triadic census distribution (Ripley et al., 2019). The *p* values, larger than 0.05, indicate high goodness of fit, or that the simulated indegree and outdegree distributions are not significantly different from those of the observed networks (see Table 3 and Figure 3). However, the geodesic distance and triadic census distributions were significantly different from those of the observed networks.

Table 3. SIENA Model Results.

Parameter	1 year	4 year	4 year (evaluation)
New tie formation (creation function)			
H1: Active tweeting	0.59** (0.18)	0.39** (0.13)	0.28** (0.10)
H2: Age similarity	1.25** (0.40)	0.80** (0.27)	0.33 (0.19)
H3: Geography similarity	0.71** (0.18)	0.66** (0.13)	0.81** (0.10)
H4: Indegree popularity	0.03** (0.00)	0.03** (0.00)	0.03** (0.00)
RQ1: Old tie maintenance/dissolution (endowment function)			
Active tweeting	0.36 (0.35)	0.04 (0.22)	–
Age similarity	1.09 (0.61)	−0.87* (0.43)	–
Geography similarity	1.01** (0.39)	1.09** (0.25)	–
Indegree popularity	0.01 (0.01)	0.01* (0.00)	–
Rate parameters			
Rate variation (1)	1.26** (0.09)	3.66** (0.16)	3.70** (0.17)
Rate variation (2)	0.62** (0.06)	2.08** (0.12)	2.11** (0.12)
Rate variation (3)	0.55** (0.06)	1.50** (0.10)	1.52** (0.10)
Rate variation (4)	0.86** (0.07)	–	–

Structural parameters (evaluation)			
Outdegree	−4.18** (0.28)	−3.78** (0.19)	−3.79** (0.18)
Reciprocity	2.23** (0.18)	1.76** (0.12)	1.82** (0.11)
Transitivity	1.67** (0.22)	1.51** (0.15)	1.50** (0.15)
Transitive reciprocated triplets	0.00 (0.01)	0.03** (0.01)	0.03** (0.01)
Indegree activity	−0.02 (0.01)	−0.04** (0.01)	0.03** (0.00)
Outdegree activity	0.02** (0.01)	0.03** (0.01)	0.03** (0.00)
Out-indegree assortativity	−0.03** (0.01)	−0.03** (0.01)	−0.03** (0.01)
Attribute effects (evaluation)			
Number of followee	0.24** (0.13)	0.06 (0.09)	0.03 (0.08)
Number of followers	−0.11 (0.16)	0.00 (0.10)	0.00 (0.10)
Twitter longevity	0.16 (0.14)	0.05 (0.09)	0.01 (0.08)
News media visibility	0.14 (0.13)	0.07 (0.08)	0.06 (0.08)
Website visibility	−0.15 (0.16)	0.03 (0.11)	−0.01 (0.10)
Mission similarity	0.17 (0.15)	0.15 (0.09)	0.17 (0.09)
Revenue	−0.59** (0.12)	−0.34** (0.08)	−0.33** (0.08)
Goodness of fit			
Individual parameter convergence *t* ratio	−0.03 to 0.07	−0.09 to 0.09	−0.07 to 0.03
Overall convergence *t* ratio	0.15	0.21	0.15
Indegree distribution *p* value	0.27	0.39	0.13
Outdegree distribution *p* value	0.21	0.15	0.14

Note. The last column presents the results when not distinguishing selection from retention using evaluation functions. *$p < .05$. **$p < .01$.

