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ORIGINAL ARTICLE

Broadcast Versus Viral Spreading: The Structure of Diffusion Cascades and Selective Sharing on Social Media

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Sharing cross-ideological messages on social media exposes people to political diversity and generates other benefits for society. This study argues that the diffusion patterns of political messages can influence the degree of selective sharing. Using a large-scale diffusion dataset from Twitter, this study found that messages that spread through multiple steps are more likely to involve cross-ideological sharing. Furthermore, the study found that this positive relationship is mediated by the distance between the sharers and originators of the messages and suppressed by the number of connections among the sharers. Overall, the study found that the viral diffusion model, in contrast to the broadcast model, increases the likelihood of cross-ideological sharing and thus increases political diversity on social media.

Keywords: Selective Sharing, Selective Exposure, Information Diffusion, Cascade Depth, Political Diversity, Social Media.

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Selective exposure is a well-known phenomenon in social media. It refers to the extent to which individuals expose themselves to attitude-consistent content by choosing to engage with users or media accounts that confirm their views (e.g., Conover et al., 2011; Garrett, 2009; Himelboim, McCreery, & Smith, 2013). Researchers have expressed serious concerns regarding the potential impacts of selective exposure on democratic processes, such as fragmentation among users, polarized communities, echo chambers, and filter bubbles (e.g., Pariser, 2011; Sunstein, 2009). The rapid development of social media has made selective exposure more complicated than ever before. In the broadcast era, individuals were primarily exposed to mass media content directly, but today's social media users are exposed to messages that are shared by their networked friends. Thus, exposure to diverse views depends on the content that individuals' social networks have shared on social media platforms (Bakshy, Messing, & Adamic, 2015). Given this, selective sharing—the extent to which individuals share

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attitude-consistent content—has recently received increasing attention, although different researchers have used different terms for the phenomenon (e.g., An, Quercia, Cha, Gummadi, & Crowcroft, 2014; Barberá, Jost, Nagler, Tucker, & Bonneau, 2015; Coppini et al., 2017; Shin & Thorson, 2017).

Selective exposure and selective sharing are two different concepts. Selective exposure is an individual-level concept that concerns the psychological process of choosing information and its consequences on individuals, such as increasing opinion extremity (Huckfeldt, Mendez, & Osborn, 2004; Stroud, 2010) or political participation (Knobloch-Westerwick & Johnson, 2014; Mutz, 2002a). Selective sharing, meanwhile, is a societal-level concept that integrates individual choices into a social process. Information spreads among users, thus partially determining the content to which those users will be exposed on social media. In the broadcast era, exposure to homogenous and biased media content could naturally lead to audience fragmentation (e.g., Stroud, 2011). However, with social media, the societal-level consequences of selective exposure depend on the degree of selective sharing in users' social networks.

Studies have examined both the pervasiveness of selective sharing and its social and psychological predictors (e.g., An et al., 2014; Coppini et al., 2017). However, this line of research has paid little attention to the structure and social process of the diffusion patterns involved. Social media content can spread in a broadcast way (one-to-many), a viral way (person-to-person), or through a combination of the two (Goel, Anderson, Hofman, & Watts, 2016). Different diffusion patterns may exert different influences on selective sharing (Mutz & Martin, 2001). Therefore, instead of examining psychological mechanisms, the present study aims to empirically test the relationship between diffusion patterns and the degree to which people engage in selective sharing. More specifically, it reports on how the depth of diffusion cascades can increase the likelihood of cross-ideological sharing on Twitter. A diffusion cascade refers to the collection of diffusion paths that is found as a message spreads within a social network.

Literature review

Selective exposure versus selective sharing

Selective exposure and selective sharing are two closely related concepts (An et al., 2014; Weeks & Holbert, 2013): Any content shared by an individual must first be viewed by that individual, while shared content is viewed by more individuals in a social network. Nevertheless, selective exposure and sharing differ in form, driving mechanisms, and consequences. Selective exposure was first detailed during the broadcast era (Frey, 1986; Sears & Freedman, 1967). Specifically, empirical research has shown that partisans are more likely to select news sources that are consistent with their political beliefs and orientations. For example, American conservatives are more likely to choose Fox News, and American liberals are more likely to select CNN and NPR news programming (Iyengar & Hahn, 2009).

