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Broadcast information diffusion processes on social media networks: exogenous events lead to more integrated public discourse

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Abstract

Understanding information diffusion is vital to explaining the good, bad, and ugly impacts of social media. Two types of processes govern information diffusion: broadcasting and viral spread. Viral spreading is when a message is diffused by peer-to-peer social connections, whereas broadcasting is characterized by influences that can come from outside of the peer-to-peer social network. How these processes shape public discourse is not well understood. Using a simulation study and real-world Twitter data (10,155 users, 18,000,929 tweets) gathered during 2020, we show that broadcast spreading is associated with more integrated discourse networks compared to viral spreading. Moreover, discourse oscillates between extended periods of segregation and punctuated periods of integration. These results defy simple interpretations of good or bad, and instead suggest that information diffusion dynamics on social media have the capacity to disrupt or amplify both prosocial and antisocial content.

Keywords: social media networks, information diffusion, discourse networks, network science, computational social science, open science

Social media is a social network that constitutes massive online social connections and a platform for information diffusion (Kwak et al., 2010). Together, online social connections and activities construct a public discourse, which serves as a sphere to form opinions, exchange ideas, inform and educate others, and maintain online social activities. These communication activities focus on different media events and social issues, occur through different formats of diffusion processes, shape the dynamics of public discourse, and lead to different social outcomes.

We hypothesize public discourse on social media as a dynamic system that is driven by an oscillation between viral versus broadcast diffusion processes (Liang, 2018). These processes appear driven by endogenous and exogenous events, respectively (Crane & Sornette, 2008). Moreover, these dynamics are associated with segregation, characterized by fragmented participation of modular communities across various topics, and integration, which indicates concentrated and integrated collective participation on certain topics. This dynamic transition from segregation to integration can have distinct impacts on society in good, bad, or ugly ways.

For instance, an integrated public discourse motivates collective participation in the public dialogue on social media. This facilitates political engagement (Wojcieszak, 2009), opinion deliberation and expression (Stromer-Galley, 2017), can mobilize pro-social movements (Dunivin et al., 2022), and can increase the diversity of voices and accessibility of cross-cutting information (Stromer-Galley, 2006) thus promoting democracy (Tucker et al., 2017). In addition, an integrated public discourse can quickly orient the public's collective attention to breaking social crises (Bento et al., 2020) and trigger societal responses to urgent issues (De Domenico & Altmann, 2020). At the same time, a segregated public discourse potentially separates social media users into self-connected communities and can result in information echo chambers (Cinelli et al., 2021), political polarization, and the spreading of negative emotions (Del Vicario et al., 2016b) and false information (Del Vicario et al., 2016a).

Existing literature primarily examines public discourse in case studies, which offer a static snapshot of a specific moment in time, or focus on the dynamics of messages from a content-centric perspective. Theoretical frameworks and empirical studies exploring public discourse dynamics from a user-centric perspective are less developed (c.f., Freelon et al., 2018). To bridge this gap, we zoom in on one social media platform, Twitter, and investigate Twitter discourse dynamics and the information diffusion processes associated with these dynamics. By building time-varying discourse social networks with nodes as Twitter users and edges as the pairwise textual similarity of users' tweets, we show that discourse dynamics oscillate between segregation and integration, are influenced by the type of information diffusion patterns (i.e., viral versus broadcast spreading), which are, in turn, associated with important endogenous and exogenous social events. We aim to understand public discourse dynamics, its relationship with information diffusion regarding viral and broadcast spreading on social media, and its connection with events dynamics happening in the real world.

In what follows, we introduce key concepts of discourse dynamics between segregation and integration, and review the theoretical framework of information diffusion with a focus on viral versus broadcast spreading. We then show the

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relationship between discourse dynamics and information diffusion patterns by simulating an artificial discourse network with both viral and broadcast spreading events, and further confirm our hypothesis by an empirical observational study with large-scale data collected from Twitter in the year of 2020.

Discourse segregation

Social networks on social media are a system characterized by the community structure of social connections and communication activities. Real-world and online social networks are highly modular (Girvan & Newman, 2002). Modularity means the level of network divisibility into subnetworks or communities, indicated by dense intra-module connections and sparse inter-module connections (Newman & Girvan, 2004), and reflects a type of social segregation. Communication networks are often segregated, a phenomenon that is described as audience fragmentation (Tewksbury, 2005; Webster, 2005), the fragmentation of collective attention on heterogeneous topics (Weng et al., 2012), the echo chamber effect (Cinelli et al., 2021), or the polarization of public political opinions. These segregation properties emerge as a result of: (a) contagious information diffusion mechanisms, (b) heterogeneous and concentrated interests among distinct communities (Java et al., 2007), and (c) individuals' selective exposure and selective sharing favoring attitude-consistent community members (Aruguete & Calvo, 2018). We discuss each in turn, below.

First, previous studies usually describe information diffusion as a form of contagion where message exposure increases the probability of propagation of the message (Centola, 2010). Importantly, contagion is governed by social reinforcement processes that regulate message sharing (Centola, 2010), meaning that clustered social connections facilitate information spreading, whereas nonclustered social structures hamper information transmission. Thus, the process of social reinforcement decreases the likelihood of spreading across communities via cross-community connections to different communities in the network (Centola & Macy, 2007). As a result, impeded cross-community information diffusion builds up an information gap that segregates public discourses into smaller communities.

Second, public discourse on social media consists of distinct messages about users' daily social activities that reflect personal and shared interests within communities (Java et al., 2007). These concentrated interests (e.g., sports, music, politics) are regulated by the community structure of the social network, thereby increasing intra-module and decreasing inter-module similarities of public discourse. Consequently, these segregated heterogeneous public interests (Weng et al., 2012) lead to segregated public discourse into different interest communities.

Third, people's attention to diverse messages on social media is not uniformly distributed. Instead, people selectively seek information that comes from sources that are consistent with their preexisting opinions (Bakshy et al., 2015) or share similar cultural backgrounds (Taneja & Webster, 2016). In addition, people's message-sharing behaviors are also biased toward audiences that share similar opinions (Shin & Thorson, 2017). Empirical evidence has shown ideological and partisan influences on selective sharing (Barberá et al., 2015; Tyler et al., 2022) and ideological congruence of exposure on social media (Wojcieszak et al., 2022). Thus, selective exposure and selective sharing together potentially create an information filter bubble within particular communities, which results in similar people forming social connections in segregated communities, which is also known as social homophily (McPherson et al., 2001).

