The Role of Online Media in Mobilizing Large-Scale Collective Action

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Abstract
This study investigates the role of online media in mobilizing large-scale collective action. Adopting the theoretical framework of collective action space, we formulated the organizing process of collective action into a model with two dimensions—hierarchy and closure—and analyzed how they influence mobilization. The model was tested against Twitter data collected during the 2020 Hong Kong protest, including a total of 54,365 tweets posted by 14,706 distinct users between 1 May and 31 May 2020. Social networks analysis metrics—k-coreness and brokerage of individual users in their following networks—were employed to quantify the organizing process of the protest and estimate their effects on message virality. The results showed that messages generated by users who occupied peripheral positions (i.e., lower k-coreness) and by those connecting others within closed communities (i.e., lower brokerage) were more likely to diffuse than those generated by central users or those who bridged different communities. That is, online media facilitate mobilization in a decentralized yet fragmented fashion.

This article concludes with a discussion of the theoretical implications of the current findings and suggests the directions for future research on collective action on online media.

Keywords
collective action space, organizing process, message virality, Twitter user network, Hong Kong protest

The past decades have witnessed the utilization of online media for mobilizing large-scale social movements. Well-known examples include the use of social networking sites in the Occupy Wall Street in 2011 (Bennett & Segerberg, 2012) and Twitter and Telegram in the 2020 Hong Kong protest (Kow et al., 2020). These incidents have led to the expectation that media technologies have fundamentally transformed the underlying logics and mechanisms of collective action. Specifically, online media were expected to enable decentralized forms of communication (Benkler et al., 2015), circumvent formal and centralized authorities (Bennett & Segerberg, 2012), and facilitate loosely but well connected network structure of participants (Dahlberg-Grundberg, 2016). Empirical research, however, has not necessarily supported these expectations, rather presenting evidence that is counterintuitive; the network structure of collective action facilitated by online media was not always decentralized or well connected, but instead, often highly centralized and fragmented (González-Bailón & Wang, 2016). For instance, online movements were facilitated by core actors (Isa & Himelboim, 2018) and protest networks usually showed fragmented and hierarchical structures (Wang & Chu, 2019). In fact, evidence of the relation between cross-cutting network structure and activism is mixed, which is partly due to the complicated relations formed online (Hecksher & McCarthy, 2014). From this perspective, González-Bailón and Wang (2016) stressed that valid and reliable measurement of participant networks should be developed first before assessing their effects on collective action.

As part of the effort to fill the gap between theoretical expectations and empirical evidence, this study takes a social networks analysis approach to examine the impacts of the organizing process on online mobilization. To this end, we adopted the theoretical framework of collective action space proposed by Flanagin et al. (2006). This framework views the organizing process of collective action as a set of communicative tasks, including identifying target groups, contacting them, setting agendas, and organizing action, and classifies these tasks by two dimensions—the modes of engagement and interaction (Bimber et al., 2009). We operationalized these two dimensions as network metrics—k-coreness and
brokerage. The $k$-core approach classifies nodes into different subgraphs where each node has at least $k$ connections to others, demarcating different levels of hierarchy (Kitsak et al., 2010), and the brokerage measures one’s ability to connect different groups that would have been disconnected otherwise (Gould & Fernandez, 1989). Both metrics were adopted to characterize the positions and roles of individuals in the large-scale network of participants. Then we tested their influences on mobilization against empirical data collected during the 2020 Hong Kong Protest. We found that decentralized, leaderless network structure facilitates mobilization. Nonetheless, unlike common beliefs that online collective action benefits from heterogeneous, cross-cutting networks (e.g., Srinivasan, 2014), the results suggested that closed and tightly knitted networks promoted collective action in online media, implying a need of redundant networks and closed community for inducing participation in collective action (Centola & Macy, 2007; Putnam, 2000).

The rest of the article is organized as follows. We first revisit the theoretical connection between communication technologies and collective action, focusing on the communicative and organizing functions of online media in collective action. Based on the framework of collective action space (Bimber et al., 2009; Flanagin et al., 2006), we then examine the organizing process in two dimensions and their influences on online mobilization from a network perspective. We detail the procedure of data collection and analysis and report the results in the following sections. The final section discusses the theoretical implications of our findings and the directions for future research.