By definition, selective sharing is a different social behavior, which refers to individuals' tendency to selectively share attitude-consistent messages (Shin & Thorson, 2017). In the traditional media environment, sharing behavior is hard to observe, record, or process. Meanwhile, sharing in general is both constant and massive in volume, which makes data collection and analysis even more difficult. However, the sharing information on social media platforms is automatically recorded and immediately ready for analysis. Empirical studies have documented selective sharing in a wide range of online contexts. For example, political bloggers typically share hyperlinks aligned with their own political ideology rather than with the opposing side (Adamic & Glance, 2005). Twitter users are more likely to retweet messages from users who share similar political attitudes (Barberá et al., 2015; Conover et al., 2011). However, these studies also suggest that there is a significant proportion of cross-ideological retweeting.

In addition to having differences in definition, selective exposure and selective sharing are driven by different mechanisms. Selective exposure emphasizes the consumption of information, while selective sharing is a more active and deliberative behavior. Previous studies have found that people may occasionally expose themselves to opinion-challenging messages out of the desire to gain useful information (Knobloch-Westerwick & Kleinman, 2012; Valentino, Banks, Hutchings, & Davis, 2009) or even by accident (Brundidge, 2010). However, sharing opinion-challenging messages is much less common than selective exposure to opinion- challenging messages. This may be due to differences in the driving mechanisms between selective exposure and selective sharing (Coppini et al., 2017; Shin & Thorson, 2017).

The preference for attitude-consistent information arises because individuals are motivated to reduce cognitive dissonance elicited by attitude-inconsistent information (Garrett, 2009). This mechanism may be involved in both selective exposure and sharing. However, selective sharing is more visible to other users than selective exposure. Sharing is a social activity intended for or motivated by an imagined social media audience (Marwick & boyd, 2011). In selective sharing, sharers are conscious of their actions and their audience, whereas selective exposure occurs in a backstage setting in which no audience exists (Shin & Thorson, 2017). Coppini et al. (2017) argue that individuals tend to act differently depending on whether their choices are public or private, as the researchers find that motivations related to identity and opinion management are more likely to be activated when sharing is public. Overall, individuals' identity presentation and management, as well as image curation, combine to serve as an additional reason for selective sharing.

Finally, the impacts of selective exposure and sharing on democratic processes may operate at different scales. The direct consequences of selective exposure always occur at the individual level. For example, selective exposure has been found to be related to political intolerance (Mutz, 2002b), polarized attitudes (Stroud, 2010), and political participation (Knobloch-Westerwick & Johnson, 2014; Mutz, 2002a). Many societal-level consequences of selective exposure, such as polarized communities on social media, are indirect. By contrast, the consequences of selective sharing appear at the societal level. First, because sharing is related to information diffusion, biased sharing can increase the probability that people are exposed to attitude-consistent content by increasing that content's visibility. Second, selective exposure is an individual-level choice, and selective sharing can connect and reinforce those choices by spreading particular messages on social networks. Therefore, selective sharing is a complementary process to selective exposure (Shin & Thorson, 2017).

The impacts of selective exposure and sharing on democratic processes are also different, in that the influence of selective exposure is a reception effect, whereas the influence of selective sharing is a sender effect (Pingree, 2007). Theories of selective exposure have considered media audiences to simply be consumers of information, so reception effects (i.e., the media's effects on the receivers) have been examined extensively. However, given that social media platforms allow for a wide variety of sharing, commenting, and posting behaviors, researchers have challenged the reception-effects approach and begun to investigate sender effects, such as the impact of political discussions on the senders (Coppini et al., 2017). As a sender effect, sharing information may have beneficial effects on the senders, such as deepening their political deliberation (Pingree, 2007).

Broadcast versus viral diffusion

The above discussion shows that selective exposure and selective sharing are two closely related but different concepts. It is selective sharing that integrates selective exposure into a social process. If everyone in a society chose to view and share only messages consistent with their own attitudes, fragmented and even polarized social communities would likely emerge. Moreover, information can spread in different ways and show varied effects on both individuals and society. Therefore, it is worth investigating selective sharing in detail.