Discourse integration

Collectively, public discourse on social media is often segregated, as demonstrated by a fragmented information diffusion process, community-concentrated attention, and the emergence of polarized political ideologies and public opinions. However, communication networks on social media are a constantly evolving system. Social connections can be reconstructed by destroying old and creating new connections as a response to temporal information sharing and posting (Myers & Leskovec, 2014). Modular patterns of information diffusion can be interrupted in response to novel social events and breaking news (Lin et al., 2014; Wu & Huberman, 2007). These social events and breaking news trigger messages that quickly dominate the social media content, which are quickly picked up by lay users and further transmitted (Heiberger et al., 2022; Mont'Alverne et al., 2022). Thus, we should expect a system whose dynamics transition between segregation and integration.

We argue that, in response to an urgent social activity or issue, modular community structures can be temporarily replaced with an integrated and highly connected network. This change should display several characteristics including defragmentation of collective attention (He & Lin, 2016), increased discourse similarity among diverse social agents, and decreased modularity in the public discourse network. Discourse network integration may result from: (a) mass media as an effect of intermedia agenda setting, (b) information diffusion that breaks the community structure through weak ties (Bakshy et al., 2012), and (c) trending topics that temporarily dominate people's collective attention in the competition for popularity. We consider each element of this argument in more detail, below.

First, intermedia agenda setting (Harder et al., 2017) describes how mass media outlets amplify the salience of and sustained attention to specific topics (Langer & Gruber, 2021) and control information diversity (Stern et al., 2020), particularly during times of extraordinary events. Media users who consume diverse mass media outlets are exposed to cross-ideology information (Mutz & Martin, 2001), which can mitigate the echo chamber effect. Empirical studies found that a diverse diet of news is consumed by people from social media (Scharkow et al., 2020), which suggests a strong interplay between the traditional broadcast news media and social media. As a result, the intermedia agenda setting that comes from the mass media is capable of triggering a national conversation and centralizing collective attention (Langer & Gruber, 2021), thus moving the discourse network from segregation to integration.

Secondly, the modular pattern of the public discourse network depends on the lack of information bridges connecting disparate communities and the contagion process, which together traps the flow of information across communities and increases the difficulty of information diffusion across communities (Onnela et al., 2007). However, when a piece of information that attracts the interest of multiple communities permeates diverse communities, there is an increase in the information's popularity across many communities (Weng et al., 2013). Thus, decreased modularity, as affected by cross-community information diffusion, leads to convergence across communities and pushes the discourse network from segregation to integration.

Thirdly, information (e.g., memes, hashtags, topics) fiercely compete with each other for popularity, which is constrained by a finite amount of collective attention (Weng et al., 2012). A segregated discourse network can be characterized by heterogeneity of content because of the distinct interests of different communities. However, segregated attention can be temporarily interrupted by bursts of high popularity content, described as trending topics (Naaman et al., 2011), which gain imbalanced attention compared to other content (He & Lin, 2016). These bursty trends can substantially decrease the amount of network modularity, increase the concentration of attention in communication networks, and globally shift the public's attention toward a few hubs (Lin et al., 2014). These trends should lead to the temporal defragmentation of discourse networks (He & Lin, 2016) and drive the discourse network to become more integrated.

In summary, public discourse oscillates between segregation and integration. However, it is unclear how information diffusion patterns shape these segregation versus integration dynamics. In what follows, we review different types of information diffusion in terms of broadcast spreading and viral spreading, and consider how each might contribute to integration versus segregation dynamics.

Diffusion dynamics: broadcast versus viral spreading

Information diffusion on social media can be categorized into two types of processes: broadcast and viral spreading (Liang, 2018). Each has distinct good, bad, and ugly impacts on public discourse in aspects such as political variety (Liang, 2018), innovation adoption (Zhai et al., 2021), challenging "dominant knowledge" (Jackson & Foucault Welles, 2015), and the spreading of false information (Vosoughi et al., 2018).

A common approach is to distinguish broadcast versus viral spreading based on the structural characteristics of the network such as cascade trees or the follower network (e.g., Goel et al., 2016; Liang, 2018). However, this approach is not without its own limitations in that it does not necessarily account for the fact that information can diffuse in ways that ignore structural characteristics of the network. Therefore, we define viral spreading as information diffusion that is driven by peer-to-peer interaction through links on social media, while broadcast spreading is defined as information diffusion that can also be driven by external influences that may come from outside of the peer-to-peer social network (Figure 1A and B). This definition is motivated by the fact that public discourse is influenced by both within-network peer-to-peer interactions (captured by prior research examining cascade tree structures) and broadcasting mechanisms from exogenous sources, such as mass media, news websites, video, and algorithmic recommendations, which are important but comparatively less studied sources of information diffusion (Zhang et al., 2016). We expect that these two types of spreading patterns can be distinguished by several characteristics: the network structures of diffusion cascades (Goel et al., 2016), the sources of diffused information (Myers et al., 2012), and the volume of information diffusion via hashtag frequencies (Crane & Sornette, 2008). Why?

With our definition above, broadcast spreading can be understood to occur independent of the structural follower network. When this happens, a message from a single source is received by a large audience with a shallow diffusion structure. By comparison, and sticking with our definition, information diffusion via viral spreading is constrained by the peer-to-peer social network topology. Therefore, information diffusion via viral spreading can only occur via multilevel branching as a message diffuses through multiple sources (Figure 1C and D, Liang, 2018; Goel et al., 2016). This characteristic can be measured by the structural virality of the cascade tree, defined as the average distance between all pairs of nodes in the cascade tree (Goel et al., 2016). Cascades that spread more in-depth are considered more viral, and cascades that spread more in-breadth are considered more broadcast.

Research on structural virality has revealed important diffusion mechanisms for selective information sharing (Liang, 2018) and information spreading during individual critical events (Liang et al., 2019). However, there are limitations to this method. Structural virality ignores information from multiple sources such as trending topics, search, algorithmic recommendations, advertisements, retweets from unfollowed accounts, and so on. All these sources play a role in content diffusion on social media (Lehmann et al., 2012). Moreover, previous studies show that structural virality is typically low and independent of diffusion size (Goel et al., 2012, 2016), which is important for diffusions that influence public discourse. Thus, when investigating aggregated diffusions on social media across time, structural virality might offer less insight for the influence of different types of diffusion on public discourse.

Viral or broadcast information diffusion patterns can also be characterized by their distinctive information sources (Zhang et al., 2016). Essentially, viral spreading comprises information diffusion via peer-to-peer structural networks while broadcast spreading can diffuse information from sources external to the peer-to-peer network, especially during critical events (Lehmann et al., 2012) such as health crises or political events (Lin et al., 2014).