### The Communicative Nature of Collective Action

The questions about the relationship between communication technologies and collective action are rooted in free-rider problems (Marwell et al., 1988; Olson, 1965). Free-rider problems occur when a collective goal can be achieved even when not all individuals contribute, whereas its benefits are to be equally distributed to all the individuals regardless of their contributions. In that case, self-interested individuals are incentivized to free ride on the efforts of others instead of paying their shares (Bennett & Segerberg, 2012; Olson, 1965). As a solution for free-rider problems, the role of formal and institutionalized organizations has been emphasized (e.g., tax collector model; Coleman, 2017) to ensure the contribution of every individual and to coordinate their actions. The major roles of formal organizations include convincing others and providing incentives (Olson, 1965), which can be seen as communicative and organizational in nature (Bimber et al., 2005). In this regard, organizing processes relying on formal organizations are often hierarchical and occur within clear organizational boundaries (Flanagin et al., 2006). The development of communication technologies, however, is expected to change the organizing process to a more horizontal and cross-cutting manner. This section reviews previous literature on the changes in the organizing process of collective action due to the development of communication technologies.

### Mobilization in Online Collective Action

Collective action, defined as “actions taken by two or more people in pursuit of the same collective good” (Marwell et al., 1988, p. 4), entails the challenge of persuading, or even compelling, self-interested individuals to contribute their private resources to achieve collective goals. In this sense, communicative and organizational efforts are essential for the success of collective action. Flanagin and colleagues (2006) further elaborated the idea of the communicative nature of collective action in an Internet era, arguing that collective action entails efforts for making people cross private–public boundaries by expressing or acting on their interests in a way that is observable to those who share common interests. From this perspective, for online collective action, the primary goal is to enhance visibility as it is essential for identifying people with common interest, which is “the first key mechanism of facilitating collective action through social media” (Wang & Chu, 2019, p. 396).

Furthermore, mobilization, defined as the process by which parties or groups induce other people to join collective action (Rosenstone & Hansen, 1993), is also essential for collective action, particularly in online contexts. This is because most online collective action, such as online protests and petitions, involve the act of crossing the private–public boundaries. As long as individuals express their voices online, they make their private interests and concerns noticeable to others, and thereby transit their voices from private domains to public spheres. Hence, their voices may induce the neighbors in their networks (i.e., those who have access to the voices) to join the movement (Bennett & Segerberg, 2012). This is what Theocharis (2015) called “the act of (digital) communication as a form of mobilization, understood as integral to political participation” (p. 5). This study therefore focuses on the effectiveness of online mobilization as an indicator of the success of online collective action. Following Goel et al. (2015), we conceptualize online mobilization as prompting people to contribute to the spread of one’s voices (i.e., to enhance visibility in the context of online collective action).

### Communication Technology as an Organizing Agent

From the communicative perspective, the major obstacles to collective action can be interpreted as a set of organizing challenges; that is, how to contact, motivate, persuade, and coordinate the self-interested participants to contribute (Bimber et al., 2005). As discussed earlier, formal organizations used to undertake these tasks (Flanagin et al., 2006), resulting in hierarchical organizational structures with the
interactions among participants being limited within clear organizational boundaries (Bimber et al., 2009).

Internet-based communication technologies developed in the past decades, however, have gradually taken over the key roles played by formal organizations, thus profoundly changing the way of organizing people for collective action (Bennett & Segerberg, 2012; Bimber et al., 2005; Dahlberg-Grundberg, 2016). First, communication technologies effectively resolve free-riding problems by reducing the cost of participation (Margetts et al., 2015). Since the border line between public and private domains becomes blurred in online environments, it is less costly to cross the boundary between the two domains (Bimber et al., 2005; Flanagin et al., 2006). More importantly, communication technologies can serve as organizing agents (Hampton, 2003). For instance, various functions equipped in social media, such as mention, retweet, and hashtag, make it easy for distributed individuals to find and connect with relevant others, to be exposed to the voices of those who share similar concerns, and thereby, to form groups and communities without centralized authorities (Wang & Chu, 2019). Taken together, online media play the role that formal organizations used to play. Accordingly, it is reasonable to expect that the organizing process of online collective action would be decentralized and horizontal rather than hierarchical, and also, open and loosely connected rather than confined to interest groups or movement organizations (Bennett & Segerberg, 2012; Srinivasan, 2014).

These expectations, however, have been challenged by empirical studies. For instance, Gerbaudo’s (2012) study found the dominant roles of key players commonly observed across different social movements, including the Occupy Wall Street, the Indignados in Spain, and the Egyptian protests during the Arab Spring. Similarly, González-Bailón and Wang (2016) found that the Twitter network of Indignados movements were significantly fragmented, and centralized individuals played essential roles in organizing collective action. Dahlberg-Grundberg (2016) also found that the online protest network of the Arab Spring, whose structure had been horizontal at the beginning, gradually became centralized as a few participants gained prominent positions over time.

Organizing Process: An Angle to Delineate Collective Action

To delineate how collective action is organized and communicated, it is necessary to investigate the organizing processes of collective action. As Bimber et al. (2012) pointed out, the fundamental issue of collective action is pertaining to the process of organizing, which consists of a set of communicative tasks (Bimber et al., 2009). In this sense, collective action can be analyzed by looking at how people interact with each other, how agendas are established, and how actions or engagements are coordinated. Flanagin et al. (2006) brought up the framework of collective action space to theorize these communicative tasks by looking at the modes of engagement and interaction. Based on this framework, we propose network measures—$k$-coreness and brokerage—to quantify the organizing process (see Figure 1).

