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Spatiotemporal Diffusion Modeling of Global Mobilization in Social Media: The Case of the 2011 Egyptian Revolution

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This study explores transnational diffusion of social movement information in social media by introducing a mathematical model. Although the literature extensively discusses social media uses in social movements, few studies have examined a spatiotemporal dynamic diffusion process. Even fewer have taken into account international relational factors that may interplay with the diffusion process. This study addresses this gap by examining different notions of spatial proximity—each of which pertains to the level of democracy, diaspora size, economic relations, and physical distance—and applying them to a mathematical "diffusion-advection" model. The model was validated by tweets during the Egyptian revolution of 2011. The spatial diffusion was most effectively explained when the model was fitted using a democracy-based spatial arrangement. Although the diffusion of ad hoc reporting and action supportive messages were particularly in high volume during the most active protest period, situation-verifying information was diffused at a steady pace throughout the entire period examined. By demonstrating the model's validity with the Egyptian revolution Twitter data, the article reveals the potential of using mathematical modeling in social movement research.

Keywords: social media, spatiotemporal diffusion model, transnational social movement, mobilization, Egyptian revolution, Twitter

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Recent social movements such as the Arab Spring and the Occupy movement have reignited scholarly discussions surrounding the value of information and communication technologies (ICTs) in promoting social change. Because of the popularity of social technologies, the recent emergence of decentralized, personalized, and spontaneous networks of large-scale global publics may be paradigm shifting beyond formal organization-driven mobilization (Bennett & Segerberg, 2012; Bimber, Flanagin, & Stohl, 2005). In general, social movements entail two modes of mobilization: Action mobilization refers to actual participation in events, and consensus mobilization refers to acquiring informational and emotional assets supportive of the causes of movements (Klandermans, 1984; Kwon, Nam, & Lackaff, 2011). With regard to action mobilization, ICTs promote not only off-line gatherings but new genres of online collective actions, such as sending mass e-mails to a target organization (also known as e-mail bombing), creating parodies in the form of cultural jamming, and organizing virtual sit-ins or online petitions (Van Laer & Van Aelst, 2010). Although digital actions may demand less of a time commitment and fewer skills and risks compared to traditional demonstration, these actions often produce high-impact political outcomes (Van Laer & Van Aelst, 2010). With respect to consensus mobilization, ICTs facilitate a large-scale exchange of opinions and information through which movement supporters construct a collective identity.

Information diffusion is important for both action and consensus mobilization. To achieve large-scale participation and support, information should reach the maximum number of sympathetic audiences, often beyond geographical boundaries. The success of mobilization is measurable by "the extent to which the [collective] goods are known and valued" (Klandermans, 1984, p. 586). That is, one way to gauge the impact of social movements is to examine the scope of information diffusion. The success of local actions often relies on the visibility of support from the global community that may not be a direct beneficiary of the action yet nonetheless is willing to put considerable pressure on the target government for change (Della Porta & Kriesi, 1999).

Although social media has evolved into a major channel for garnering global support, surprisingly few studies have systematically examined diffusion dynamics underlying social media–assisted mobilization. This study aims to contribute to social movement scholarship by developing a *spatiotemporal* diffusion model based on two premises. First, online social movements can be studied as a diffusion phenomenon. More precisely, we consider the rate of social media diffusion to be a proxy measure of the magnitude of mobilization. This premise is in line with research that adopts various diffusion theoretic models (e.g., Andrews & Biggs, 2006; Granovetter, 1978; Oliver & Myers, 2003; Strang & Soule, 1998). Second, online social movement is contextualized within a larger landscape of global civil society, which is influenced by persisting international relational factors (Smith & Wiest, 2005; Zhukov & Stewart, 2013). Drawn from these premises, this study attempts to integrate global structural factors into a social movement diffusion model. Specifically, we develop a spatiotemporal diffusion model by extending a mathematical model. For the model validation, we use a real data set of tweets spread during the Egyptian revolution in 2011.

Theoretical Background

Information Diffusion in Social Movement Mobilization

The widespread use of ICTs in recent decades has prompted much discussion regarding strategic advantages of ICTs in speeding up cost-efficient recruitment (Bennett, Breunig, & Givens, 2008; Bimber et al., 2005; Diani, 2003). The discussions have been drawn from antiglobalization movements in the late 1990s (e.g., Ayres, 1999; Van Aelst & Walgrave, 2002), antiwar protests in the early 2000s (e.g., Bennett et al., 2008), and the Arab Spring (e.g., Bennett & Segerberg, 2012; Lim, 2012; Tufekci & Wilson, 2012) and the Occupy movement (Castells, 2013).

The principle underlying the success of ICT-driven social movements remains consistent with older forms of collective action: Information diffusion is key to mobilization, an indispensable prerequisite to give salience to protest efforts (Turner & Killian, 1987). Information spread in online networks can easily increase the "noticeability" of other individuals' beliefs and behaviors, which would otherwise be visible only within a small local group setting (Bimber et al., 2005; Olson, 1965). Individuals decide whether to join the action based on the comparison of their own attitudes/behaviors to the visible attitudes/behaviors of others (Granovetter, 1978). That is, information diffusion online enhances the visibility of protest and helps sustain a positive cycle of consensus and action mobilization. Social media is particularly instrumental in interconnecting supportive communities and enabling viral diffusion of movement-relevant information across group boundaries (Nahon & Hemsley, 2013).

The importance of information diffusion is substantiated by scholars' frequent use of diffusion theoretic concepts to discuss the roles of interpersonal contacts and mass media effects (McAdam & Rucht, 1993; Della Porta & Kriesi, 1999) or the roles of international institutional actors (Ayres, 1999; Keck & Sikkink, 1998) in disseminating the movement's ideas. Few researchers, however, have developed a quantitative diffusion model in an attempt to systematically generalize the dynamic process. The existing diffusion models are of three types: threshold models, evolutionary models, and event history diffusion models.

First, *threshold models* (Granovetter, 1978) develop a mathematical procedure based on a time-variant logistic function. These models assume that the time of an individual's joining a movement depends on the individual's behavioral threshold—the number of participants is large enough for the individual to believe that participation is a right choice. The individual will join the movement when the number of participants surpasses his or her behavioral threshold. Threshold models propose that diffusion reaches a ceiling—or equilibrium—when the difference in threshold between newer participants and prior participants no longer exists. Granovetter (1978) suggests that the success of a protest is determined by the condition that affects the equilibrium point.

Second, *evolutionary models* (Oliver & Myers, 2003) are an advanced version of threshold models. They assume that an individual's participation is affected by exposure to not only protest-inducing behaviors and ideas but protest-repressive ones—that is, the costs or negative consequence of participation. Therefore, the decision to participate depends on "the net effect of the diffusion of two [opposing] ideas" (Oliver & Myers, 2003, p. 10). Also, unlike threshold models, which focus on individual decisions made within a single movement event, evolutionary models consider coevolving relationships among different events throughout a movement cycle.