A related approach for examining the viral versus broadcast distinction characterizes the temporal dynamics of information diffusion. Broadcast spreading of information can be triggered by exogenous influences beyond peer-to-peer social networks, such as mass media broadcasting, news media websites, advertisements, or algorithmic recommendations, and corresponds to an abrupt growth in content popularity followed by a gradual decay process (Figure 1E), whereas viral spreading of information, such as viral memes, opinions, or rumors, often emerges from endogenous sources, grows gradually, and decays abruptly (Figure 1F, Crane & Sornette, 2008; Lehmann et al., 2012). Thus, broadcast spreading shows a bursty nature as a sudden response to the occurrence of critical social events, which trigger a global information super-spreading event, and can be illustrated by abrupt bursts in content popularity (Lorenz-Spreen et al., 2019) that are separated by inter-event time intervals.

In summary, we understand these three ways of characterizing viral versus broadcast spreading as complementary. However, there is a gap in our knowledge. How information broadcast versus viral spread influences global discourse is not well understood. To address this gap, we capitalize on the

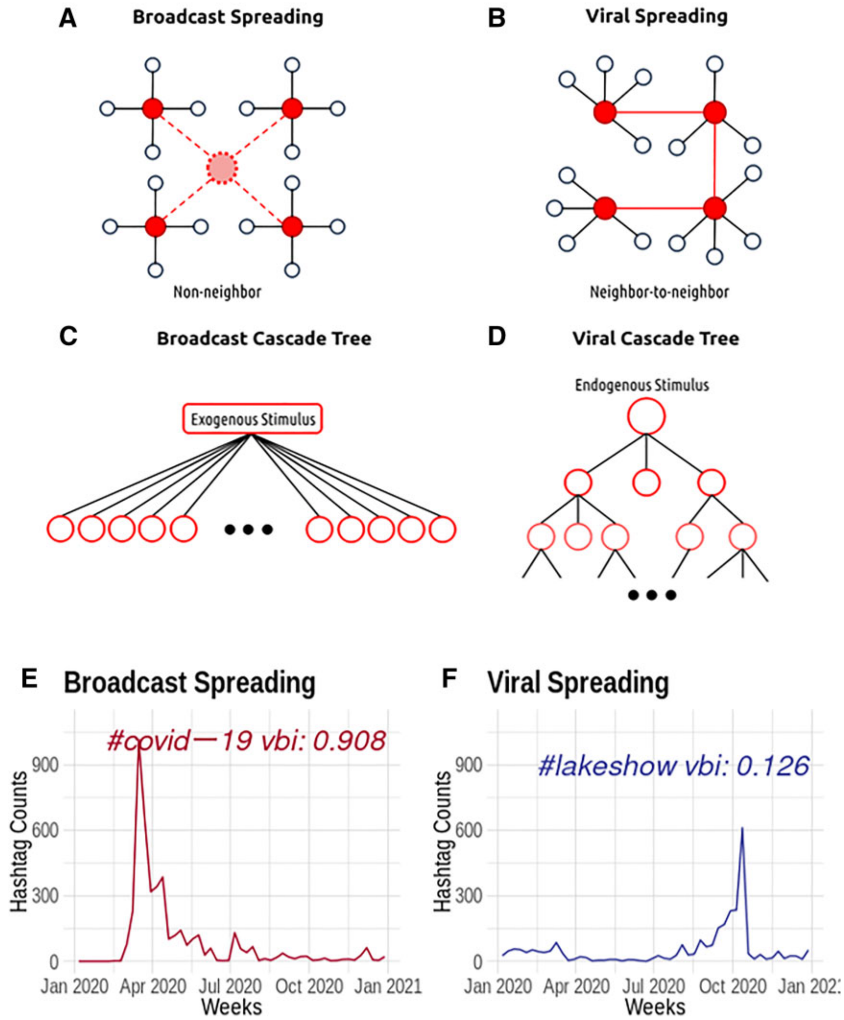

Figure 1. Diffusion structures on Twitter. (A) Broadcast spreading is defined as message diffusion from a single broadcaster to many recipients without following structural peer-to-peer connections. (B) Viral spreading is defined as message sharing among neighbors through social connections. (C) Broadcast spreading can be characterized by a cascade tree, which follows a one-step and one-to-many diffusion process of messages. (D) Viral spreading can be characterized by a step-to-step and many-to-many diffusion process of messages. (E) Broadcast spreading has an asymmetric hashtag distribution with a fast peak and slow decay, whereas (F) viral spreading slowly builds to a peak, and then rapidly decays.

temporal properties of the third approach to classifying broadcast versus viral spread, and link it with global discourse dynamics.

Broadcast versus viral spreading influences on discourse integration versus segregation

Regarding the dynamics of discourse network segregation versus integration, viral spreading takes the form of peer-to-peer diffusion, which is regulated by a modular social network topology (Onnela et al., 2007), thus constraining diffusions to be clustered within communities of social networks (Aral & Walker, 2012). These processes indicate that the viral spreading of information diffusion contributes to the fragmentation of audiences in social media (Cinelli et al., 2021) and a segregated state of the public discourse network.

On the other hand, broadcasting processes are shallow in depth (Goel et al., 2016), grow from a small number of hubs (Lin et al., 2014), and can ignore the structural peer-to-peer network (Zhang et al., 2016), which does not necessarily follow the modular social network connections (Weng et al., 2013). Therefore, broadcast spreading can penetrate across network communities and impact public discourse globally.

Evidence for this hypothetical mechanism of viral versus broadcast spreading on discourse dynamics entails artificially constructing a discourse network on which we can simulate viral versus broadcast information diffusion events and measure the resulting dynamics. Thus, in a simulation of viral versus broadcast spreading events on a discourse network, we expect that:

> *(H1a) Increases in broadcast spreading in a simulated social network will be associated with corresponding increases in network integration and (H1b) decreased network segmentation.*

In addition, these simulated dynamics should also be observable in real-world empirical public discourse data, which would provide increased confidence in the influence of different types of information diffusion on public discourse. The integration and segregation dynamics of public discourse in real-world scenarios are influenced by complex factors.