Hierarchical and Horizontal Organizing Processes

Collective action space (Flanagin et al., 2006) classifies the organizing processes of collective action by the modes of
engagement and interaction. First, the mode of engagement includes the following two ends: institutional and entrepreneurial engagement. Institutional engagement refers to a form of collective participation wherein the centralized, leadership-driven organizations set agendas, make decisions, and mobilize resources. Collective actions with the institutional mode of engagement tend to show hierarchical and bureaucratic network structures. By contrast, entrepreneurial engagement is characterized by flexible and dynamical structure, in which participants are connected by their communication patterns instead of formal affiliations (Bimber et al., 2009). Participants in the entrepreneurial engagement mode have more opportunities to set their own agendas and greater autonomy to mobilize resources. Examples include what Bennett and Segerberg (2012) called the personal action frames in leaderless, decentralized movements, such as “We Are the 99%” in the Occupy Wallstreet Movement. The level of hierarchies of the organizing process ranges from institutional (most hierarchical) to entrepreneurial (most horizontal) engagement.

From the collective action space framework (Flanagin et al., 2006), the level of hierarchies is manifested by two aspects. First, hierarchical structure determines the roles that most participants should play. In the institutional mode of engagement, the vast majority of participants do not have the power to set the agenda or mobilize resources, whereas only a few centralized leaders can do so. Moreover, different hierarchical levels indicate different role relationships among participants. In the institutional mode, there are distinct leaders and followers whereas, in the entrepreneurial mode, participants are peers of each other.

Previous studies, however, measured the level of hierarchy in collective action in different ways. For instance, Doerfel and Taylor (2017) measured the level of hierarchy by the dispersion of degree centralities in participants’ networks, in which uneven distributions of degree centralities indicate hierarchical network structures. In Dahlberg-Grundberg’s (2016) study, the level of hierarchy was operationalized by the existence of distinct leadership. By contrast, Wang and Chu (2019) explained the entrepreneurial, horizontal engagement on Twitter by network homophily, arguing that individuals organize themselves by homophily attachment without formal organizations. Most of these studies use the existence of central leaders or organizations to approximate the hierarchical level, ignoring the structural properties. Conceptually, hierarchy is a structural property; that is, while few are at the core of power, most of others are at the periphery surrounding the core (Flanagin et al., 2006). In this sense, leadership exists in the structural recognition by others. On one hand, the few leaders are connected to each other, composing the core; on the other hand, the existence of the core is made possible only if there are many lower ranked others surrounding them. To take into account this conceptual characteristic, we adopted a k-core decomposition approach (Seidman, 1983), which incorporates the relative relationship between the core and the periphery to explicate hierarchy. We will discuss it in the “Method” section.

Closed and Open Community Structures

The second dimension of the organizing process of collective action concerns the mode of interaction. At one end, participants engage in repeated interactions with known others over time (i.e., personal interactions). The other end involves no personal or direct interactions with known others (i.e., impersonal interactions; Flanagin et al., 2006). In the personal interaction mode, the key element is the development of interpersonal relationships and the group identification. As Bimber et al. (2012) pointed out, the relationship-sustaining activities are the key element in this type of interactions. In the impersonal mode of interaction, however, personal relationship or identity does not matter, as participants are mainly connected by exchanging information about interests, goals, and concerns. In this sense, the key characteristic that differentiates the two modes of interaction is the difference in network or community structure (i.e., whether it is a tightly connected or cross-cutting network; see Liang & Fu, 2019). The personal interaction mode is represented by a well-clustered, usually local, community, which involves stocks of social capital, such as social networks, norms, and trust (e.g., Putnam, 2000). The impersonal interaction mode mainly refers to online networks (Bimber et al., 2005; Flanagin et al., 2006), where participants are connected by information flows. Therefore, the community structure of impersonal interactions is more open and cross-cutting, consisting of more weak ties (Burt, 2004; Granovetter, 1983).

We adopted the network concept of brokerage to differentiate the level of closure or openness of a community of online participants. By definition, brokerage is a process by which intermediary actors (i.e., brokers) facilitate exchange between those who would have been disconnected otherwise (Marsden, 1982). Therefore, brokers tend to occupy cross-cutting positions of networks (Granovetter, 1983). In network literature, brokerage measures the ability of a node to span structural holes that hinder resource exchanges or information flows (Burt, 2004; Gould & Fernandez, 1989).