Last, *event history diffusion models* are similar to evolutionary models in that they explore the diffusion process across different events. These models are differentiated, however, in that they involve statistical testing of relative effects of diffusion-related covariates on the rate of protest adoption, including individual attributes such as infectiousness (how influential one's protest behavior is to everyone else in the system) and susceptibility (how responsive a participant is when a protest occurs) (Andrews & Biggs, 2006; Myers, 2000; Strang & Soule, 1998).

Spatial Diffusion for Transnational Movement Mobilization

With their focus on temporal changes, the three models described above largely overlook a spatial dimension. Even when spatial components are considered (e.g., Myers, 2000), the spatial concept is treated as a covariate rather than a key determinant of the diffusion rate. This article builds on previous diffusion modeling efforts by addressing both temporal and spatial dimensions. Spatial understanding may be particularly useful in the context of online social movements that are transboundary by nature, involving global publics across different political, cultural, and economic contexts.

In transnational online social networks, consensus mobilization may easily take on a global scale: An ostensibly local event could draw extensive global attention and participation. For example, many non-Arabic tweets during the Arab Spring demonstrate Twitter as a venue for global citizens to express their support for local regime change and to interact with on-the-ground activists (Bruns, Highfield, & Burgess, 2013). However, not every global citizen has an equal share of participation. For instance, during the Arab Spring, most Twitter activities were made by Latin alphabet-based-language speakers (i.e., English), although the volume of Arabic-language tweets grew steadily over time after the peak period (Bruns et al., 2013).

Broadly speaking, global unevenness in social media activities reflects the preexisting order of world economy and geopolitics (Chang, Shoemaker, & Brendlinger, 1987). For example, the North–South divide exists online, with citizens of affluent countries in the Northern Hemisphere enjoying greater access to digital resources needed for global activism participation than citizens of countries in the Southern Hemisphere (Shumate & Dewitt, 2008; Smith & Wiest, 2005). In addition to an economic divide, other factors may affect the level of social media participation of some regions. For example, a country's democracy is a strong predictor of the presence of its citizens in transnational activism network (Keck & Sikkink, 1998; Smith & Wiest, 2005). Also, uneven international news flow leads to disproportional global awareness of certain events (Chang et al., 1987; Kim & Barnett, 1996; Wu, 1998). Dyadic relations such as geographic distance, economic relations, and cultural closeness also determine the level of engagement with each other's political struggles (McAdam & Rucht, 1993; Zhukov & Stewart, 2013). Furthermore, global migration creates a diaspora community that is prone to participating when the social movement unfolds in their home country (Cochrane, 2007; Sassen, 2002).

Such global unevenness is likely to persist in the digital realm. After all, the pattern of international information flow remains largely unchanged in the Internet age (Barnett, 2001; Graham, 2014; Park, Barnett, & Chung, 2011). Although the global digital divide in activism has been discussed from institutional perspectives (i.e., relationships among nongovernmental or intergovernmental organizations and media organization–driven news flows), the discussion needs to embrace personalized forms of activism rising in the social media realm. Specifically, Bennett and Segerberg (2012) distinguish a personalized process of mobilization from an organization-driven process. Personalized networking is also referred to as the rise of a conscience community, which is differentiated from professional or nonprofit organizational networks (Aunio & Staggenborg, 2011). The literature has not yet fully addressed the role of international relational factors in this personalized global network online.

Research Purpose

As the discussion above suggests, information diffusion indicates the scope and success of movement mobilization. The current study introduces a mathematical model that explains spatiotemporal information diffusion in social media. A mathematical model is a representation in mathematical language of the beliefs about how a system functions. Most mathematical models applied in the communication discipline fall into the category of empirical models, in which the collected data are used to specify the correlation structure among a set of measured variables (e.g., a statistical analysis using regression models). Lesser known are mechanistic models, for which fundamental knowledge on the laws of physics or chemistry is borrowed to define the model structure. In a mechanistic model, the collected real-world data are used not to specify the model structure but to validate to what extent the model drawn from scientific laws could explain the real-world system. Although empirical models are useful to understand correlations (or covariance) among individual variables, mechanistic models help us understand the mechanisms underlying the change process as a whole. The spatiotemporal diffusion model that this study introduces is a mechanistic model in that it borrows equations previously known from physical laws to conceptually represent the diffusion process, and then uses real-world data to validate whether the model is explanatory. Accordingly, the first research question is:

R1: *How accurately does the proposed spatiotemporal model explain a social movement diffusion process in social media?*

As mentioned, international relational factors rarely have been included in discussions of social media movement networks. This gap is addressed in the current study by using different dimensions of spatial proximity in specifying spatial arrangement in the model. Specifically, spatial proximity is conceived based on four factors: democracy, economic relations, geographical distance, and the size of diaspora. By comparing the results from different dimensions of spatial proximity, this study assesses which factor explains the spatial diffusion process most effectively. Therefore, the second research question is:

R2: *Among the different international relational factors, which factor specifies the spatial dimension most effectively in explaining spatial diffusion of information?*

The model validation is based on tweets sent during the Egyptian revolution in 2011. Twitter is globally popular and is the ninth most trafficked website worldwide (alexa.com). Moreover, Twitter is particularly known as a platform for citizen engagement during an extreme event (Oh, Kwon, & Rao, 2010). Twitter offers a useful spatiotemporal data set containing the temporal metadata when a message was sent. Twitter also aggregates various bits of information from numerous websites from within and external to the Twitter system (Kwon, Oh, Agrawal, & Rao, 2012). Different types of information spread in Twitter may thus reveal different mobilization efforts. For example, tactical and strategic messages might pertain to action mobilization, whereas sharing of news coverage will increase consensus mobilization. Accordingly, we additionally explore whether the diffusion process may be differentiated contingent on the types of information. Therefore, the third research question is:

R3: Do different types of information display different spatiotemporal diffusion patterns?

A Mathematical Model

The analytic focus of a diffusion model is on a *rate of change* (or derivative) of the information volume over the course of changes in time or space. In mathematics, this change mechanism is represented by a differential equation function. The advantage of using a differential equation over an algebraic equation is that it allows for dynamic modeling, which enables it to represent the *process* of changes. Widely known diffusion models in social sciences such as the Bass model (Bass, 1969) or the threshold model (Granovetter, 1978) are based on ordinary differential equations, which explore the rate of change of a variable over *time*. To explore the rate of change not only over time but across *spaces,* a model needs to use a partial differential equation (PDE) instead of an ordinary differential equation (Wang, Wang, & Xu, 2012).