In the broadcast era, large-scale distribution of information relied primarily on mass media, such as newspapers and television. Traditional mass media and marketing efforts rely on the broadcast diffusion model, under which many individuals receive identical information directly from the same source (Goel et al., 2016). However, Katz and Lazarsfeld (1955) pointed out that interpersonal communication can play an important role in mediating the information flow between mass media and the public. Both the volume and impact of this interpersonal communication have greatly expanded in the age of social media. Online messages often go viral through a person-to-person diffusion process, which is often referred to as "the viral diffusion model." This term indicates that the diffusion of online messages can be compared to that of infectious diseases (Goel et al., 2016).

Conventional wisdom regarding selective sharing considers the diffusion process to be a broadcast model and then estimates the tendency to share attitude-consistent messages, but this treatment may overlook the complex dynamics of selective sharing. The structure of diffusion patterns (broadcast or viral) can influence selective sharing in different ways. First, the simple calculation of the percentage of sharing similar messages in a diffusion cascade cannot capture any evolutionary tendencies over time. Shin and Thorson (2017) argue that partisan selective sharing involves a reinforcing spiral process on social media. According to Slater (2007), media selectivity and media effects are mutually influenced, especially when personal or social identity are involved. Political ideology is a salient social identity in online political discussions (e.g., Liang, 2014). Individuals select and share ideologically congenial information, which reinforces ideological identification; identity can, in turn, increase media selectivity. Because social identity is especially important for message sharing, the tendency of selective sharing increases over time.

Although identity reinforcement may be a long-term process, Yun and Park (2011) demonstrated that the immediate and temporary online opinion climate can significantly predict willingness to post replies in online forum discussions. Many social media platforms, including Facebook and Twitter, display the real-time number of shares, which can serve as an important gauge of the opinion climate. With an increasing number of shares over time, people supporting the original message may perceive a more congenial opinion climate, and thus increase their own likelihood of sharing. In addition, people reading the message later may be exposed to the content multiple times, and thus are more likely to share it (Hodas & Lerman, 2014). Therefore, the first hypothesis of this study is as follows:

H1: The probability of cross-ideological sharing decreases over time.

The second way in which messages can spread is through the viral model (person-to-person), which can be represented graphically as a diffusion tree (Figure 1A). People can share the same messages from different users (intermediaries) in addition to the source account. In Figure 1A, individual 2 is an intermediary between the seed

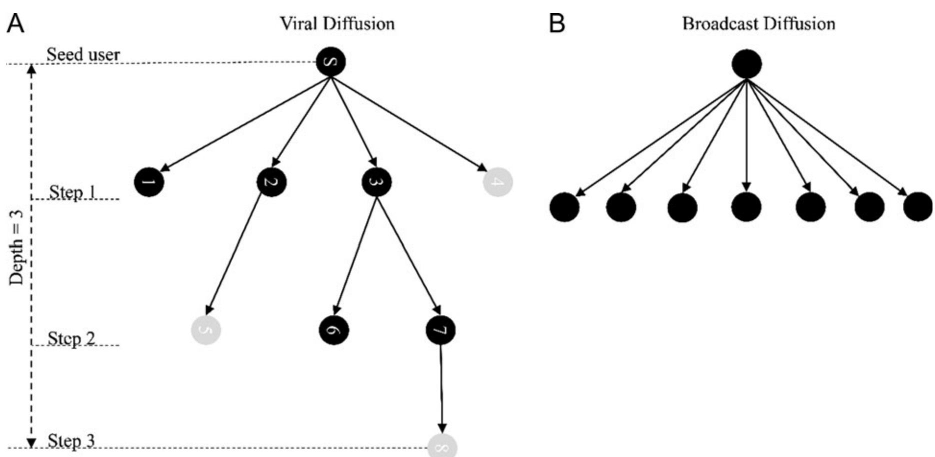

Figure 1 Examples of viral and broadcast diffusion cascades. Arrows indicate the flow of information. Step 1 users shared messages from the seed user, while the information flowed from the seed user to the step 1 users. In plot A, black and gray nodes are users from different ideology groups. Sharing between black and gray nodes indicates a case of cross-ideological sharing (i.e., S→4, 2→5, and 7→8). The probability of cross-ideological sharing in plot A increases from 25% (step 1) to 33.3% (step 2) and 100% (step 3).

user S and individual 5. A diffusion path is a chain of sharing actions. For example, S→2→5 is a diffusion path that indicates that individual 5 has shared a message posted by S through intermediary 2. A message can be diffused through different intermediaries to reach even more individuals through multiple paths. As Figure 1A shows, a message posted by seed user S could spread in four different paths: S→1; S→4; S→2→5; S→3→6; and S→3→7→8.