Information spread by broadcasting is bursty and novel in nature (De Domenico & Altmann, 2020; Wu & Huberman, 2007) and can quickly orient public attention in response to shocks. In addition, information spread via broadcasting is capable of reaching a broader audience (Mutz & Martin, 2001). Empirically, King et al. (2017) found that the publication of news stories on mass media can cause an increase in the corresponding topics in public discussion on social media immediately, and such an increase is evenly distributed regardless of political partisanship, gender, or geographical regions. Therefore, and especially at times of critical prosocial and antisocial events, we expect that information spread via broadcasting integrates the discourse network and increases the similarity among social agents in the empirical discourse network. On the other hand, during times without the occurrence of critical social events, the empirical discourse network would remain segregated since more information would be constrained within peer-to-peer social network communities. Thus, we hypothesize that:

> *(H2a) Increases in broadcast spreading in real-world Twitter data will be associated with corresponding increases in network integration and (H2b) decreased network segmentation.*

The above discussion suggests that the broadcast versus viral spreading pattern is driven by contemporary media events, which compete with each other for limited attention. When critical information from external events infuses the public sphere, event-relevant topics should dominate and focus collective attention and public discourse. This concentration can be illustrated by an inequality in the popularity of competing content (He & Lin, 2016; Lin et al., 2014). For example, during an eventful time, such as the Black Lives Matter (BLM) protests, the majority of public discourse will contain BLM-related content, thus having a high volume in popularity relative to other content, and thereby triggering the broadcast spreading of messages. Conversely, during an ordinary week when no critical events are happening, public discourse will contain more equally distributed content and have low inequality in popularity of all content, leading to fragmented viral information spreading. Therefore, we hypothesize that:

> *(H3) Increases in broadcast spreading in real-world Twitter data will be associated with increases in the use of hashtags.*

Method

We report the results from two studies: simulation and empirical. H1a and H1b were tested in the simulation study. H2a, H2b, and H3 were investigated using real-world Twitter data.

Open science practices

Our project adopts open science practices (Dienlin et al., 2021), including a preregistration (https://osf.io/eqxvg), open data, and materials (https://osf.io/8fj4r/).

Simulation study

Defining the network

We provide a conceptual overview of the viral versus broadcast spreading simulation (Figure 2A, for technical details, see Section 1 in supplementary material; for robustness, we also conducted our analysis on an additional simulated network topology, see Section 2 in supplementary material). We randomly generated a scale-free social network with 10,000 nodes that represented individual users. Each node was seeded with randomly drawn values that encoded their "discourse." Over 1,000 iterations, a node's discourse was influenced by the type of spreading event. For viral spreading, a contagion model of information diffusion restricted influence to locally connected nodes, up to four nodes deep. This represented how viral spreading diffuses endogenous information among nodes in local modules. By comparison, broadcast spreading could influence any node in the network, but only one layer deep. This represented how exogenous information can ignore network topology to spread across a network. Measures of integration and segregation were calculated at each iteration (definitions below).

Empirical study

Sample and sampling plan

Users and tweets were sampled using the Academic Twitter V2 API, following a multistage pipeline. In the first stage, we pseudo-randomly sampled $n = 42,903$ users who were from the United States of America and were English speaking (see Section 3 in supplementary material). From this sample, we filtered out users with less than 100 tweets or more than 20,000 tweets. Users with less than 100 tweets were less likely to have tweets in every week of 2020. Users with more than 20,000 tweets were excluded because such a high volume of posts is not representative of the typical Twitter user. Finally, we filtered out users without a tweet in each week of 2020. The filtered list included $n = 13,640$ users with $n = 23,275,139$ tweets.

We estimated the number of bots using the Botometer V4 API (Sayyadiharikandeh et al., 2020), which assigns each user a probability score: 0 (likely human) – 1 (likely bot). What constitutes a bot is unresolved. We chose a conservative cutoff where accounts with a score ≤ 0.5 were labeled as a "human" and >0.5 were labeled as a "bot." At this threshold, 25.6% of the filtered list was labeled as a "bot." After applying all filters, our final sample consisted of $n = 10,155$ Twitter users and 18,000,929 tweets (for a rationale, see Section 4 in supplementary material).

Defining the network

We again provide a conceptual overview of the empirical network construction (Figure 2B, for technical details, see Section 5 in supplementary material). The unit of analysis in the current study is in the temporal dimension. We examined discourse in each week in order to smooth daily and hourly fluctuations of diffusion and discourse dynamic patterns. For each full week (52) in 2020, we constructed a discourse similarity network. Nodes represented each user ($n = 10,155$) and edges represented the pairwise cosine similarity between user tweets. This resulted in $52 \times 10,155 \times 10,155$ dense weighted networks. Such networks contain noise edges, but there is no known way to precisely identify a noise edge. We adopted a common practice of reducing noise by applying multiple thresholding techniques. Backbone thresholding (Majó-Vázquez et al., 2019; Serrano et al., 2009) was our primary approach; we report results for additional global thresholding approaches.