Previous studies have applied the concept of brokerage to examine the influence of community structure on the spread of information in collective action (e.g., González-Bailón & Wang, 2016; Granovetter, 1983). This study adopts a canonical approach—the Gould and Fernandez (1989) brokerage (henceforth, G-F brokerage)—to take into consideration both local and global structures. This will be discussed in detail in the “Method” section.

Online Mobilization and Organizing Processes: A Network Perspective

Taken together the arguments of the previous sections, online mobilization can be defined as a communicative phenomenon and the organizing process broken down into two
dimensions of network structure. Above all, what matters to individual participants is whether they can make their voices heard by as many others as possible (Bimber et al., 2012). In this sense, online collective action nowadays seems to follow the diffusion logic. As Liang and Fu (2019) summarized, the diffusion process on social media can be represented by “individual $A$ sharing a message $B$ posted by an individual $C$” (i.e., $A \rightarrow B \leftarrow C$). The key question of this study is thus the impact of topological characteristics of $C$ on the effectiveness of spreading messages.

**Organizing Hierarchy and Mobilization**

Will communication technologies take over the role of organizations, thus facilitating the organization-less organizing of collective action (Bimber et al., 2012)? From a network perspective, this question can be translated into whether it is the one-to-many broadcasting mode (i.e., the hierarchical structure relying on a few central nodes) or the many-to-many viral mode (i.e., the horizontal structure where individual nodes have equal dissemination power) that facilitates the flow of information in online collective action.

In general, scholars recognize the contribution of the hierarchical, broadcasting mode to information spread (e.g., Goel et al., 2015; Liang et al., 2019). As Zeng and Zhang (2013) noticed, nodes at higher hierarchical levels usually locate at the core of the network and they are likely to spread information to a large part of the network. In other words, hierarchical structure has its unique role in facilitating diffusion processes. In the context of online collective action, traditional organizations may actively utilize social media for organizing, leading to the “organizationally enabled networks” (Bennett & Segerberg, 2012, p. 756). That said, there is a dearth of evidence about how hierarchy influences the spread of online collective action. Therefore, we propose the following hypothesis:

$$H1. \text{Participants positioned at higher hierarchical levels are more likely to mobilize others to spread their messages.}$$

**Brokerage of Community and Mobilization**

Generally, the relationship between community structure and mobilization is inconclusive. As Granovetter (1983) pointed out, the disagreement lies in whether mobilization of participants depends on influencing the previously unattached individuals (i.e., by weak ties) or engaging the already attached ones (i.e., by strong ties). The former argument assumes that weak ties facilitate the spread of information across communities, while the latter assumes that strong ties play an important role in sustaining protests. In network terms, those who are embedded in a closed community may find it easier to mobilize others, whereas cross-cutting connections are essential for mobilizing participants from different communities.

When it comes to the digital era with more sophisticated evidence, studies have found that closed community structures actually help, rather than hinder the spread of information. For instance, densely connected online communities have been found positively related to information diffusion (Harrigan et al., 2012). Liang and Fu (2019), using representative Twitter data, found that network redundancy positively predicts retweet rate. These more recent findings seem to echo what Centola and Macy (2007) proposed as complex contagion. In brief, for contagions that require multiple reinforcements and imply risks (such as social movements) a clustered network structure may be more conducive.

In theory, participants embedded in both tightly connected and open structures have their unique contributions to mobilization. Empirical evidence from network research, however, suggests that closed community structures are conducive to information spread. We follow the logic of complex contagion to propose the following hypothesis:

$$H2. \text{Participants positioned within closed communities are more likely to mobilize others to spread their messages.}$$

**Method**

**Background**

We selected the 2020 Hong Kong protest against the national security law as a case study. The law was issued by the National People’s Congress in Beijing and meant to curb actions that threaten national security. Criticism, however, worries that the enforcement of this law may damage the autonomy and freedom of Hong Kong (“Hong Kong Security Law: What Is it and Is it Worrying?,” 2020). Protests have emerged in Hong Kong since the news release came out from Beijing. Our study focuses on online protests in May 2020, the period after the declaration of establishing this law. The security law has also attracted international attention (e.g., the US and the UK governments stepped in; “Hong Kong: US Passes Sanctions as Nations Condemn New Law,” 2020). This case involves not only local protests in Hong Kong, but also international grievance from foreign governments, organizations, and activists. In this regard, this case provides a good chance to observe both local and cross-cutting as well as hierarchical and horizontal structures of the participant network.