A collection of diffusion paths is called a diffusion cascade, of which Figures 1A and 1B are two examples. A broadcast model means that all people share the message directly from the seed user (Figure 1B). On the other hand, diffusions following the viral model have many intermediaries. The diffusion trees are composed of many person-to-person diffusion paths (Figure 1A). A central difference between the figures is the cascade depth, which is the number of generations or steps in a diffusion tree. A large depth value suggests a long chain of information diffusion and thus implies viral spreading. The length of the chain indicates how far the original message has spread. In Figure 1A, the cascade depth is three. Individuals 1–4 are the sharers at step 1, individuals 5–7 are the sharers at step 2, and individual 8 is the sharer at step 3. For Figure 1B, the cascade depth is one, which indicates a broadcast diffusion model.

Theoretical models of information diffusion through interpersonal networks have generally been framed with analogies to contagion models of infectious diseases. Messages are assumed to move through multiple steps from their sources, in the manner of epidemics (e.g., Leskovec, Singh, & Kleinberg, 2006; Watts, 2002). Diffusion cascades with more steps indicate a higher probability of person-to-person contagion. Previous studies have found that person-to-person diffusion on social media platforms is more likely to occur between users who are already well connected in a community (Liang & Fu, 2016); users in dense communities are more likely to be homogenous with respect to political ideology or other attributes (Barberá et al., 2015; Conover et al., 2011), and thus are less likely to share opposing messages. Therefore, cascade depth is negatively associated with the probability of cross-ideological sharing. This argument is also consistent with previous studies on mass media and cross-ideological exposure. For example, Mutz and Martin (2001) found that individuals are exposed to far more dissimilar political views via mass media (broadcast) than through interpersonal communication (viral).

However, the relationship between cascade depth and cross-ideological sharing could also be positive, due to the underlying social network structures. Greater cascade depth may increase the chances that sharers come from different social communities (Weng, Menczer, & Ahn, 2013), and thus may increase the probability of cross-ideological sharing. Potential sharers who are far from seed users may be less familiar with those seed users' ideological positions, so ideological identity may be less salient in guiding their behaviors. In addition, due to the social distance between the sharers and the seed users, sharers at deeper steps may feel less psychological dissonance. Given the contradictory predictions, this study asks the following research question:

RQ: What is the relationship between the probability of cross-ideological sharing and the depth of information diffusion cascades overall?

The above discussion also suggests two mediators between cascade depth and cross-ideological sharing: connectedness among sharers and distance between sharers and seed users. Both are indicators of community structures. In social network analysis, community structure refers to the existence of sub-communities in individuals' social networks (e.g., the follower-followee network on Twitter), which is important for information diffusion (e.g., Liang & Fu, 2016). If a sharer has fewer connections with other sharers in the diffusion cascade, that sharer is more likely to be from a different community, and if all sharers are not connected with each other, they are likely to be from many disparate communities. In this situation, we would expect a larger proportion of cross-ideological sharing. The distance from the seed user has also been used as a proxy for whether an item is spreading primarily within one community or across many communities (Cheng, Adamic, Dow, Kleinberg, & Leskovec, 2014). Although both connectedness among sharers and distance between sharers and seed users suggest the existence of community structures in diffusion cascades, these indicators play different roles in bridging the relationship between cascade depth and cross-ideological sharing. The lack of any direct connection between seed users and the deep-level sharers can facilitate cross-ideological sharing. Thus, the following hypothesis can be made:

H2: The relationship between the probability of cross-ideological sharing and cascade depth (a) is suppressed by users' connectedness within the cascade and (b) mediated by whether sharers are direct followers of the seed user.