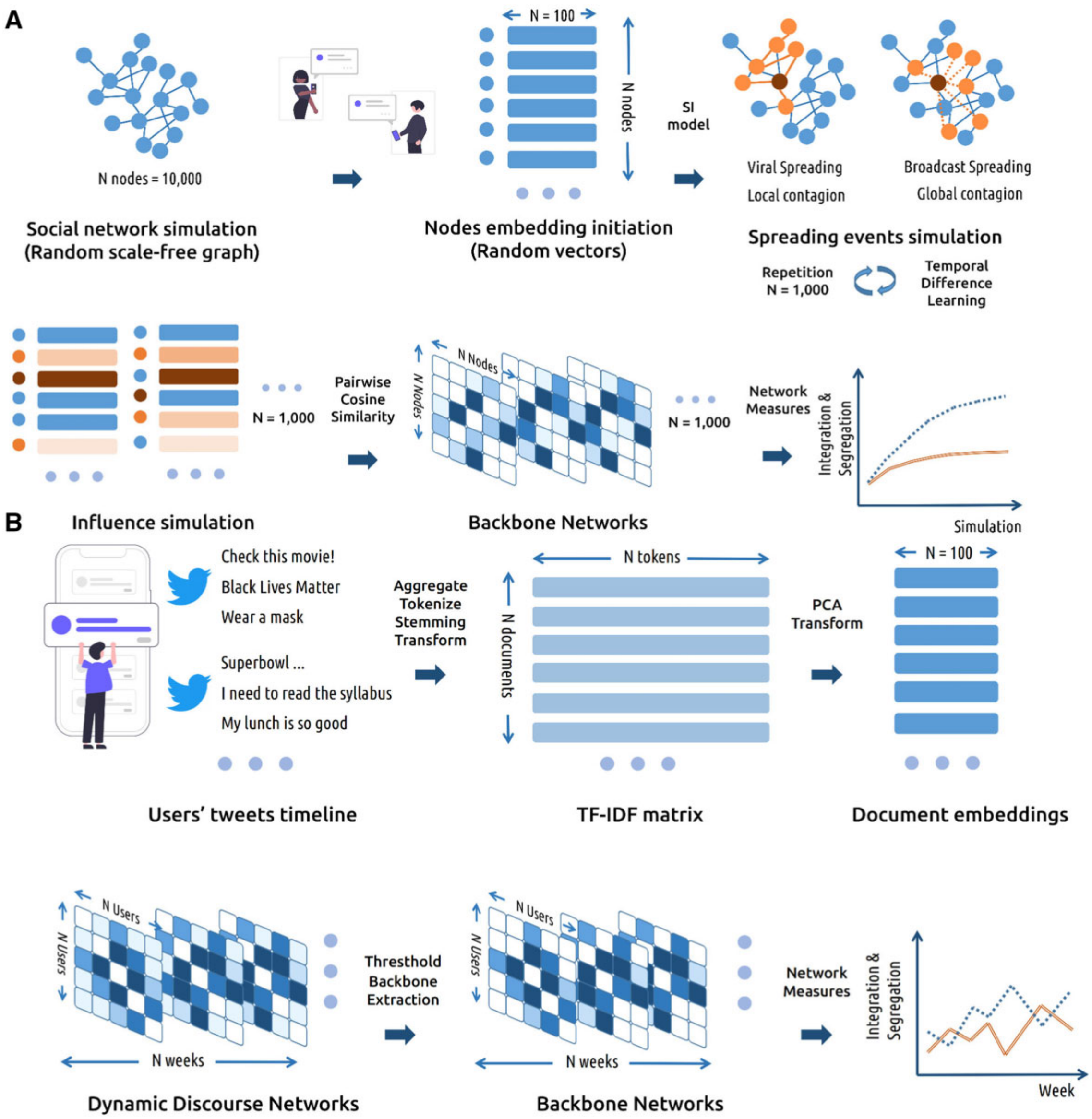

Figure 2. Conceptual diagram of the analytical pipeline. (A) The network simulation model followed a multistage analysis. (B) The empirical Twitter network analysis followed a nearly identical pipeline to the simulation analysis.

Independent measures

Viral versus broadcast spreading index (*vbi*)

We developed a novel continuous measure to distinguish between viral and broadcast spreading. The *vbi* ranges from 0 to 1 with values closer to 1 indicating broadcast spreading and values closer to 0 indicating viral spreading (for rationale and calculations, see Section 6 in supplementary material). For robustness, we also examined additional approaches to defining this index (Section 7 in supplementary material).

Dependent measures

Integration

Integration (for an operational definition, see Section 8 in supplementary material) is the average weighted degree of all possible discourse network edges. Edge weights take a value from 0 to 1. Therefore, integration also ranges from 0 to 1, with higher values indicating higher integration.

Segregation

Discourse network segregation was calculated as modularity, which captures the level of nonoverlapping partitioning of the network into communities, with a higher value indicating higher segregation (for an operational definition, see Section 8 in supplementary material). Calculating modularity requires assigning nodes to communities. To do this, we employed a Louvain community detection algorithm (Blondel et al., 2008), which optimizes network modularity. Importantly, this algorithm is nondeterministic. Therefore, for the empirical Twitter data, we applied this algorithm 100 times for each discourse network for each week and took the average modularity score as our measure of discourse segregation. Modularity was calculated just once for simulated data.

Week eventfulness

In "eventful" weeks (e.g., #Covid19, #BLM), fewer topics dominate discourse on Twitter, whereas in "normal" weeks, discourse on Twitter is characterized by many topics. We quantified week eventfulness using the top 100 Twitter hashtags across all 52 weeks. Specifically, we calculated the Gini coefficient for hashtag usage (He & Lin, 2016). A Gini coefficient of 0 means that each hashtag has the same frequency of use within a given week, and therefore represents a "normal" week. By comparison, a Gini coefficient of 1 means that only one hashtag has a high frequency of use within a given week, and this would represent an "eventful" week.

Results

Simulation study

We compared the effect of each type of simulated spreading event on network integration and segregation (Figure 3A and B). Two regression models were fit: a full model with terms for the number of events and a dummy variable for broadcast (1) versus viral spreading (0), and a reduced model with only the number of events term. The models were compared using analysis of variance (ANOVA).

For integration, the full ($F(2, 1997) = 3977.0$, $p < .001$, *Adj.* $R^2 = 0.799$) and reduced ($F(1, 1998) = 737.7$, $p < .001$, *Adj.* $R^2 = 0.269$) models were significant. The full model better fit the data ($F(1, 1997) = 5147.8$, $p < .001$, $R^2 = 0.526$). The spreading type variable was significant and positively signed ($b = 0.039$, $t(1997) = 71.75$, $p < .001$). The model comparison between the full and reduced model suggests that H1a was supported.

For segregation, the full ($F(2, 1997) = 3977.0$, $p < .001$, *Adj.* $R^2 = 0.799$) and reduced ($F(1, 1998) = 832.3$, $p < .001$, *Adj.* $R^2 = 0.294$) models were significant. Again, the full model better fit the data ($F(1, 1997) = 5028.1$, $p < .001$, $R^2 = 0.505$). The spreading type variable was significant and negatively signed ($b = -0.0002$, $t(1997) = -70.91$, $p < .001$). H1b was supported.

Simulation results at different model parameters

Simulations are powerful because they allow for interrogating different parameter levels. Therefore, we simulated different levels of learning (α; 0.1–0.4) and infection rate (β; 0.1–0.4). Results (Section 1 in supplementary material) are largely consistent with our preregistered parameters. For all levels of α, viral spreading is associated with low and sustained levels of integration, and elevated and sustained levels of segregation. For broadcast spreading, increases in α correspond to dramatic increases in integration and decreases in segregation. A similar pattern is observed for all levels of β.

Empirical study

To test H2a, the *vbi* score based on temporal hashtag popularities for each week was regressed on the integration score for the backbone network for each week. The overall model