**Data Collection**

As an arena connecting Hong Kong with the world, Twitter has been utilized by the local participants to advocate their appeals. International participants also used Twitter as an outlet to express their concerns about this issue (“Hong Kong Security
Law: What Is it and Is it Worrying?” 2020). Given the advantage of containing both local and international voices, the data were collected from Twitter, using a data scraping tool—Twitter Intelligence Tool (TWINT).1 Following the practices for content retrieval and analysis (Shen et al., 2020), we retrieved relevant tweets using a comprehensive list of keywords, including “Hong Kong,” “democracy,” “security law,” “autonomy,” and their combinations as well as the corresponding Chinese keywords.2 After removing duplicates, we retained a total of 54,365 original and unique tweets between 1 May 2020 and 31 May 2020. We then retrieved the public profiles of the 14,706 users that created the tweets.

Descriptive Statistics of the Participant Network

A directed network was constructed, in which nodes were individual participants, and a directed edge was formed from one to another participant, if the former followed the latter. As discussed earlier, enhancing visibility can be seen as the primary goal of an online collective action, and therefore, anyone who contributes to promoting the visibility of the online movement is deemed as a “participant.” In other words, those who posted at least one tweet about the protest, regardless of their stances, were seen as participants in our analysis. Even though some of them might oppose the protest, their participation spreads the information to their networks and might induce others to join. The network was composed of 14,706 nodes and 459,100 edges, and contained six weakly connected components, the largest of which contained 14,425 nodes (98.09%) and 459,004 edges (99.98%). In the following analysis, we used the largest component. The clustering coefficient of the network was .09, which was much greater than the density (.002), suggesting that the network was highly clustered. The average path length was 3.81, implying that every node could reach every other node within four steps.

Furthermore, community detection was implemented to identify clusters formed by participants. We adopted the Louvain community detection algorithm (Azaouzi et al., 2019). The algorithm returned five large communities and four small ones (each has less than 20 members) with the modularity, \( Q = .39 \), suggesting the existence of clear community structure in the network. This indicates that participants of the same community were closely connected with each other but loosely related to those of other communities.

Measures

Because most variables were highly skewed (see Table 1), we applied log-transformation to the variables to achieve normality and statistical reliability required for our analysis.

**Mobilization.** We conceptualized online mobilization as prompting others to participate in an online collective action by spreading the action-related voices. Therefore, we first operationalized such capability as the average retweet counts of individual users (i.e., total retweet counts divided by total number of HK-protest posts). Note that retweet count in this study refers to the total number of direct retweets without any further edits or comments, which usually imply political endorsement (Wong et al., 2013). The distribution of retweets is highly imbalanced (about 70% of the users did not receive any retweet); therefore, instead of using the raw scores, we further divided the users into two groups (zero retweet received vs. non-zero retweet received).

**Hierarchy.** To measure the level of hierarchy of each participant, we adopted a k-core decomposition approach proposed

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**Table 1. Descriptive Statistics.**

| Variables          | Mean (SD)          | Min. | Max. | Median |
|--------------------|--------------------|------|------|--------|
| N of following     | 1.728 (7,500.54)   | 0    | 301,280 | 347 |
| N of followers     | 26,508 (779,280.10)| 0    | 301,280 | 229 |
| Degree             | 63.28 (168.95)     | 1    | 7,135 | 16     |
| Hub                | 0.08 (0.12)        | 0    | 1    | 0.03   |
| Authority          | 0.01 (0.05)        | 0    | 1    | 0.0002 |
| k-coreness         | 7.83 (14.12)       | 0    | 55   | 1      |
| Brokerage          | 6.95 (93.54)       | −3.93| 5,358.33 | −3.93 |
| Log (N of following)| 5.90 (1.71)        | 0    | 12.57 | 5.87   |
| Log (N of followers)| 5.48 (2.57)       | 0    | 16.60 | 5.38   |
| Log (Degree)       | 2.78 (1.60)        | 0    | 8.41 | 2.77   |
| Log (Hub)          | −5.52 (4.59)       | −13.82| 0   | −3.61  |
| Log (Authority)    | −9.20 (3.97)       | −13.82| −0.01| −8.65  |
| Log (K-coreness)   | 0.46 (2.21)        | −13.82| 3.67 | 0.76   |
| Log (Brokerage)    | −8.17 (6.86)       | −13.82| 8.58 | −13.82 |
| Being retweeted (binary) | 0.30 (−) | 0 | 1 | 0 |

SD = standard deviation.

N = 14,425.
The $k$-core of a network refers to a maximal subgraph where each node has at least $k$ connections to others. Therefore, the $(k+1)$-core is always a subgraph of the $k$-core (i.e., there are always fewer nodes in higher cores), as illustrated in Figure 2. What it reflects is the hierarchical structure of the network, where nodes are gathered into highly connected groups and then further assemble around groups at higher level (Xiao et al., 2016). In this approach, the coreness of a node, say $k$, means that the node belongs to a $k$-core but not to any $(k+1)$-core. That is, it indicates the hierarchical order of the node. Therefore, nodes with greater coreness are located more closely to the cores of the network (Carmi et al., 2007). This approach takes into account the typology of the network and therefore circumvents drawbacks of local metrics, such as degree centralities (Kitsak et al., 2010). For instance, nodes with high-degree centralities can be at the end of a peripheral branch, and such nodes are not necessarily close to the core of the network (e.g., node $k$ in Figure 2). Previous studies have applied $k$-coreness to measure the hierarchical order of the Internet (Carmi et al., 2007) and keyword networks (Xiao et al., 2016).