Method

Data collection

The data were collected from Twitter, which is the only popular social media platform that permits intensive tracing of diffusion paths. Because the focus of the current study is about selective sharing with respect to political ideology, only politically-relevant messages were collected. The ideal dataset might be a random sample of political tweets and their retweets. Although it is possible to obtain a random sample of tweets from Twitter's streaming API, it is difficult to identify politically-relevant tweets based on 140 characters. Using keywords searches, such as for popular political hashtags, may introduce additional biases. First, it is a near-impossible task for human beings to generate a reliable and comprehensive list of keywords for document retrieval (King, Lam, & Roberts, 2017). Second, only 20% of tweets contain hashtags (Liang & Fu, 2015). The presence of hashtags can increase the number of retweets (Liang & Fu, 2015) and cross-ideological exposure (Conover et al., 2011). Instead, the current study collected the tweets posted by members of the U.S. Congress, under the assumption that all tweets posted by the Congress members were politically relevant. Although these tweets cannot represent all political tweets, they are politically important in themselves, because traditional politicians are still influential and are opinion leaders on Twitter (Dubois & Gaffney, 2014).

This study first obtained a list of Congress members with Twitter accounts from the Govtrack.us website (https://www.govtrack.us/developers/data) in December 2016. The list included all current and previous Congress members. Their tweets posted before December 2016 were collected using Twitter's timeline API, which limits retrieval to only the most recent 3,200 tweets from each user. Ultimately, the study obtained 1,081,787 tweets from 445 representatives and senators with valid Twitter accounts. Among them, 78% (845,850) were original posts.

In order to investigate the diffusion patterns, this study further excluded any original tweets with fewer than five retweets (67.5%) or more than 1,000 retweets (0.4%). Filtering out less-shared tweets was necessary, because such tweets have too few data points in their diffusion cascades. Filtering out extremely popular tweets was to exclude the very few extreme cases that may be valuable for other studies, but are not suitable for discovering general patterns of information diffusion. The remaining 271,779 tweets served as the population of the current study; they received more than 800 million retweets. It would be enormously time-consuming to collect all these retweets due to Twitter's technical constraints, so a random sample of nearly 70,000 original tweets was used for the next step of the study.

Retweets of the original tweets were collected in May 2017 to ensure that as many retweets as possible would be captured. Because the public API only provides the most recent 100 retweets for each original tweet, this study obtained retweets from a commercial data analytics platform, Crimson Hexagon (https://www.crimsonhexagon.com/), which can provide all retweet IDs by keyword search (e.g., @username). Therefore, only the official retweets (i.e., by clicking the retweet button) were collected. Modified tweets were included when the tweets were modified after clicking the retweet button. This study then obtained all other variables of these retweets (e.g., posting time and user name) through public APIs based on the tweet IDs. Ultimately, the dataset contained 942,395 retweets from 44,747 original tweets that were posted by 337 Congress members. A total of 297,566 Twitter users were involved.

In addition to the retweet content, the retweet objects also inclued the retweeters' user names. This study also collected all retweeters' followed Twitter friends (i.e., followees). The followees were essential to constructing several key variables in the formal analyses, as the followees were used to reconstruct the diffusion paths, estimate users' ideological positions, and construct the follower-followee networks among the retweeters for each diffusion cascade.

Measures

Diffusion cascades

The first task was to reconstruct the diffusion paths of the original tweets posted by Congress members. Information diffusion on Twitter depends largely on the official retweet function, which is similar to the share feature on Facebook. A diffusion path is a chain of retweeting actions. However, it is technically difficult to trace these paths on

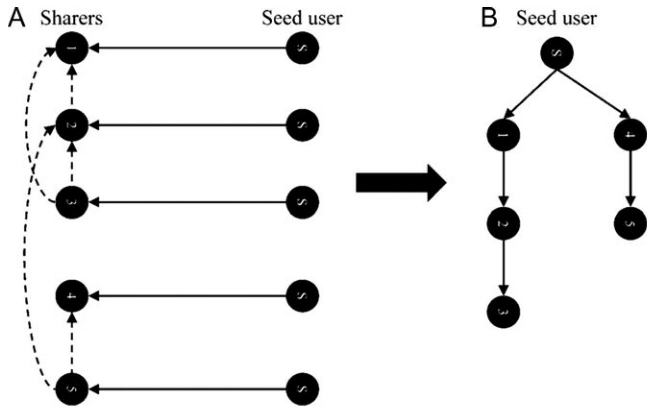

Figure 2 The method of reconstructing a diffusion cascade. The solid arrows indicate information flow, while the dashed arrows indicate the following relationship.