PDE models are widely used in physics, biology, and other fields to describe the process governing the diffusion of an object (e.g., sands, pollutants) or energy (e.g., heat). The current model extends a PDE-based "diffusive-logistic" model (Wang et al., 2012; Wang, Wang, Xu, Wu, & Jia, 2013) that was recently developed to predict news diffusion via online social networks. Specifically, we extend the model by adding the "advection" term, which denotes the tendency of an object (information, in the current context) to move along with a discrete set of locations.[2] The model is thus called a diffusive-advection logistic model, or simply a *diffusion-advection model*.

The advection term represents substances of an entity to be carried by a bulk motion of the transport medium (Logan, 2001). For example, suppose an infectious disease is diffused by mosquito bites. Although random diffusion may occur due to the autonomous and random search movement of individual mosquitos, wind currents also may result in an advection movement of large masses of mosquitos and consequently cause a quick advance of infection (Takahashi, Maidana, Ferreira, Pulino, &

[2] Any change in the amount of information was assumed to restrict to one spatial dimensional line labeled as the spatial variable *x*. PDE models are continuous in both space and time. The locational (or spatial) points were based on a discrete set of points (*Ux*) in the x axis, which were then extended into a continuous interval.

Yang, 2005). Analogously, global information diffusion in social media may be driven by two mechanisms: random diffusion, by which individual users share information relatively autonomously and randomly, and advection movement due to larger global geopolitical forces such as democracy, migration, physical distance, and other significant forces. Therefore, the use of diffusion-advection equations may appropriately distinguish the two mechanisms, thereby shedding light on the role of international relational forces in facilitating the spread of information.

For formalization, suppose that a series of spatial points is arranged by a certain criterion, *U*(*x*), as well as a set of time points, T(*t*). Let $I = I\ (x, t)$ be the volume of information at location *x* and at time *t*. The mathematical formalization of the diffusion-advection model is:

$$\frac{\partial I}{\partial t} = \frac{\partial\left(d\,e^{-bx}\frac{\partial I}{\partial x}\right)}{\partial x} - g(x)\frac{\partial I}{\partial x} + r(t)I\left(h(x) - \frac{I}{K}\right), \qquad (1)$$

where $\frac{\partial\left(d\,e^{-bx}\frac{\partial I}{\partial x}\right)}{\partial x}$ in the equation represents the random diffusion process across *U*(*x*) by unexamined forces. The second part, $-g(x)\frac{\partial I}{\partial x}$, is the advection term, which denotes the bulk information shift across spatial points due to an examined structural force .The third part, $r(t)I\left(h(x) - \frac{I}{K}\right)$, is a logistic function that captures the intrinsic growth of information over time *within* a particular location. This logistic function is what most ordinary differential equation diffusion models are based on (see Appendix A for the details of formalization and each notation). Among the notations, we are most interested in the *value of advection parameter,* $g(x)$*, because it represents the magnitude of information shifted across locations thanks to the examined structural force.*

Model Validation: The Egyptian Revolution Tweets

The 2011 Egyptian Revolution

Recently, Egyptian activism has shifted from brick-and-mortar organizations to decentralized bodies of new generational activists who take advantage of social media in spreading information and reinforcing solidarity (Abdelraham, 2011). Social media became prominent when Facebook was first employed in 2008 to mobilize a textile workers' strike in Mahalla, on the Nile Delta in Egypt. The local initiation of the strike spread rapidly via the April 6 Youth Movement Facebook group, which 70,000 Egyptian Facebook users joined. Most of the members stayed home on the strike day as planned via Facebook (Faris, 2008). The April 6 movement became a landmark of social media–driven mobilization without traditional organizational leadership. However, the subsequent strike on May 4, which employed the same Facebook mobilization strategy, ended in failure, suggesting that technology can never be a game changer by itself (Faris, 2008).

Since the April 6 movement, Egyptian activism has continued to garner global support (Lim, 2012). The success of the January 25 demonstration, which triggered the historic two-week revolution in 2011, was largely due to the development of global dissident spheres on- and off-line, including social media, which contributed to inform, coordinate, and mobilize protesters. The literature on the 2011 Egyptian revolution insightfully describes sociopolitical and historical conditions underlying the large-scale mobilization (e.g., Lim, 2012; Lynch, 2011). In some studies, social media content was examined to understand the nature of dissident spheres (e.g., Bruns et al., 2013; Hamdy & Gomaa, 2012; Papacharissi & De Fatima Oliveira, 2012). This study contributes to the literature by systematically presenting the information diffusion process in social media.

Data Collection

As of 2011, Twitter did not allow keyword search for historical data older than five days. The only way to access historic data was to retrieve available posts by backtracking user IDs of those who may have tweeted around the time of the Egyptian revolution. Therefore, we took the following three steps to collect historic data: (1) identify the Twitter user IDs of those who tweeted around the time of the Egyptian revolution, (2) backtrack all identified user IDs to retrieve all their posted content on Twitter,[3] and (3) perform a keyword search to identify relevant tweets.

Twitter's public Streaming API was used with the search keyword *Egypt* between January 25 and February 20, 2011 (EST), eight times per day, for an hour each session. Through this process, a total of 50,778 Twitter user IDs were identified. A backtracking API tool was then developed to retrieve all identified users' past tweets. Using Microsoft SQL Server, the data were cleaned by using the keyword *Egypt* as a filtering parameter. Most tweets before January 24 were irrelevant to the revolution, and the volume of tweets declined from February 14. Accordingly, our focus was on the time window between January 24, 2011, and February 13, 2011. Given time lags between Egypt and the United States, the time frame was adjusted such that all major events were included.

It is noteworthy that Twitter sampling is not always perfectly transparent. The backtracking method is qualitatively different from streaming data collection, resulting in a somewhat limited collection. Streaming API also often results in a much smaller data set than the costly Firehose Stream (Driscoll & Walker, 2014; Morstatter, Pfeffer, Liu, & Carley, 2013). Nonetheless, compared to a short-term (e.g., hourly) and high-volume observation, a longer period (e.g., daily) with medium-volume observation could result in a relatively smaller discrepancy between the public Streaming API and Firehose Stream (Driscoll & Walker, 2014).

Geographical information and message types were manually coded. For coding, we drew a stratified random sample that represents 5% of the original data set of 253,016 tweets based on a daily volume. As a result, 12,694 tweets were drawn, of which 81.6% were in English, 11.7% were in Arabic, and 6.7% were in other languages. The Arabic tweets were translated by a bilingual graduate student and were included in the modeling. Other foreign languages were removed.

[3] Backtracking was limited to 3,200 recent tweets per profile. Although this could be a potential limitation, data omission due to this limitation is expected to be minimal, assuming that few users could have sent more than 3,200 tweets for a couple of days.