The hierarchical level was measured by computing the coreness score for each node, using the igraph package (ver. 1.2.6) with R. In particular, we partitioned nodes by the communities detected, computed the coreness scores for the nodes within their communities, and further normalized the scores by the relative size of each community.

Brokerage. We adopted G-F brokerage to measure the degree to which individual users played a role in connecting different communities in the network. Unlike other measures on brokerage, such as betweenness centrality or structural constraint, that view actors as equivalent if they occupy the same position, G-F brokerage takes into account role differences of actors (Gould & Fernandez, 1989). In particular, this approach categorizes nodes into five types of brokers. The five types of brokers were illustrated in Figure 3; for instance, the broker is called gatekeeper if it belongs to the community of the receiver. This approach provides more nuances of different actors’ relations.

In this study, we divided actors into different subgroups by community detection, following the Louvain practice in the igraph package with R. The Louvain algorithm follows a bottom-up approach: (1) every node is assigned to a different community initially, (2) each of them is then merged into their neighbors’ communities based on the rule of the optimization of modularity, (3) the communities identified are treated as supernodes and steps (1) to (3) are repeated iteratively until there is no more increase of modularity, then (4) the supernodes are unfolded level by level until the initial graph is recovered (Blondel et al., 2008). We adopted this approach because it enables to detect high modularity community structure of large-scale network with short computational time (Azaouzi et al., 2019). We then computed the brokerage scores using the sna package (ver. 2.6) with R.

Control Variables. The basic network properties, including degree, hub, and authority are included as control variables. In addition, publicly available information of users, such as total number of followers and followees, which have been found to be relevant to information diffusion (Song et al., 2016), were included as control variables. The descriptive statistics of the variables are presented in Table 1.
Results

Figure 4 visualizes the following network of 14,425 users who posted tweets related to the 2020 Hong Kong Protest. A clear community structure was identified in the network. The boundary of each community was indicated by contour lines of different colors. Nodes with higher brokerage scores were located at the intersections of different communities. The size of nodes indicates their $k$-coreness scores; larger nodes occupy higher hierarchical positions. Nodes with red borderlines represent users whose tweets were retweeted. The network visualization reveals a clear pattern that messages generated by users who occupied peripheral positions (i.e., lower $k$-coreness) and by those connecting others within communities (i.e., lower brokerage) were more likely to be retweeted than others, partly supporting our hypotheses.

To further test our hypotheses, we conducted a series of logistic regression analyses with the chance of being retweeted as the dependent variable. All the control and independent variables, after log-transformation, largely follow the normal distribution; namely, the data are appropriate for conducting logistic regression. The first regression model included general Twitter activities of individual users (the numbers of followers and followees) as control variables. The second model added network properties of individual nodes (degree, hub, and authority centralities, Newman, 2010). The final model added the two key variables—$k$-coreness and brokerage. As shown in Table 2, both the number of followers and followees were found as significant predictors of retweet rate across all the three models. The more followers users have on Twitter, the more likely their tweets get retweeted ($\log \text{odds}=0.48, SE=0.01, p<.001$ in Model 1) whereas the more followees, the less likely ($\log \text{odds}=-0.25, SE=0.02, p<.001$ in Model 1). In terms of the network properties of individual users, degree centrality (i.e., direct contacts among participants) was positively associated with retweet rate ($\log \text{odds}=0.44, SE=0.03, p<.001$ in Model 2), hub centrality (i.e., users that can tell us where the authorities can be found) was negatively associated with retweet rate ($\log \text{odds}=-0.08, SE=0.01, p<.001$ in Model 2), and authority (i.e., users containing useful information) was positively associated with retweet rate ($\log \text{odds}=0.11, SE=0.01,$
Finally, $k$-coreness ($\log \text{ odds} = -0.02, SE = 0.01, p < .001$ in Model 2) and brokerage ($\log \text{ odds} = -0.04, SE = 0.01, p < .001$ in Model 3) were negatively associated with retweet rate, partly supporting our hypotheses.

**Discussion**

What is the role of online media in collective actions? To approach this question, this study examined the extent to which online media take over the role of conventional movement organizations. The logic is straightforward: if online media, rather than brick-and-mortar organizations, become a key organizing agent in collective actions, entrepreneurial engagement, and cross-cutting interactions should become the main driving forces behind the success of collective actions. Nonetheless, it must be admitted that verifying or falsifying such a “simple” logic involves complicated empirical examination. This section discusses the implications of our current findings as well as the cautions and limitations reflected by this study.