Twitter. First, the population of retweets is required, which can only be obtained via purchase from Twitter. Second, Twitter's official API only returns the users who originally posted the tweets, rather than the users from whom the retweeters directly retweeted. For example, if user 2 retweeted a tweet originally posted by user S through user 1 (so that 2←1←S), the Twitter API returns 2← S and exludes the intermediate user (see Figure 2A). Eventually, for any original tweets, the official API returns a list of retweeters under the assumption that all retweeters (sharers 1–5 in Figure 2A) retweeted a given message directly from seed user S.

To solve this problem, we needed to find the intermediaries in diffusion paths and then reconstruct the diffusion cascades (see Figure 2). This study first sorted the retweets in chronological order from earliest to most recent. For the first retweeter, sharer 1, the message was directly retweeted from S. For the second retweeter, sharer 2, assuming that 2 follows 1, the present study considered the most recent user to be the intermediary. Therefore, we obtained the diffusion path 2←1←S. For the third retweeter, sharer 3, assuming that 3 follows both 1 and 2, this study considered the most recent one, sharer 2, to be the intermediary (3←2←1←S). Finally, we converted a list of retweeters (Figure 2A) with time stamps into a diffusion cascade (Figure 2B). The R code is available online (https://github.com/rainfireliang/RetweetingPaths). A similar idea has been applied to reconstruct sharing cascades on Facebook (Dow, Adamic, & Friggeri, 2013). According to the algorithm, the study identified 940,290 retweeting cases from the 44,747 original tweets posted by the 337 elected officials.

Cross-ideological sharing

Cross-ideological sharing was measured by comparing the ideological difference between adjacent participants in a diffusion tree. For example, if user A (who leans left) retweets a message from user B (who leans right), that qualifies as a case of cross-ideological sharing (see Figure 1). If retweeters are from the same ideology group, it is classified as a within-ideology case of sharing. The present study coded cross-ideological sharing as 1 and within-ideological sharing as 0. However, before that step, we had to identify the ideological preferences of all 297,566 retweeters in the diffusion cascades.

Ideological positions

Ideological positions were estimated using the R package "tweetscores," which was developed by Barberá (2015). This method was chosen because it assumes that users prefer to follow the social media accounts of elected officials whose political views are ideologically similar to their own. Relying on this assumption, Barberá (2015) developed a statistical model that simultaneously estimates the positions of political elites and ordinary Twitter users. The original model has been validated using officials' party affiliations and ordinary users' campaign contribution records. The resulting score of the model is a continuous variable (mean = 0). The current study dichotomized the variable into left (<0) and right (>0) leanings. Of the 337 Congress members in our dataset, there are 167 Democrats, 161 (96.4%) of whom are classified as on the left. Among the 169 Republicans, 158 (93.5%) are classified as on the right. For other participants, 169,426 (56.9%) are on the left and 102,483 (34.4%) are on the right.

Using the followee data of all retweeters, a follower-followee network among retweeters for each diffusion cascade was constructed to indicate the underlying structure of the relationships among users who shared similar interests. Based on these follower-followee networks, for each retweeter in each diffusion cascade, connectedness was measured by the number of followees who also retweeted the message. High connectedness indicates that a retweeter is well connected within the local community. The same retweeter may have multiple connectedness values in different cascades. Based on the same data, this study also measured the approximate distance between sharers and seed users by examining whether a retweeter was following the seed user.

Data analysis

The data are multilevel in nature: the first level is retweet, the second is tweet, and the third is the seed user. The data were organized such that each row represents a retweeting action (who retweets from whom). The retweeting actions are nested in diffusion cascades. A diffusion cascade can be represented in multiple rows, and a seed user can initiate multiple cascades. Therefore, it is appropriate to employ a multilevel analysis to model the probability of cross-ideological sharing for all retweets as nested in tweets that are nested in seed users. In order to test the mediation effects on the multilevel data, a multilevel mediation model using a structural equation model was employed (Hayes, 2013). This study estimated the random intercept (fixed slope) multilevel mediation model, with all variables measured at the first (retweet) level.

This study estimated political ideologies and diffusion paths based on the following relationships, which are evolving over time. The following networks that were collected do not represent the networks at the point of retweeting. Although networks at the point of retweeting are difficult to collect, it is possible to estimate to what extent collecting following networks retrospectively can influence the results. In order to test the robustness of the findings, the study divided the diffusion cascades initiated in 2016 into 12 sub-datasets by month, and then performed the multilevel mediation analysis for each subset. If all estimates are consistent over time, then the evolving networks will not influence our conclusions.