Location Classification

Two types of geographic information are available in Twitter (Leetaru, Wang, Cao, Padmanabhan, & Shook, 2013): geo-metadata and self-disclosed place cues. Although geo-metadata provides more accurate information, access to it is restricted by Twitter privacy settings—users need to enable the location-sharing feature to send geo-referenced tweets. Accordingly, few tweets (2%) include geo-metadata (Leetaru et al., 2013). Geo-tagging was not yet popular in 2011. And the widespread use of virtual private networks to bypass government censorship could render metadata unreliable.

Subsequently, we relied on self-disclosed information, tracked by looking up profiles, additional contact information from personal home pages or other social media sites hyperlinked to the profiles, location cues revealed through the use of locative apps, and other indicators within the content of the tweets. Although self-disclosed information could induce a self-report bias, we were able to trace 82% of the identified users' geographical information. We excluded tweets sent by Twitter and tweets with unknown or ambiguous location cues, such as those sent by transnational organizations (e.g., Amnesty International, the United Nations, Marxists.org, and Anonymous) and bogus profiles (e.g., Mubarak's profile, Lawrence of Arabia).

The information was initially coded on a country level, with high intercoder reliability Cohen's κ = .960. Later, it was decided to recode on a global region level for several reasons. First, a fair portion of users were associated with multiple countries within the same regional bloc—for example, a user profile mentioning Egypt and the United Arab Emirates without any additional cue as to which country the user was in at the moment of tweeting. Second, economic trade and migration data were only available on a regional level. Third, many countries had too few tweets to be used for the model validation. Although this higher-order classification might not fully capture a nation-level diffusion pattern, it increased consistency in coding.

Seven global regions were classified based on the Economist Intelligence Unit's (2010) *Democracy Index* and the World Bank's (2010) *Internet Users* data: Western Europe (WE), Eastern Europe (EE), North America (NA), Latin America/the Caribbean (LA), Asia/Australasia (Asia), Middle East/North Africa (MENA), and Sub-Saharan Africa (S-Africa). Some countries ambiguously designated as either WE or EE were categorized as WE if the country was either a member or a potential candidate of the European Union. Because Egypt was the home country of the revolution, it was treated as a separate single entity from MENA and was designated as the origin locational point (x_1). In total, the data contained eight location points.

Message Types

To answer R3, tweets were categorized into three types: *ad hoc reporting*, *situation verifying information*, and *collective action supportive messages* (see Table 1). The typology was developed from the literature on collective behavior (Turner & Killian, 1987), which suggests that collective behavior evolves from improvised information sharing into collective identity reinforcement and strategic action mobilization. Recent studies suggest that social media involves additional distinctive processes in which the authenticity of the shared information is verified (Oh et al., 2010).

Table 1. Content Analysis Framework.

Ad hoc reporting	
Definition	Firsthand observation without presenting any supporting materials; includes an immediate update about a situation or problem *without* providing additional sources
Examples	*"Riot Police covering downtown Cairo, the #jan25 riots are starting"* *"My mobile phone connection keeps getting cut every 15 secs . . . Bad coverage or purposeful strategy?"*
Situation verifying information	
Definition	Verification by a third party (mass media, officials, governments, and advocacy organizations) or with solid supporting evidence such as a photo, video, or interview.
Examples	*"Egypt's frustrated young wait for their lives to begin and dream of revolution http://bit.ly/iceIYZa"* [whose URL provides the access to a *Guardian* news article] *"RT @tobeornot1st: http://twitpic.com/3t95u"* [in which the URL directs to a photo of an Egyptian protester standing in front of police officers]
Collective action supportive messages	
Definition	(1) An expression of solidarity, a sense of belonging to protest communities, and/or opposition to the regime; or (2) The sharing of action-related skills, knowledge, or tactics (If ad hoc reporting or verifying information accompanies the action-supportive message, we prioritized this category, coding it as an action-supportive message.)
Examples	*"My heart is with all my people in #Egypt"* *"Mubarak, You're done, just leave, please don't waste time and blood"* *"The voice of revolution will still be heard. Blocking twitter will not affect a thing"* *"Egyptian activists, I made cartoons for #Jan25 http://twitpic.com/photos/CarlosLatuff Take them to the streets of #Egypt"*

Some tweets were not categorized into any of the types (e.g., those that contained doubts about the movement's success, random questions, and concerns about negative impact). Such tweets were rare, however, and they were excluded from further analysis. Three individuals coded the content after receiving extensive training, with an acceptable range of intercoder reliability (Cohen's κ between .709 and .732).

Spatial Proximity Based on International Relational Factors

We considered Egypt as the origin location x_1. To arrange spatial proximity of each regional point U (x_1, x_2 . . . x_8) from Egypt, we defined the proximity in four different ways based on each international relational factor: (1) Physical distance–based proximity: An average distance between Cairo and the capitals of countries in each region was computed to capture a region's physical proximity to Egypt. The shorter average distance was considered closer to Egypt; as such, $U_{proximity}(x)$ = {Egypt, MENA, EE, WE, S-

Africa, NA, Asia, LA}. (2) Population-based proximity: A region with a larger diaspora community (i.e., migration) was considered more influential, and thus closer, to Egypt; as such, $U_{disapora}$ (x) = {Egypt, MENA, WE, NA, Asia} (missing regions have no information). (3) Economic relation–based proximity: A bilateral economic trade[4] with Egypt was used as criterion to define economic proximity; as such, U_{trade} (x) = {Egypt, MENA, WE, NA, Asia, S-Africa, Asia, LA}. (4) Ideology-based proximity: The influence of democratic ideas was conceived as an ideological proximity; as such, $U_{democracy}$(x) = {Egypt, NA, WE, LA, EE, Asia, S-Africa, MENA}, assuming the more democratic regions engage in more actively in transnational activism network (Smith & Wiest, 2005) and thus exert more influence on (and thus are "closer to") Egyptian protesters. The data about the democracy level of each region were drawn from the Economist Intelligence Unit (2010) *Democracy Index*, bi-trade relation data from Egyptian International Trade Point (2010), and migration data from the Migration Policy Centre (2013; the data pertained to the year 2009. For all criteria, the most updated data prior to the revolution were referenced.

The Internet Penetration Effect[5]

Tweet volume may be significantly correlated with the Internet penetration in a region.[4] If a diffusion model captures a tweeting pattern that occurs *disproportionately* from the Internet penetration effect, the results could be a more accurate indicator of Twitter diffusion during the protest period. Therefore, two series of modeling were performed. The first set of modeling was based on the raw tweet volumes ("raw tweets" hereafter). The second set was based on the residual values—computed as the difference between the observed and predicted value of a tweet volume from the regression on the Internet penetration effect ("residuals" hereafter). The residuals-based modeling intends to check whether the model explains properly the pattern of tweet volume change *unaccounted for* by the Internet penetration. The Internet penetration data were acquired from World Bank (2010).