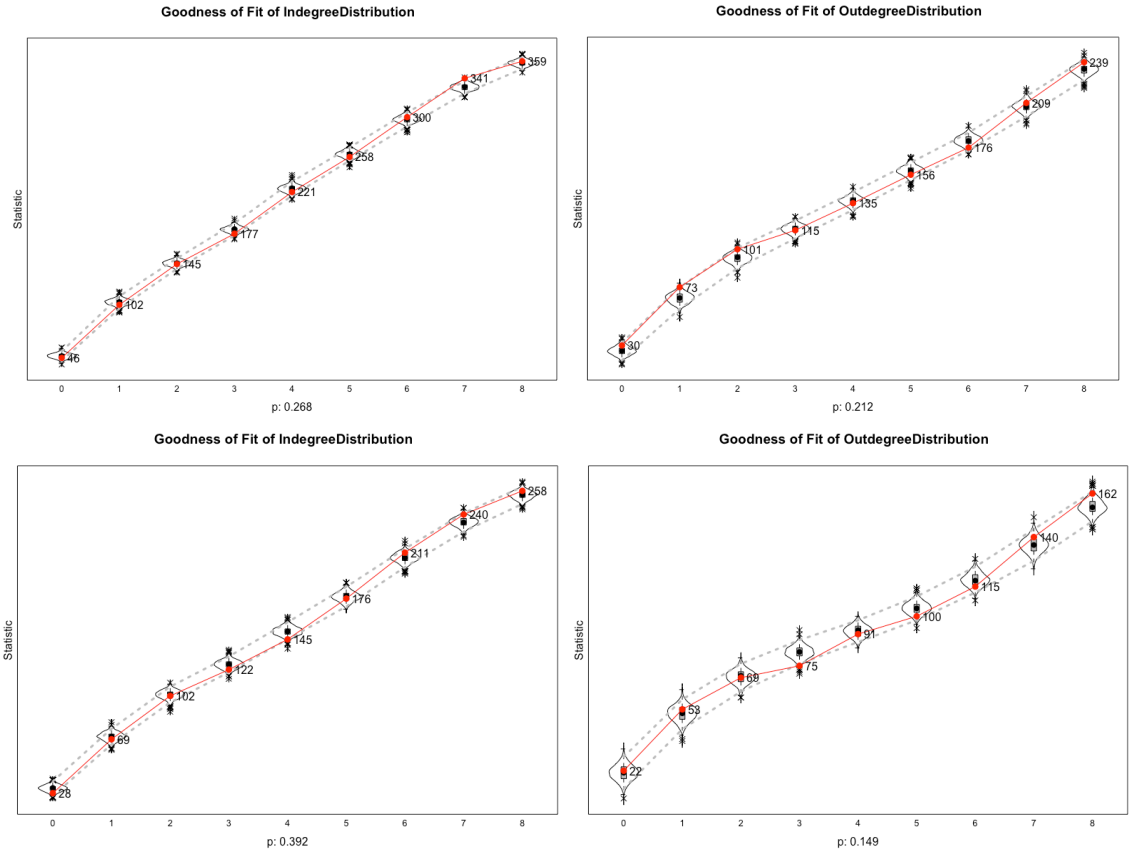


Figure 3. Goodness of fit for SIENA models.

Discussion

Building on an emerging body of works that treat interorganizational networks as dynamic systems of communication, this research seeks to enrich our understanding of the factors that shape new tie formation and old tie maintenance, respectively. Based on the evolutionary approaches to the study of social networks (Monge et al., 2008) and drawing on the MTML framework (Monge & Contractor, 2003), this study provides critical insight into the mechanisms by which NPOs self-organize interorganizational follower-followee networks on social media. SIENA results suggest that various informational, organizational, and structural factors are related to the selection and retention of interorganizational relations in unique ways. Specifically, tweeting frequency influences selection processes only, whereas indegree popularity, age similarity, and geographic similarity influence both selection and retention processes. These three factors all have a positive influence on selection, but their influence on retention varies. I unpack each finding individually below.

First, organizations tend to follow NPOs located in the same state and maintain ties with these organizations over time. Geography-based homophily accentuates the common economic, political, and

cultural environments influencing organizations in the same geographic area (Atouba & Shumate, 2015; Huang & Sun, 2014). This commonality creates incentive among NPOs located in a single state to establishing public affiliations with each other to make the social issue salient to their common stakeholders and mobilize resources and action in online interorganizational communication networks. Although previous research has demonstrated the influence of geography-based homophily on online and off-line NPO networks (e.g., Atouba & Shumate, 2015; Huang et al., 2015; Lee & Monge, 2011), this research extends extant research by showing that it independently shapes both the selection and retention of ties.

This study also shows that organizations exhibit a preference to form and maintain ties with organization alters with high indegree popularity. Hence, preferential attachment characterizes follower-followee networks. By following popular actors, NPOs not only enhance their status but also use the emergent self-organizing networks to identify credible leaders and advance the network visibility, which is critical to collective action online (Lai et al., 2017; Shumate & Lipp, 2008). However, in contrast to Shumate's (2012) study of NPO hyperlink networks, which revealed that ties to organizations with high indegree popularity were more likely to dissolve over time, this study suggests that ties to popular NPOs have greater staying power. Shumate (2012) speculated that NPOs tended to remove hyperlinks to popular NPOs because those ties were probably weak and were not reinforced via reciprocated hyperlinks or other types of relations. The disparate finding likely reflects the difference between website-based networks and Twitter, as the latter makes it much easier to keep up with new followers' feeds and reciprocate follow relations, even for popular organizations with many followers.