Results

Descriptive statistics

Of the 940,290 retweets, 83.2% were directly retweeted from seed users. On average, the depth of a typical diffusion cascade in our data was less than 2 (M = 1.23, Mdn = 1, SD = .76, Max = 48). Of the information cascades, 33.5% had a depth of 1, 79.0% had a depth of 2 or less, and 93.2% had a depth of 3 or less. Even though the maximum depth reached was 48, only a very small number of tweets (0.6%) spread further than six steps. In terms of the difference between the viral and broadcast models, most of the original tweets posted by Congress members spread in a broadcast fashion.

Selective sharing was predominant: 84.3% of the retweets occurred between users with the same ideology. However, there was a significant proportion of cross-ideological sharing (11.0%), while 4.7% of the retweets involved either neutral or unidentifiable users. Because this study primarily focuses on retweeting patterns with respect to ideological preferences, this study removed all cases with neutral or unidentifiable users from further analysis ($N = 895{,}257$). In the new dataset, the overall proportion of cross-ideological sharing was 11.6%. More than half of the cross-ideological retweets were posted by users on the left (54.0%). Nevertheless, right-leaning users were more inclined to share cross-ideological messages than their left-leaning counterparts in term of probability (12.2% vs. 11.1%, $\chi^2 = 243.63$, $p < .01$).

In addition, the proportion of cross-ideological retweets also depended on the temporal order of retweeting and the cascade depth. According to Figure 3A, later retweets were less likely to be cross-ideological. Because the temporal order, by definition, includes the total number of retweets, Figure 3A also implies that tweets with more retweets were more ideologically homogenous. According to Figure 3B, the proportion of cross-ideological retweeting generally increased with cascade depth and reached a maximum value of 26.4% at step 7, after which it declined. However, few cascades had a depth greater than seven steps (0.1%), so these percentages had very large standard errors.

Hypothesis testing

As noted above, the present study's data are multilevel in nature. In order to test the relationships between and mediation effects of the probability of cross-ideological sharing, time order, and cascade depth formally, this study employed a multilevel structural equation model. Table 1 presents the results.

According to Model III in Table 1, the direct effect of cascade depth on cross-ideological retweeting is positive ($B = .040$, $p < .01$, 95% CI [.032, .047]), which indicates that an increase of one additional step in the diffusion cascade increased the