Results

Descriptive Analyses

Removing the uncategorized tweets, the final sample included a total of 11,876 tweets. 4,628 of the tweets were ad hoc reporting, 3,572 tweets situation verifying, and 3,676 tweets action supportive messages. The slope change for each communication type was noticeable at a different period (see Figure 1).

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[4] The regional ranking was based on the average import and export dollar amounts.

[5] Twitter penetration data would be ideal for validation purposes. Unfortunately, Twitter penetration data prior to 2011 were not available.

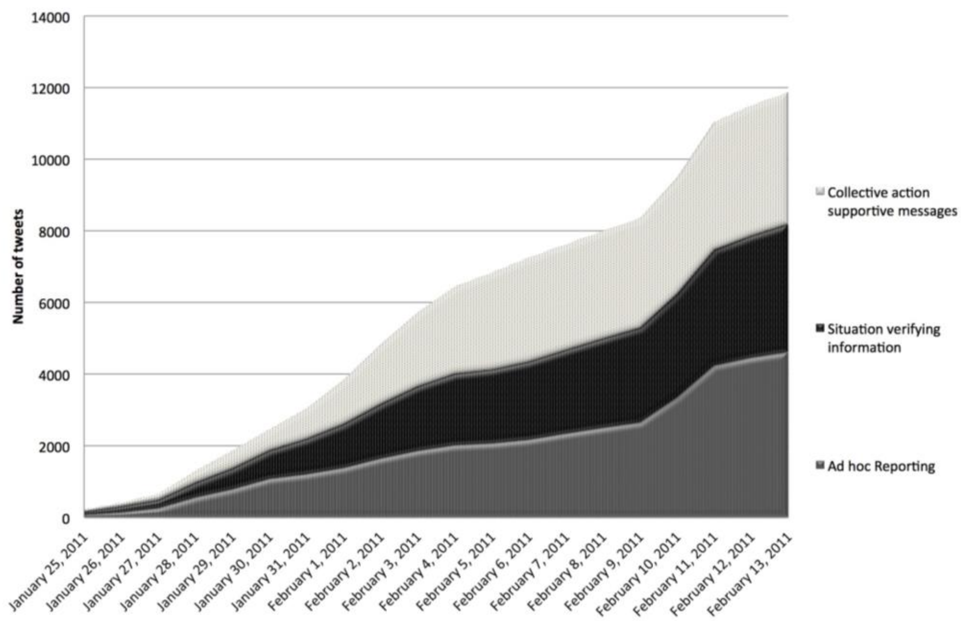

Figure 1. Cumulative increase in the number of tweets by each communication type (N = 11,876).

The volume of collective action supportive messages sharply increased the first week of February, when several key events took place, such as the brutal violence in Tahrir Square against protesters (February 2) and Cairo's largest protest, called "The day of departure" (February 4). The volume of ad hoc reporting messages slightly increased on January 27, right after the Egypt Internet was unblocked, and was followed by a sharp increase around the period of Mubarak's resignation (February 11). Meanwhile, the volume of situation verifying messages grew steadfastly throughout the period.

The chart shown in Figure 2 represents the daily volume of each message type. Three peaks were observed during the period: January 27 (after unblocking the Internet), February 2 (when the pro-Mubarak forces violently crushed protesters), and February 11 (when Mubarak resigned). Based on this descriptive chart, we split the data into three time frames: the *beginning period* (January 25–31), the *active protest period* (February 1–7), and the *regime turnover period* (February 8–13).

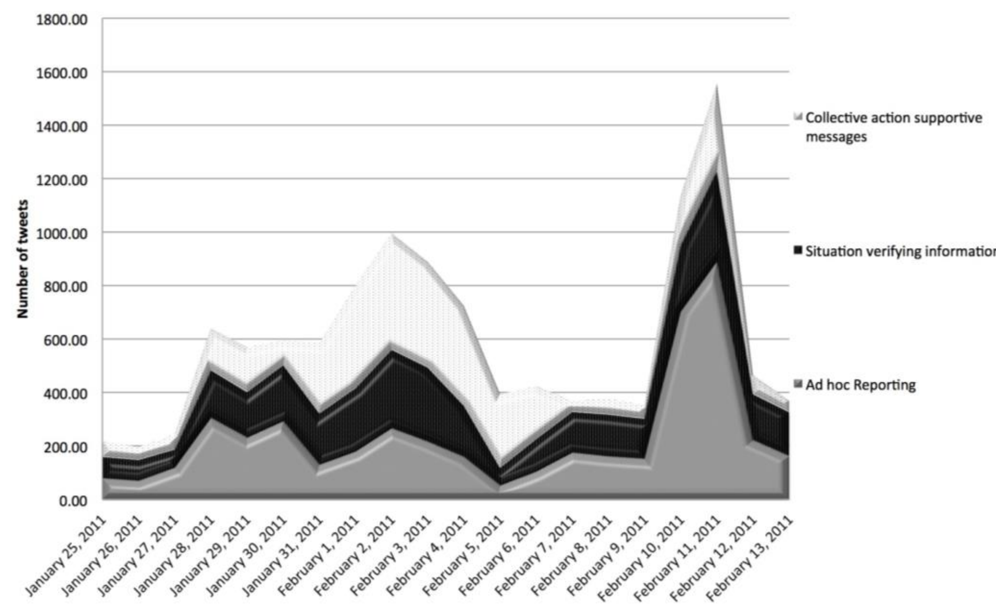

Figure 2. Daily tweet volume by each communication type (N = 11,876).

Model Validation (RQ1)

An important part of mathematical modeling is to validate how accurately a model explains the system of interest. One common way to perform model validation is to examine whether the model fits empirical data. To do so, simulations are run by analytic software (i.e., MATLAB), through which a series of parameter values postulated in the mathematical equation are computed. The size of a parameter value is analogous to a coefficient size resulting from a regression analysis. Based on the computed parameters, the model is simulated iteratively to obtain the predicted value. The model quality is then expressed by the accuracy—to the extent that the observed values correspond with the predicted values. The model accuracy is measured by the difference between the predicted values and the actual observed values, as such:

$$accuracy = 1 - \frac{|predicted\ value - actual\ value|}{actual\ value}. \tag{2}$$

The model validation in this study was performed as follows: First, the tweet data were split into 36 sub-data sets based on three message types, four spatial arrangements, and three time frames (3 × 4 × 3 = 36). Second, the simulation was performed against each sub-data set to check the model fit, each resulting in the accuracy score as well as parameter values. Third, for in-depth interpretation of validation results, two series of simulations were run: one with the raw tweet and another with the residuals (i.e., an unaccounted variance from the Internet penetration effect).