On the other hand, active tweeting increased tie formation, but not tie maintenance. This is in contrast to previous research, which reveals that social actors tend to dissolve ties with social actors who tweet frequently, which researchers attributed to information overload for the receiving actors (Liang & Fu, 2017). However, the same study found that the influence of active tweeting on the retention of ties is contingent on the nature of connected actors' tweets, such as information similarity and redundancy (Liang & Fu, 2017). Future research might employ content analysis and text mining for a more in-depth understanding of how information overload, similarity, and redundancy jointly influence tie dissolution.

In the meantime, findings showed that NPOs tend to dissolve ties with organizational alters of the same age. This may be explained from the community ecology and niche density perspective (Monge et al., 2008), which posits that as an organizational community develops over time, competition increases and cooperation decreases. This finding advances previous research in two ways. First, although previous longitudinal research on NPO networks largely examines the impact of cohort effects on off-line interorganizational networks (e.g., Atouba & Shumate, 2015; Shumate et al., 2005), this research suggests that cohort effects are also important in shaping online interorganizational networks. Second, although previous research suggests that organizations tend to select their cohorts for relationship building, this research distinguishes the influence of cohort effects on two distinct processes—new tie formation and old tie maintenance. Indeed, findings reveal that cohort effects have opposing effects on selection and retention processes.

In summary, the different dynamics in new tie formation and old tie maintenance processes highlight the necessity of understanding the longitudinal change of interorganizational networks using an

evolutionary lens (Monge et al., 2008; Shumate, 2012), as well as the need to distinguish selection and retention processes in future longitudinal network research. Although all four hypothesized factors positively influence new tie formation, once ties have been formed, the effects of these four factors on tie maintenance are differential—some may become insignificant (i.e., active tweeting), some may become negative (i.e., organizational age), and some are still positive (i.e., geography and indegree popularity). These findings suggest that future research needs to predict the presence or absence of ties (e.g., Choi et al., 2018; Margolin et al., 2015; Weber, 2012), and that it needs to more vigorously partition network selection from retention to illuminate the influence of each factor, reflecting the fact that retention is conditional on selection. For instance, this study reflects that if we had used only evaluation functions in SIENA (see last column in Table 3), we would not know that (1) tweeting frequency influenced selection, but not retention, and that (2) organizational age influenced both selection and retention processes, but in opposing ways. As I speculated at the outset, some factors that only influence one of the two processes may be insignificant in relation to the other or have inaccurate parameter estimates.

Theoretical Contributions

This study makes four theoretical contributions to the study of interorganizational communication, social networks, online collective action, and networked relationship management. First, this study unpacks the mechanisms underlying the two fundamental processes in the evolution of interorganizational communication networks, contributing to scholarship in the evolutionary approaches to social networks (Margolin et al., 2015; Monge et al., 2008; Shen et al., 2014). The findings reveal that different factors influence new tie formation and old tie maintenance in disparate ways. Hence, scholars should distinguish tie formation from maintenance/dissolution in future research on the longitudinal change of social networks for a more nuanced understanding of network evolution. Although prior longitudinal network studies have contributed to our knowledge of how organizational actors evaluate network ties over time (e.g., Choi et al., 2018; Weber, 2012), a more nuanced approach to network evolution is necessary for a more accurate understanding of the differential factors that predict new tie formation and old tie maintenance.

Second, this research contributes to a growing body of communication scholarship on the longitudinal research of interorganizational networks. This study demonstrates that various informational, organizational, and structural factors are related to the longitudinal change of NPO follower-followee networks, extending our understanding of interorganizational networks as dynamic systems of communication (Monge et al., 2008; Shumate, 2012; Shumate et al., 2017; Weber, 2012). Future research in interorganizational networks on social media needs to incorporate informational, organizational, and structural factors for a fuller understanding of the longitudinal change of these networks.