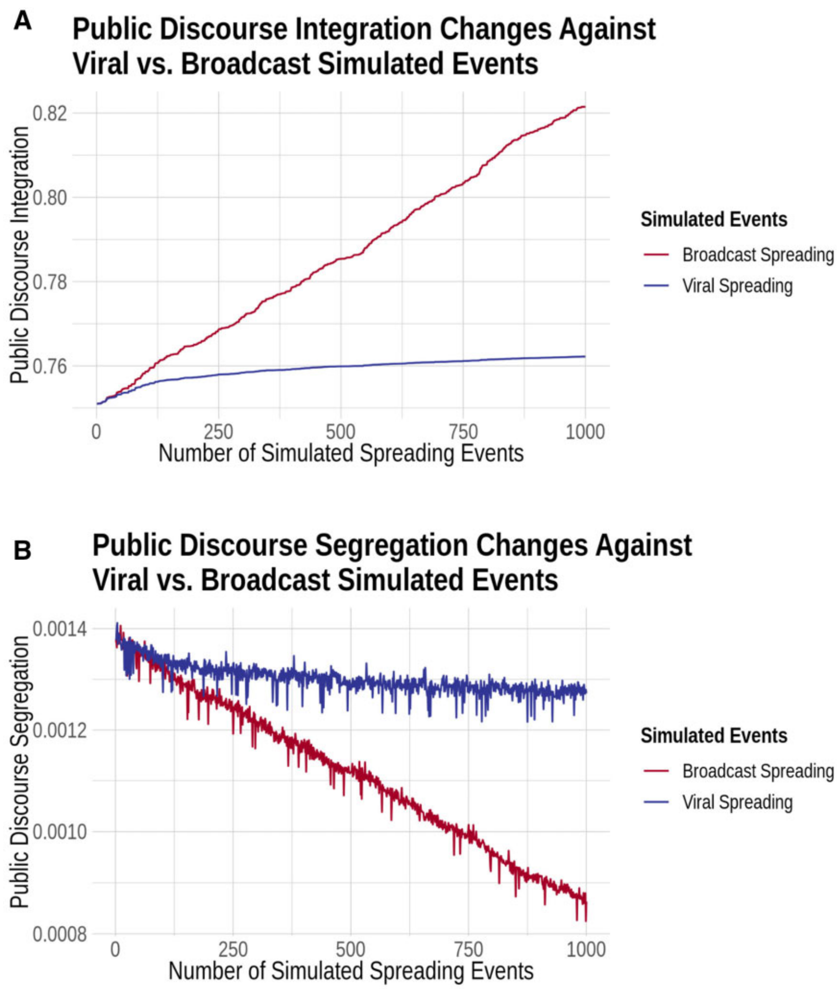

Figure 3. Simulation results. (A) Integration and (B) segregation results for the simulated discourse network.

was significant ($F(1, 50) = 4.723$, $p = .035$, Adj. $R^2 = 0.068$) and *vbi* had a significant positive effect on the network integration ($b = 0.073$, $SE = 0.033$, $t(50) = 2.173$, $p = .035$; Figure 4A). Therefore, H2a was supported.

As a test of test H2b, the *vbi* score for each week was regressed on the segregation score for the backbone network for each week. The overall model was significant ($F(1, 50) = 5.46$, $p = .023$, Adj. $R^2 = 0.080$) and showed that *vbi* has a negative effect on network segregation ($b = -0.190$, $SE = 0.081$, $t(50) = -2.337$, $p = .024$; Figure 4B). H2b was supported.

As an additional post hoc robustness check, we examined H2a and H2b by testing the relationship between the percentage of broadcast spreading, evaluated by the percentage of peer-to-peer connection between retweets with each week (as described in Section 7 in supplementary material). The percentage of broadcast spreading had a significant positive relationship with discourse integration ($b = 0.305$, $SE = 0.103$, $t(50) = 2.973$, $p = .005$) and had a negative relationship with discourse segregation ($b = -0.802$, $SE = 0.249$, $t(50) = -3.229$, $p = .002$).

As a robustness check, we tested H2a and H2b by examining the confidence intervals of the regression coefficients of *vbi* on integration and segregation at different network thresholds. The results (Figure 4C) show that the relationship between *vbi* and network integration (H2a) is robust regardless of thresholding. The relationship between *vbi* and network segregation (H2b), though in the expected direction, is only significant for the backbone threshold. We also tested H2a and H2b on the dataset after filtering out verified users, and the result is robust to the exclusion of verified users (Section 9 in supplementary material).

H3 predicted a positive relationship between *vbi* and week eventfulness. Supporting H3, week eventfulness varies with *vbi* for different weeks in 2020 (Figure 5A). A regression model ($F(1, 50) = 22.31$, $p < .001$, Adj. $R^2 = 0.295$) also shows that *vbi* is significantly positively associated with week eventfulness ($b = 0.493$, $SE = 0.104$, $t(50) = 4.724$, $p < .001$; Figure 5B).

H2a, H2b, and H3 were also tested using an alternate *vbi* calculation (Section 10 in supplementary material), different Botometer thresholds (Section 11 in supplementary material), and using time series models that account for autoregressive elements in the data (Section 12 in supplementary material). Results are largely consistent regardless of analytical strategy.

Discussion

Social media connects people and amplifies different aspects of our humanity in good and bad ways. Social media helps recruit massive and diverse individuals into discussions about particular social issues, thereby integrating public discourse, increasing the diversity of voices, and promoting political engagement. Social media can also segregate public discourse

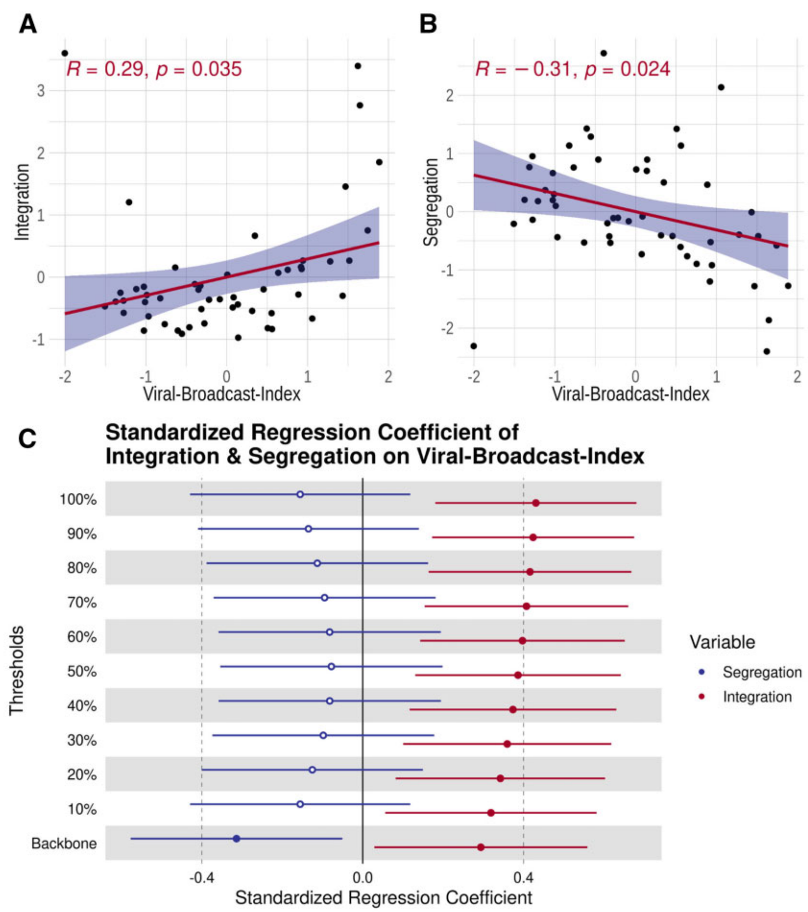

Figure 4. Results for the empirical Twitter dataset. Regression models show (A) a positive relationship between standardized (Z-score) values for *vbi* and discourse network integration and (B) a negative relationship between standardized (Z-score) values for *vbi* and network segregation. (C) Standardized *vbi* regression coefficients, plotted for different thresholds.