Table 2 summarizes the model accuracies. All were above 90% when the raw tweet volume was considered. The accuracy decreased, however, to between 70.62% and 94.11%, when the Internet penetration effect was controlled. Although the decline in accuracy may suggest that the Internet penetration effect indeed accounted for diffusion pattern nontrivially, PDE-based diffusion model with an average of 75% prediction accuracy has been discussed as acceptable (Wang et al., 2013).

Table 2. Model Accuracy Tests (% of Accuracy).

Message type	Proximity	Model 1: raw tweets Jan. 25–31	Model 1: raw tweets Feb. 1–7	Model 1: raw tweets Feb. 8–13	Model 2: residuals Jan. 25–31	Model 2: residuals Feb. 1–7	Model 2: residuals Feb. 8–13
Ad hoc reporting	Democracy	92.88	91.72	92.19	92.01	83.73	80.70
	Geographic	92.20	92.56	90.90	93.27	77.07	78.98
	Diaspora	93.44	94.95	92.86	86.03	73.03	71.19
	Trade	91.02	91.22	92.03	93.35	76.48	79.32
Situation verifying information	Democracy	94.88	91.89	94.55	94.11	85.41	80.81
	Geographic	94.31	92.18	93.44	88.71	80.92	80.47
	Diaspora	95.17	90.73	96.04	78.49	80.96	70.62
	Trade	93.13	92.35	93.91	91.44	81.63	79.25
Collective action supportive messages	Democracy	93.28	92.63	92.89	90.26	89.49	72.50
	Geographic	93.98	91.92	94.01	90.02	78.83	71.12
	Diaspora	94.50	92.12	96.04	84.68	78.03	74.13
	Trade	93.36	93.38	93.91	90.05	81.63	71.02

Figure 3 presents a graphical summary of model validation results from the democracy-based proximity data sets using residuals. This figure includes the graphs of model fitting and of two parameters computed: local growth $h(x)$ and advection tendency $g(x)$. The model would be perfectly accurate if the observed (blue dotted) line exactly matched the predicted (red dotted) line in the model-fitting graph. Also, the lines representing local growth $h(x)$—the index of temporal diffusion rate within a specific location point—are almost parallel to the predicted lines (red dotted line) of the model-fitting graphs. This pattern indicates that the tweet volume change was largely explained by the temporal within-local growth. However, the addition of the advection term $g(x)$—the index of spatial diffusion rate—resulted in the highest model accuracy. For the complete reports on the graphical summary based on the raw tweets, see Appendix B.

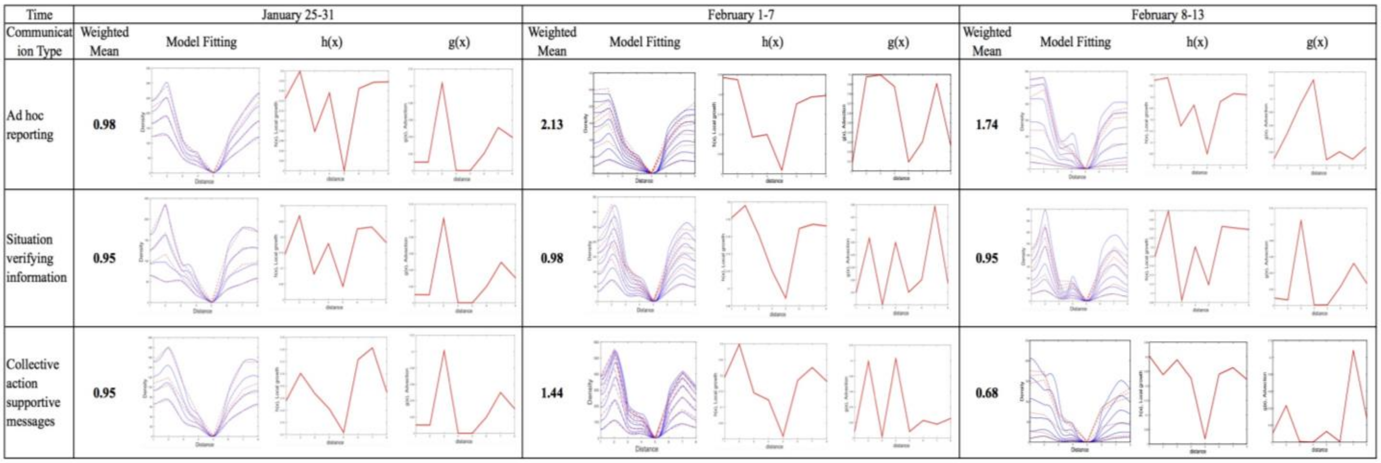

Figure 3. The model validation results (using the democracy-based proximity and the residuals): On all graphs, the x axis represents location points, with x_1 = Egypt. The y axis represents (1) residuals in model-fitting graphs (blue lines = observed values, red lines = predicted values), (2) average coefficients of the within-location growth rate in h(x) graphs, and (3) average coefficients of the spatial diffusion rate in g(x) graphs.

International Relational Factors and Information Diffusion (RQ2 and RQ3)

In addition to validating the model, RQ2 asks which international relational factor contributed to information diffusion the most. Interpreting the advection parameter, $g(x)$, responds to RQ2. The advection parameter $g(x)$ measures *spatial spreadability*, a moving tendency of information from the previous neighboring point (*x-1*) to the current location point (*x*). That is, the $g(x)$ value is contingent not just on the volume of information at its own location but on the volume produced at the *neighboring* locations. The greater value of $g(x)$, the greater the likelihood of information spread from one location to the other.

The $g(x)$ is computed per location point. To compare the impact of international relational factors, the $g(x)$ values of all location points were aggregated into a composite value representing the spatial spreadability in each data set. Specifically, the following weighted mean of $g(x)$ was computed as a composite score:

$$WM = \sum g(x)(MaximumDistance + 1 - x). \quad (3)$$

Here, the rationale for multiplying (maximum distance + 1 – *x*) was to give more weight to a location closer to the origin (Egypt), assuming that the closer it was to Egypt, the more influential it would be. As a result, 36 weighted mean values were computed, each of which was associated with each sub-data set.

When the model fit the raw tweets, either democracy- or diaspora-based proximity showed the largest weighted mean values across communication types and time windows. When the residuals were fitted, however, only the *democracy-based proximity* resulted in noticeably large weighted mean values across the communication types and time windows. Table 3 presents the results of weighted mean values from the democracy-based proximity arrangement.

Table 3. Spatial Spreadability Comparisons Based on Weighted Means of g(x).