**Entrepreneurial Engagement and Decentralized Mobilization**

The results of regression analyses suggest that $k$-coreness negatively predicts the probability of being retweeted. That is, the messages generated by those residing at lower hierarchical levels and positioning away from the core of power were more likely to be retweeted, implying higher chances of mobilizing others to participate. In this sense, the results suggest that peripheral participants, rather than centralized leaders, have more opportunities to set their own agendas and mobilize resources (Flanagin et al., 2006).

On one hand, the results support many theoretical claims about the role of media technologies in collective action. For instance, online media contribute to decentralizing communication and organization among participants (Benkler et al., 2015), substantiating the claims about leaderless collective action (Margetts et al., 2015) and organization-less movements (Bimber et al., 2012). Theoretically, current online collective actions resemble what Bimber et al. (2005) referring to as crossing the private–public boundaries; thereby, expressing grievance per se counts as participation. In this sense, it is reasonable to expect that online collective action tends to be more self-motivated than organization-driven. Empirically, considering the Hong Kong context where many formal organizations have been involved yet still the hierarchical level does not help with mobilization, the claims that online collective action relies less and less on formal organizations are strengthened. To further understand the context, we took a closer look at both highest and lowest hierarchical participants. To list a few, the most central users include @New York Times World (media outlet) and @Rachel Blundy (editor for @AFPFactCheck); whereas the typical peripheral ones include @RTHK English News (a Hong Kong broadcaster) and @Eric Cheung (a freelance journalist in Hong Kong). Their social roles are quite similar in that most of them are media outlets, public figures, and journalists. Yet, it is notable that participants at lower levels of hierarchy were more locally based (i.e., they live and work in Hong Kong) than the most central ones. In this sense, the trend of decentralization may not simply mean the rise of ordinary people. Although the global core participants might lose their influence, the local opinion leaders still matter. This corresponds to what Heekscher and McCarthy (2014) depicted as “swarming” networks in online collective actions: Multiple communities with their own centers (i.e., local opinion leaders) working together in a myriad, coordinated, and dispersed manner is more effective than following a unified campaign blueprint or

### Table 2. Logistic Regression on the Chance of Being Retweeted.

|                      | Model 1                  | Model 2                  | Model 3                  |
|----------------------|--------------------------|--------------------------|--------------------------|
|                      | log odds                | SE                       | z                        |
| General Twitter activities |                          |                          |                          |
| Followers            | .48***                   | 0.01                     | 34.97                    |
| Followees            | −.25***                  | 0.02                     | −13.51                   |
| Network centralities of users |                |                          |                          |
| Degree               | .44***                   | 0.03                     | 13.62                    |
| Hub                  | −.08***                  | 0.01                     | −8.66                    |
| Authority            | .11***                   | 0.01                     | 11.95                    |
| Collective action space dimensions |                |                          |                          |
| $k$-coreness         | −.02*                    | 0.01                     | −2.09                    |
| Brokerage            | −.04***                  | 0.01                     | −4.04                    |
| AIC                  | 14,194                   | 12,797                   | 12,781                   |

AIC: Akaike information criterion; SE: standard error. All predictors were log-transformed.

*p < .05; *p < .01; ***p < .001.

$p < .001$ in Model 2).
engaging in a massed confrontation. It also echoes what Bimber et al. (2009) stressed as the hybrid forms of organizing; that is, hierarchical organizations are reconstituted as networked forms. In this sense, the finding serves as a point of departure for future studies on networked local mobilizers and collective action.

However, we should carefully compare the current findings to other previous findings to avoid overgeneralization. First, some studies have found that online collective action networks are centralized rather than decentralized (e.g., Dahlberg-Grundberg, 2016; González-Bailón & Wang, 2016). Note that the current findings are not necessarily contradictory to these previous studies. Since the evidence found in this study does not speak to the structural properties in the 2020 Hong Kong protest, but rather the influence of such properties on the spread. Second, previous network studies also found different results. That is, nodes residing at higher hierarchical levels have greater power and efficiency to facilitate information spread (e.g., Liang et al., 2019; Zeng & Zhang, 2013). The discrepancy may be due to the contextual difference between generic networks and collective action networks. In generic networks, hierarchical players function as the center of diffusion, resembling the broadcasting mode that facilitates quick reach to the peripheral ones (Liang et al., 2019). In the participant networks of collective action, given the personalization of collective action (Bennett, 2012), a few central nodes may not be able to cover diverse, or even contradictory, claims and interests and therefore hinder the growth of the action, which was reflected by the existence of multiple communities and cores in the user network (Figure 4). The importance of the local, not global, opinion leaders discussed earlier corroborates this speculation. Future studies may take into account the diversity of claims and appeals (e.g., topic modeling) to examine this possibility. Practically, building a platform that allows multiple mobilizers to network and coordinate by themselves might be more effective for scaling up a collective action than relying on a few central organizers (Heckscher & McCarthy, 2014).