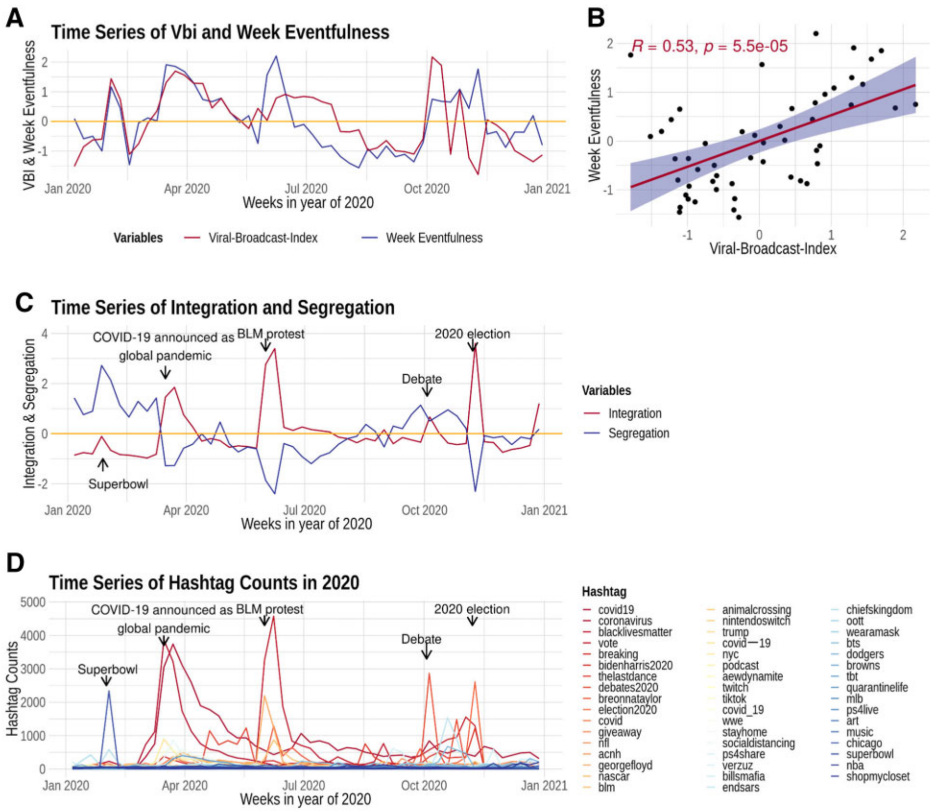

Figure 5. Results for the empirical Twitter dataset. (A) Time series plot showing standardized values (Z-score) for week eventfulness and the *vbi* index. (B) A regression model shows a positive relationship between standardized (Z-score) values for *vbi* and week eventfulness. (C) Standardized values (Z-score) for integration and segregation show a clear correlation, and (D) integration spikes during important exogenous events.

into modules, lead to political polarization, and speed up the spreading of false information. There is a temptation, particularly among lay audiences, to understand the effect of social media as either good or bad. Similarly, it might be tempting to understand our results as: segregation is bad, integration is good. Our study points toward a more complex interpretation. Instead of treating the effects of social media as categorically good or bad, a better approach might be to treat social media as an oscillating dynamic system, which can lead to good or bad effects depending on the contemporary social events and information diffusion patterns. Said differently, these diffusion patterns can result in segregation or integration for both prosocial and antisocial topics.

Discourse network dynamics oscillate between integration and segregation

We constructed a dynamic discourse network by connecting a large-scale sample of Twitter users with edges measured as the pairwise similarities between their tweets for each week in the year 2020. We showed that public discourse on Twitter is a dynamic system that oscillates between integration and segregation. As integration increases, segregation decreases correspondingly (Figure 5C; Section 13 in supplementary material). These discourse dynamics are bursty in nature. Specifically, the discourse network's default mode is characterized by stable and low levels of integration that are punctuated by momentary spikes in integration and decreased segregation. These integration bursts usually happen during eventful weeks and seem to result from broadcast spreading of information triggered by extraordinary social events. During times of broadcast spreading, the discourse of previously fragmented social agents becomes integrated and collective attention is concentrated on specific events. This is evident in hashtag usage, which follows the same pattern as discourse network integration (Figure 5D). Usage of any one hashtag remains low in ordinary weeks. During eventful weeks, usage of a specific hashtag increases abruptly and has an extended relaxation period, which is characteristic of broadcast spreading.

These dynamics are observational. It is difficult, and possibly ethically fraught, to intervene on the Twitter discourse network. Therefore, and to better probe the relationship between discourse dynamics and viral versus broadcast information spreading patterns, we conducted a simulation study. Simulated viral spread followed the underlying social network structure in a one-to-one contagion mode of multiple levels in depth and broadcast spreading diffused widely by ignoring the underlying social network structure in a one-to-many contagion mode of a single level in depth. We found that different types of information diffusion exert clear differences on the simulated discourse network. Broadcast spreading monotonically increased the integration of the simulated discourse network as the number of spreading events increased, but the integration of viral spreading quickly saturated at a lower level compared to broadcast spreading (Figure 3A). Similarly, discourse network segregation decreased for broadcast spreading events, but saturated quickly for viral spreading (Figure 3B). Thus, the simulated discourse network under viral spreading tends to become stably segregated while the discourse network under broadcast spreading tends to become more and more integrated.

Broadcast spreading increases discourse network integration

There is a robust positive relationship between *vbi* and discourse network integration. We also see that, at least for the backbone-thresholded network, *vbi* has a negative relationship with discourse network segregation. Viral spreading of information seems to make people focus on different topics, which is associated with a fragmented and modular discourse network structure. By comparison, broadcast spreading concentrates discourse on specific issues, which leads individuals to share similar messages, and is associated with a public discourse network that is more defragmented and integrated. In sum, public discourse on social media appears governed by dynamic shifts between viral and broadcast spreading.

To further probe this, we examined the relationship between *vbi* and week eventfulness and observed a significant positive relationship. This suggests that broadcast spreading is triggered by important events (Section 14 in supplementary material). Research shows that popularity-dominating external events facilitate exogenous information diffusion covered by mainstream media or the Twitter Timeline (algorithmic ranked tweets or topics), and drive information diffusion patterns from viral spreading to broadcast spreading (Bartal et al., 2020). Together, this suggests that social media is not an isolated system, but instead one that constantly receives and dynamically reacts to information from external sources in the real world. In summary, we found that public discourse is a dynamic system that oscillates between segregation and integration, and appears driven by the bursty information diffusion of external real-world social events.