		Model 1: raw tweets			Model 2: residuals		
Message type	Proximity	Jan. 25–31	Feb. 1–7	Feb. 8–13	Jan. 25–31	Feb. 1–7	Feb. 8–13
Ad hoc reporting	Democracy	**1.21**	**1.72**	1.12	**0.98**	**2.13**	**1.74**
	Geographic	0.04	0.00	0.04	0.26	0.40	0.38
	Diaspora	1.17	0.83	**1.19**	0.09	0.18	0.19
	Trade	0.27	0.15	0.27	0.24	0.03	0.03
Situation verifying information	Democracy	0.94	0.96	**1.31**	**0.95**	**0.98**	**0.95**
	Geographic	0.09	0.06	0.04	0.32	0.40	0.31
	Diaspora	**1.41**	**2.54**	1.18	0.10	0.24	0.10
	Trade	0.31	0.33	0.24	0.30	0.03	0.32
Collective action supportive messages	Democracy	**1.39**	1.68	0.98	**0.95**	**1.44**	**0.68**
	Geographic	0.11	0.23	0.04	0.32	0.30	0.16
	Diaspora	1.14	**2.52**	**1.41**	0.09	0.19	0.10
	Trade	0.57	0.27	0.24	0.31	0.03	0.32

Note. Bold type indicates the largest value of weighted mean of *g(x)* within each time frame and communication type. Model 2 shows a consistent high weighted mean value of democracy.

Last, RQ3 asks whether different types of information showed a different diffusion pattern. As illustrated in Figure 4, the weighted mean values (from the democracy-based proximity arrangement) for ad hoc reporting and collective action supportive messages were particularly larger during the *active protest* period (February 1–7) than during any other time window, implying the extensive global diffusion of such messages during this time period. In contrast, the volume of situation verifying messages was relatively stable across all time periods.

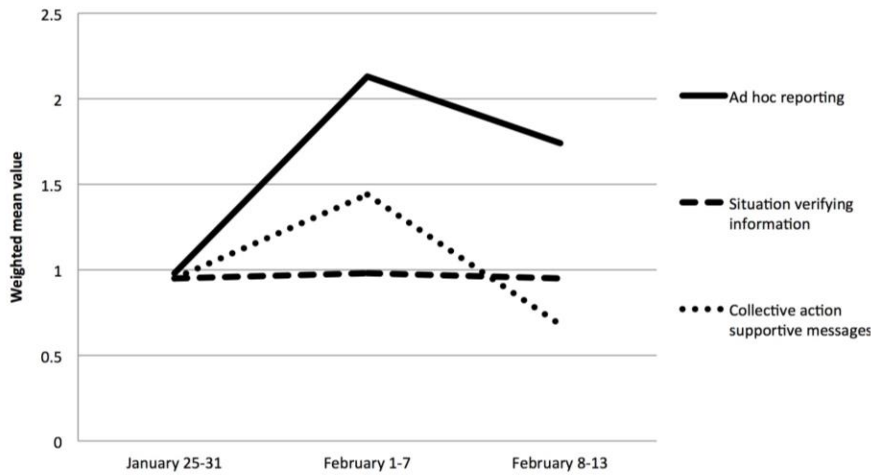

Figure 4. Comparisons of weighed mean value of advection term (g) across different communication type and time windows (Y-axis = WM values).

Discussion and Conclusions

This article develops a spatiotemporal information diffusion model to understand social movement diffusion among the networked global public. A partial differential equation–based mathematical model, a diffusion-advection model, was developed under the premise that global mobilization in social media is not disparate from existing international relational dynamics. We proposed to arrange spatial proximity in various dimensions according to physical, population, economic, and ideological relationships between the origin protest country (Egypt) and other global regions.

On the temporal aspect, the model validation revealed that the temporal local growth term $h(x)$ explained much of the diffusion pattern. This is possible because the local growth term (specified as a logistic function) is the baseline of all diffusion models. However, the addition of the advection parameter $g(x)$ to the model increased the model's accuracy. The advection term $g(x)$ represents the rate of change in volume (of either raw tweets or residuals) from one location to another. Because of our interest in spatial diffusion, the advection term was the analytic focus of this article. Specifically, a composite value of $g(x)$, weighted mean, was used to explain spatial spreadability.

On the spatial aspect, support from democratic regions may play an important role in spatial diffusion. The large value of the weighted mean suggests that the more quickly protest ideas catch on in democratic regions, the more widely they disseminate to the wider world. This result resonates with Keck and Sikkink's (1998) norm diffusion theory, which contends that latecomers seek an identity as a legitimate member of the global advocacy community by adopting human rights norms defined by the already established democratic entities. Analogous to the norm diffusion theory, supporting the Egyptian revolution could have become a transnational democratic norm via the endorsement of activists from established democracies. That said, the influence of democratic regions' endorsement seems to reaffirm the persisting unevenness in global advocacy participation. The result implies that cultural norms and political circumstances in some regions might obstruct their influence on global social change. The impact of cultural and political conditions of certain regions on the likelihood of movement participation is a much-needed research agenda.

The spreadability of ad hoc reporting and action supportive messages was particularly large during the active protest period. Although these types of messages apparently pertained to local participation—for example, real-time updating from on-site scenes (ad hoc reporting) and coordinating protests (action supportive messages)—they may have been widely exchanged across geographical boundaries. In contrast, the volume of situation verifying messages such as mass media coverage was stable across time, perhaps indicating that the spatial spread of media coverage was less affected by the protest cycle. That is, the diffusion pattern between the user-generated content and institutionalized messages could be differentiated. Uncovering this difference calls for future research.

The model validation results should be interpreted within the constraints of the data collection and processing. First, only the English string *Egypt* was used for search without an Arabic keyword. Also, the other languages that accounted for 6.7% of the sample were excluded from modeling. These aspects could cause the bias toward English. Second, as in other geography research, a modifiable area unit problem—meaning that adopting different types of area units might generate different results—is a potential issue. If the unit of analysis were a country rather than a region, the results might be different. The predefined location groups—that is, countries fixed to be included in a regional unit x based on the Economist Intelligence Unit (2010) *Democracy Index*—could also influence the results. The interpretations could be different if we reconfigured the group compositions contingent upon the proximity criteria rather than predefining them. Last, whereas retweets were frequently observed in the sample, their function was not explicated due to coding difficulty (boyd, Golder, & Lotan, 2010) and unavailability of retweet network data. Retweet is an important function that facilitates information diffusion in Twitter. Future research may explore the ways in which retweet practices—or other content redistribution activities—can be addressed in modeling social movement diffusion.

Despite its limitations, the current study contributes to an understanding of the spatiotemporal diffusion of social movement ideas. Given the paucity of mathematical modeling, this study adds an innovative approach to social movement scholarship. Especially, the PDE-based model is a novel approach that accounts for both space and time dimensions. Mathematical/statistical models help explain a system systematically and predict an unknown event. The parameters computed from the empirical validation can be applied to predict the trajectory of similar events in the future, for which the data access may be limited. Considering that social media manifests an effective platform for mobilization, leveraging social media data to explore social movement diffusion may contribute to the understanding of spontaneous emergence of collective actions in contemporary sociodigital environment.