Related and third, this study adds to a growing body of research on the processes that produce follower-followee networks on social media (e.g., Huang & Sun, 2014; Kwak et al., 2012; Peng et al., 2016). Based on the conceptualization of NPO follower-followee networks as facilitators of collective action (Huang et al., 2015; Huang & Sun, 2014), this study thus contributes to a more rigorous understanding of collective action more specifically. Taken together, evidence of active tweeting, homophily, and preferential attachment supports the proposition that NPO follower-followee networks are intentional choices of public affiliation and representational communication that facilitate online collective action. The findings of this

study suggest that several network theories and information diffusion theories should be integrated to offer more generalized and richer descriptions of follower-followee networks. Hence, this research also contributes to the refinement of the MTML framework in the study of social networks (Monge & Contractor, 2013).

Finally, this study advances research on networked relationship management, offering "more comprehensive explanations for organizations' relationship building and relational outcomes through social media use" (Lai et al., 2017, p. 224). This study highlights the significance of dynamically configuring network relations to achieve optimal relational outcomes for public relations and strategic communication purposes (Sommerfeldt & Yang, 2017). In a practical sense, the findings highlight the necessity for organizations to configure and reconfigure their network ties over time. Specifically, the findings suggest that organizations may gain legitimacy in the social media space by affiliating with high-status organizations and those in their same geographic location. Intriguingly, although organizations may connect with their cohorts at the early stage of an interorganizational network to advance a common network goal, they need to strategically break these ties for more organizational benefits at later stages of network development.

Limitations and Future Research

This study represents a significant step in examining interorganizational networks as dynamic systems of communication. It has three limitations. First, it only investigated large ENPOs in the United States. However, smaller NPOs working in different social issue areas and from different countries may have different patterns of evolution. In particular, the evolution mechanisms for smaller NPOs may be distinct from larger NPOs, as previous research suggests that organizations of varying sizes have different network-building strategies (Shumate, Fu, Cooper, & Ihm, 2016). Second, the quantitative measures used in this study, such as news media coverage, only provided a rough picture of the activity and visibility of organizations. Future research may employ more sophisticated measures (e.g., news sentiment) and computational approaches. Finally, this study only examined follower-followee networks among NPOs on Twitter. Future research could integrate other types of interorganizational communication networks, such as retweet and mention networks (e.g., Lai et al., 2017; Peng et al., 2016) and across media platforms (Fu & Shumate, 2017) to advance our understanding of interorganizational network multiplexity.

Overall, the relatively high values of Jaccard coefficients in this research indicate that follower-followee networks exhibit a tendency of network inertia, what Kim, Oh, and Swaminathan (2006) call "a persistent organizational resistance to changing interorganizational network ties" (p. 715). Unfollowing on Twitter is significantly less frequent than removing hyperlinks from websites. For instance, the average monthly Jaccard coefficient was 0.78 in Shumate's (2012) study of NPO hyperlink networks. Indeed, previous research suggests that unfollowing activity is infrequent on Twitter (Liang & Fu, 2017). One possible explanation is rooted in the technical features of Twitter, which make navigating mutual friends and organizations that have just followed or unfollowed easier (Xu et al., 2013). Compared with hyperlinks, removing ties is more visible to others on Twitter. Hence, hyperlink users experience relatively little normative pressure to maintain ties. In contrast to previous research of NPO hyperlink networks (Shumate, 2012), this research reveals that ties to popular NPOs tend to be sustained. Taken together, these findings suggest that future research directly comparing the hyperlink and follower-followee networks of the same set of NPOs would illuminate how technological affordances and materiality influence network evolution.

Conclusion

Against a backdrop of using social media for collective action and relationship management, research on interorganizational communication networks on social media has made solid progress (Huang & Sun, 2014; Lai et al., 2019; Yang & Saffer, 2018). Studying the longitudinal change of interorganizational communication networks is theoretically important because it can reveal how individual organizations and the entire network respond to ecological and environmental changes to achieve organizational and network goals. Moreover, studying network change over time allows researchers to ascertain the causal relations between network structures and network outcomes (Brass et al., 2004; Monge & Contractor, 2003). This research highlights the importance of distinguishing selection from retention processes in the longitudinal study of social networks. Further research is needed to distinguish the demographic, ecological, and environmental factors (Baum, 1996) shaping the two fundamental processes in the evolution of interorganizational networks. To do so, future research might integrate the ecological and evolutionary approaches (Lee & Monge, 2011; Monge et al., 2008) to more robustly explain longitudinal network change.

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