This negative correlation between segregation and integration was not preordained. Operationally, our measures for integration and segregation are orthogonal (Section 8 in supplementary material). That we see a strong negative correlation (Section 13 in supplementary material) between the two lends divergent validity to our results. At the same time, it is informative to note instances where segregation and integration are positively related. For example, the superbowl hashtag (Figure 5C and D) was associated with increased network segregation and integration. It seems that a large community of individuals was involved in tweeting about the superbowl, which increased discourse network integration. For everyone else during this time period, they continued to tweet about other distinct topics, which increased discourse network segregation. The implication is that some topics associated with broadcast spreading can lead to network segregation, as well as integration.

Social media: the good, the bad, and the ugly

Academic and lay audiences alike express genuine concerns about negative consequences associated with social media use. Research shows that, under certain circumstances, people who use social media can be susceptible to political polarization, misinformation, or find themselves in an echo chamber. Our research suggests that these processes can be disrupted by broadcast spreading, driven by exogenous events, which integrates discourse on social media and promotes wide and diverse participation on urgent social issues.

At the same time, it is possible that broadcast spreading could be triggered by antisocial events, censorship, or authoritarian regimes (Lukito, 2020). This point is particularly interesting from a normative perspective. Public discourse is an information system that is not self-sustained by peer-to-peer diffusions, but rather vulnerable to broadcasting information. This suggests that social media could be easily influenced by external manipulations, which could be imposed by unscrupulous social media companies, malicious actors, government intervention, or some combination of all three.

For example, current algorithmic recommendation systems on social media (a source of broadcast diffusion) appear to emphasize strong emotional responses and moral outrage that is designed to facilitate sustained engagement (Brady et al., 2021). One consequence of these algorithms is that emotional and morally charged content is more likely to be shared and to diffuse on social media and appears to do so among polarized ideologies (Brady et al., 2017; Hasell, 2021) and lead to a series of cascading negative social outcomes (Brady et al., 2020). Unfortunately, many algorithmic recommendation systems are a black box, which makes it difficult to directly study their social impacts.

Similarly, online bots are often used to shape public discourse around public events such as the war in Ukraine, political elections, and more recently, the death of Mahsa Amini. Research shows that bots attract considerable attention during such events (González-Bailón & De Domenico, 2021). One interesting finding from our project is that, when we filtered out fewer bots, social media integration increased during periods of broadcast spreading, which were also associated with important real-world events (Section 11 in supplementary material). This provides further evidence that bots can have important anti-social influences on public discourse.

When it comes to the effects of broadcast and viral spreading, the good seems to come with the bad. The oscillation dynamics of public discourse on social media point to future research linking these discourse dynamics with good, bad, and ugly effects. They also suggest a need for algorithmic transparency, as well as increased focus on the role of bots, particularly during contentious events.

Limitations

Structural virality (Goel et al., 2016) directly evaluates the depth and breadth structure of the cascading tree and provides an appropriate estimate of virality for each individual hashtag. However, this measure is not suitable for the current study where the majority of the observable diffusion events are tiny cascades with a few nodes (Goel et al., 2012). To overcome this challenge, we drew on previous research (Lehmann et al., 2012) to develop a novel *vbi* measure by evaluating the distinct temporal distribution of the popularity of the spreading hashtags. The first limitation of our study is that it is unclear if structural virality and the *vbi* capture the same dynamics, and therefore future research should investigate the convergent validity between these two measures. Although, our sensitivity analyses (Section 7 in supplementary material) suggest a strong relationship between the two.

Second, our simulation study specified viral spreading events using a simple contagion model. Recent research shows that more complex contagion models (Centola, 2010) may better explain information diffusion patterns on social media. Therefore, our simple model might be imperfect for simulating discourse integration versus segregation dynamics. Nevertheless, we specified a parsimoniousness contagion model instead of a complex contagion model and achieved informative results. This calls into question which contagion model best explains what types of information diffusion on social media. Therefore, future work should focus on simulated model comparison in order to determine the diffusion process that best fits empirical data.

Third, the current study is focused on Twitter. Notably, different social media platforms vary depending on the demographics of their user base, format of the information content, mechanisms of diffusion, policies for information censoring, and so on. One limitation of our project is that we do not know how well these discourse dynamics generalize to other social media. Therefore, we encourage future studies across different platforms to better understand the core mechanisms of discourse dynamics.

Fourth, our study examined the public discourse dynamics at a relatively low temporal resolution, in weeks. This resolution was deliberately selected to temporally smooth daily fluctuations in tweets. This temporal smoothing increased the amount of the tweet data for each sampled Twitter user, thereby improving semantic similarity measurement reliability. Future studies that are designed to explore discourse dynamics in a higher or lower time resolution and can potentially provide novel insights for the dynamics of discourse network on social media.

Fifth, our study used the term frequency-inverse document frequency (TF-IDF) method to construct the semantic embeddings of tweets. This method is a simple and efficient approach to estimating the textual similarities of concatenated text data. It also is highly reproducible. However, more advanced machine learning-based approaches such as doc2vec (Le & Mikolov, 2014) or BERT (Devlin et al., 2019) might perform better in representing the semantic meaning of language data. Thus, benchmark studies to compare the performance of these methods are needed and we encourage future studies to implement these approaches when studying discourse networks.

Sixth, our study offers little to no insight into the psychological processes associated with these information diffusion patterns. Previous research has shown that reward processing (Baek et al., 2017) associated with value-based decision making (Scholz et al., 2017), shapes the decision to share information. Formally, these processes might be governed by reinforcement and norm learning (Brady et al., 2021). Future research should engage efforts to link large-scale social processes of information diffusion with individual-level psychological processes (Falk & Bassett, 2017; Huskey et al., 2020; Momennejad, 2022; Weaverdyck & Parkinson, 2018).

Finally, our data were gathered among English-speaking users located in the United States of America. It is reasonable to ask how well our results should generalize to non-American and non-English speaking Twitter users. In pilot testing, we gathered data from a comparatively small ($n = 2{,}543$) sample of Twitter users that was unconstrained by language or geographic region. We observed the same pattern of results, noting that the network actually became more modular during periods of viral spread.

Conclusion

Public discourse on social media is a dynamic system that oscillates between segregation and integration. Even though social media users tend to be fragmented and segregated into different modules based on shared interests, this segregated phase can be interrupted by bursts of broadcast spreading of exogenous information triggered by external social events, and reconfigured into an integration phase, where specific topics concentrate collective discourse.

Citation diversity statement

Citation disparities exist in communication research (Chakravartty et al., 2018; Trepte & Loths, 2020; Wang et al., 2021). We quantify our citation practices by including a citation diversity statement (Section 15 in supplementary material; Zurn et al., 2020).

Supplementary material

Supplementary material is available online at *Journal of Communication* online.

Conflicts of interest: None declared.

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