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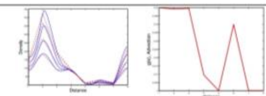
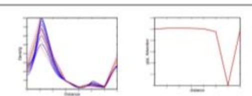
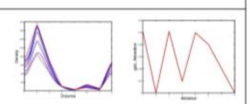
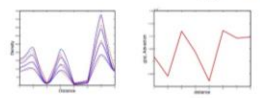
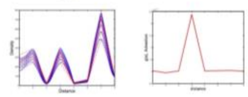
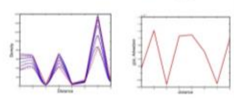
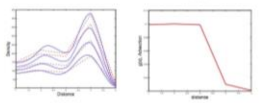
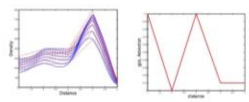
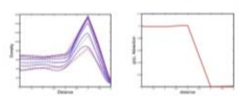
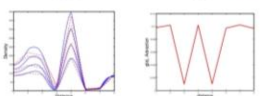
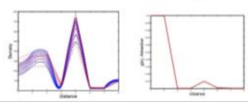
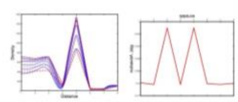
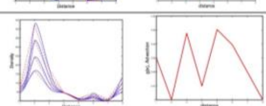
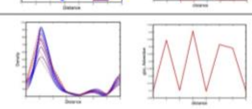
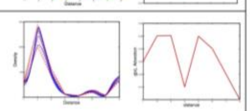
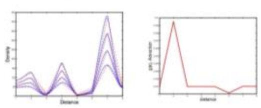
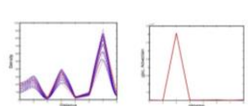
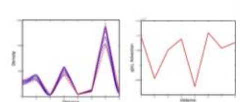
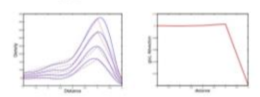
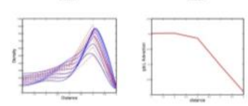
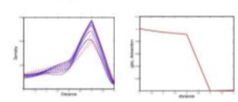
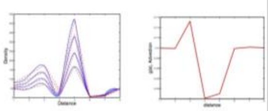
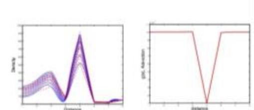
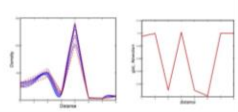
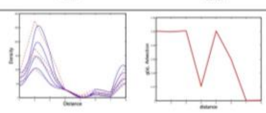
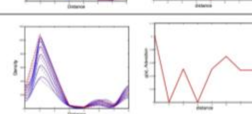
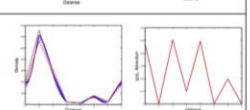
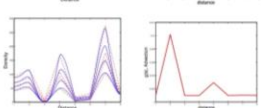
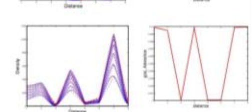
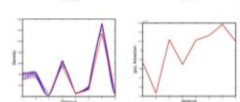
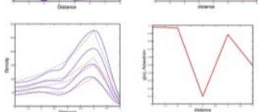
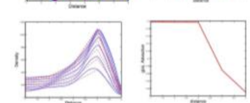
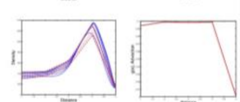
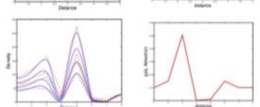
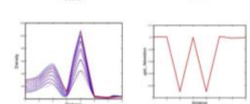
Appendix A: Model Description

Formalization	
$\frac{\partial I}{\partial t} = \frac{\partial(d e^{-bx} \frac{\partial I}{\partial x})}{\partial x} - g(x)\frac{\partial I}{\partial x} + r(t) I \left(h(x) - \frac{I}{K}\right)$ (1) $I(x,1) = \varphi(x)$ (1.1) $\frac{\partial I}{\partial x}(l,t) = \frac{\partial I}{\partial x}(L,t) = 0$ (1.2)	
Notations	
I	Tweet volume (i.e., raw tweets or residuals)
t	Time
x	Locational (or spatial) point
d and *b*	Parameters associated with unknown factors that may promote the spread of I
$\frac{\partial I}{\partial t}$	A rate of change in I at time t
$\frac{\partial I}{\partial x}$	A rate of change in I at a locational point of x
r	The intrinsic growth rate, specified as a growth function denoted by a natural exponential function (*e*). We assumed that the volume of I rapidly increases at the beginning and that the rate of growth will decrease over time and reach its peak at a certain time.
$-g(x)$	The parameter of advection term (a coefficient that determines the rate of change in I over locational points x_s. The negative sign indicates that the shift of I is directed from one spatial point to the right-side neighbor across the *x*-axis.)
h (*x*)	The parameter representing the heterogeneity of intrinsic growth rate at location *x* (a coefficient that determines a rate of change over time within a particular location *x*)
K	The carrying capacity (the maximum possible volume of I at a given location *x*)
$I(x,1) = \varphi(x)$	The initial function (the volume of tweets at time t = 1 to be $\varphi(x)$, which specifies that the initial function has to be always ≥ 0)
$\frac{\partial I}{\partial x}(l,t) = \frac{\partial I}{\partial x}(L,t) = 0$	*l* is the lower bound and *L* is the upper bound of the distance between the origin location x_1 and other locations (a differential equation model requires a boundary condition. This particular formula is called the Neumann boundary condition, which assumes zero flux of I across the boundary at *x* = *l, L*, meaning that tweets are clustered within a single location *x*.)

Appendix B: Raw Tweet Volume–based Modeling Results (bold type indicates the largest value of weighted mean).

Time		Januaray 25-31			February 1-7			February 8-13		
Communication Type	Distance	Weighted Mean	Model-fitting	g(x)	Weighted Mean	Model-fitting	g(x)	Weighted Mean	Model-fitting	g(x)
Ad hoc reporting	Democracy	**1.21**			**1.72**			1.12		
	Geographic Proximity	0.04			0.00			0.04		
	Diaspora	1.17			0.83			**1.19**		
	Trade	0.27			0.15			0.27		
Situation verifying information	Democracy	0.94			0.96			**1.31**		
	Geographic Proximity	0.09			0.06			0.04		
	Diaspora	**1.41**			**2.54**			1.18		
	Trade	0.31			0.33			0.24		
Collective action supportive messages	Democracy	**1.39**			1.68			0.98		
	Geographic Proximity	0.11			0.23			0.04		
	Diaspora	1.14			**2.52**			**1.41**		
	Trade	0.57			0.27			0.24