**Clustered Interaction and Diffusion**

The results also show that individuals at a more tightly knit position are more likely to mobilize others to retweet, which reflects a personal, closed mode of interaction where individuals, connected by communities or interest groups, are more likely to act for common causes (Bimber et al., 2005). In other words, the organizing of collective action seems to rely more on closely connected communities. This finding is consistent with previous network studies on network or community closure and information spread. For instance, Harrigan et al. (2012) found that closed community structure facilitates information spread. Similarly, Liang and Fu’s (2019) identified a positive relationship between network redundancy (i.e., closure) and the odds of being retweeted. Such findings are usually interpreted from two aspects. First, closed networks indicate trust, community commitment, and information relevance that facilitate information flow (Harrigan et al., 2012). Second, some issues or topics contain risks so that it requires repeated contacts to spread, which are more likely to happen within known networks (i.e., complex contagion, Centola & Macy, 2007).

However, the current findings need to be interpreted with caution. Previous studies showed that the Internet enables individualized collective or connective action (Bennett & Segerberg, 2012), in which distributed individuals can be organized without knowing each other (Hampton, 2003) or being affiliated to formal organizations (Bimber et al., 2009). By contrast, the current findings suggest that locally closed structures still matter for collective action. The discrepancy between the current and previous studies could be explained by the difference in the cultural and political contexts in which the collective actions took place. It is important to note that the impersonal and horizontal form of participation is more common in advanced democracies or post-industrial societies (i.e., mostly the Western societies) than others (Bennett, 2012; Heckscher & McCarthy, 2014). Deindustrialization, globalization, and privatization of institutions in the Western societies have led individuals to be detached from formal organizations, such as unions and communities (Beck, 1992), and thereby, lessened the importance of the relational base for collective action (Heckscher & McCarthy, 2014). Also, the liberal Internet culture and the democratic political systems catalyze the individualized, expressive forms of collective action. However, not all of these preconditions are expected in other countries or societies. Therefore, the conventional forms of leaders and organizations still play a critical role in online collective action (Gerbaudo, 2014), as observed in social movements and political protests in Africa (Gerbaudo, 2012) as well as in the Hong Kong protest in this study. This suggests that culture and levels of democracy should be considered as significant factors in understanding the mechanisms and dynamics of online collective action in future research.

We also looked into the most brokering and clustered users for more hints. The participants with greatest brokering power include @Joshua Wong (a lead activist in Hong Kong protests) and @Justitia So (a Hong Kong female updating the HK protest on Twitter); while the most clustered ones include @Olivia Rinaldi (reporter with @CBSEveningNews) and @KGNS News (media outlet). It seems that most of the brokering participants are less authoritative accounts, compared to the clustered ones. This seems to corroborate the proposition that local opinion leaders still matter. Future studies may benefit from comparing the morphology of these actors in different societies.

Last but not least, it is worth briefly discussing the influence of the control variables. The result shows that those who have more followers are more likely to get their messages spread, whereas those who have more followees are not. This is understandable as the number of followers on
Twitter indicates popularity, while the number of followees implies activity. Popular users usually have greater power to influence others. Authority score is positively related to the chance of being retweeted while hub score is not. According to Newman (2010), authority is roughly the eigenvector centrality for co-citation network (i.e., the times being cited by papers citing high-impact articles) whereas hub is the eigenvector centrality for the bibliographic coupling network (i.e., the times of citing articles that are high-impact). In the protest context, the former refers to a group of influential participants whereas the latter simply means those who follow this group of participants. Thus, it is not surprising to see their different influences. Finally, the English dominant nature of Twitter might not reflect the full picture of the Hong Kong protest. This study would benefit from data collected from Chinese social media platforms such as Sina Weibo, which includes more voices from mainland Chinese and therefore might show different dynamics. Future studies should compare multiple platforms to examine the influence of contextual nuances, such as the risks of censorship.

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Notes
1. https://github.com/twintproject/twint
2. All the phrases generated by the following Boolean operations were used as the search keywords in this study: [“Hong Kong” OR “HK” OR “HKers”] AND (“democracy” OR “terrorist” OR “one country” OR “two systems” OR “security law” OR “autonomy” OR “communist” OR “CCP” OR “freedom”)] OR [“香港” OR “香港人”] AND (“民主” OR “分裂” OR “一国两制” OR “国安法” OR “自治” OR “共产黨” OR “自由”]

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