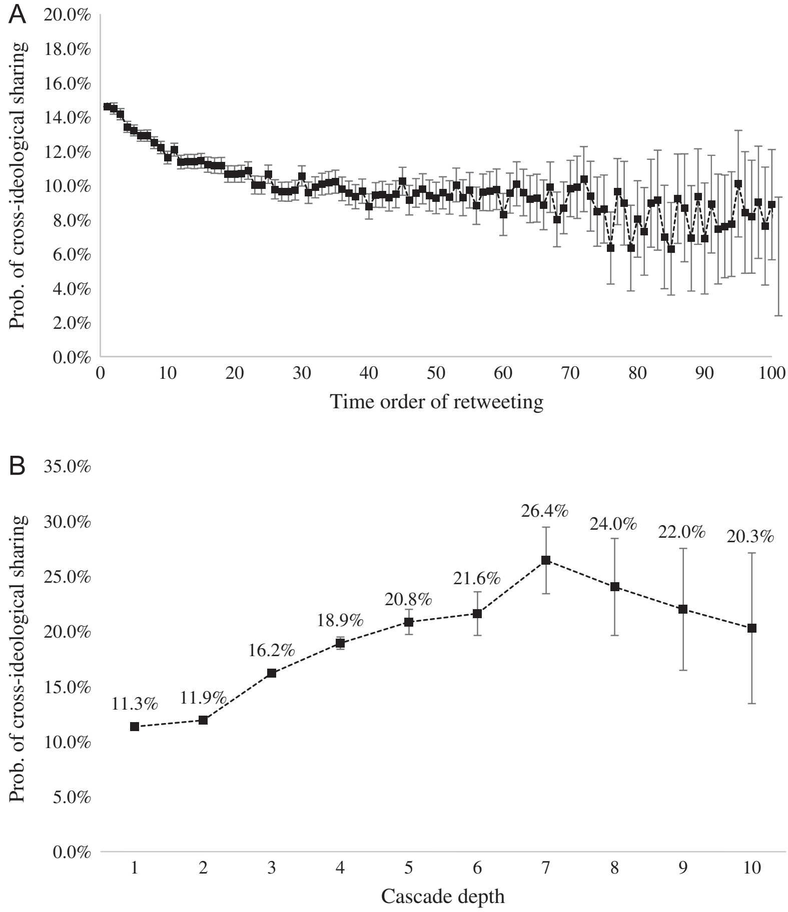

Figure 3 The proportion of cross-ideological sharing against time order of retweeting (A) and cascade depth (B). For better visualization, only the first 100 time points (97.8%) were included in A, and only the first 10 steps (99.9%) were included in B. The error bars indicate 95% CIs.

probability of cross-ideological sharing by approximately 1%. The total effect of depth is .051 ($p < .05$, 95% CI [.044, .059]) by controlling for the mediators (following or not following the seed user) and suppressors (connectedness). Regarding the research question, both the descriptive and inferential statistics suggest that cascade depth increased the probability of cross-ideological sharing overall.

As expected in H1, the direct effect of the time order on cross-ideological retweeting is negative ($B = -.082$, $p < .01$, 95% CI [−.086, −.077]). This suggests that the users who retweeted later are more likely to be from the same ideological group than the users who retweeted earlier. If the retweet is posted after one more retweet, the probability of the next retweet being cross-ideological decreases by 2%. The total effect of time order on the probability of cross-ideological sharing is smaller than the direct

Table 1 Multilevel Mediation Model in Predicting Cross-Ideological Sharing

	Model I Connectedness (*log*)	Model II Following or Not	Model III Cross Retweeting
Retweet-level fixed effects			
Mean intercept	0.554 (.010)**	−1.005 (.035)**	1.239 (.031)**
Time order (*log*)	0.021 (.001)**	−0.294 (.002)**	−0.082 (.002)**
Depth	0.157 (.001)**	−0.354 (.003)**	0.040 (.004)**
Ideology (left vs. right)	0.034 (.002)**	−0.108 (.005)**	−0.057 (.005)**
Connectedness			−0.278 (.005)**
Following			−0.154 (.003)**
Variance of intercepts			
Tweet-level	0.060 (.001)**	0.130 (.002)**	0.194 (.003)**
User-level	0.031 (.003)**	0.194 (.017)**	0.168 (.014)**
Indirect effects on cross			
Time order via connectedness		−0.006 (.000)**	
Time order via following		0.045 (.001)**	
Depth via connectedness		−0.044 (.001)**	
Depth via following		0.054 (.001)**	
Total effects on cross			
Time order		−0.042 (.002)**	
Depth		0.051 (.004)**	
Mediation/Suppression			
Time order via connectedness		6.6% (.003)**	
Time order via following		−51.7% (.014)**	
Depth via connectedness		−45.9% (.019)**	
Depth via following		57.5% (.029)**	
Marginal R^2	11.8%	25.6%	5.5%
Conditional R^2	35.8%	46.9%	32.8%
Sample size	334 users/44,674 tweets/894,317 retweets		

Note. The three models were estimated simultaneously using the structural equation model framework. In addition to the parameters reported above, the covariance between depth and time order ($B = .095$, $SE = .001$, $p < .01$) and the covariance between centrality and following ($B = .250$, $SE = .001$, $p < .01$) were estimated. Retweets with depths higher than 7 were excluded. Bayes estimation was performed. The 95% confidence interval for the difference between the observed and the replicated χ^2 values is [5809.0, 5901.7]. Marginal R^2 and Conditional R^2 were estimated based on the three separated multilevel models (Nakagawa & Schielzeth, 2013).
$^*p < .05$, $^{**}p < .01$.

effect ($B = -.042$, $p < .01$, 95% CI [−.046, −.038]), although the total effect remains negative. Therefore, H1 is supported.

The present study considered two mediators to explain the positive relationship between cascade depth and cross-ideological sharing. As stated in H2, even though both connectedness and following (whether the retweeters subscribed to posts from the seed user) are indicators of community structure in follower-followee networks, these indicators play different roles and imply different mechanisms.

First, retweeters at deeper steps are more likely to be the users who are closely connected to all other retweeters in a cascade ($B = .157$, $p < .01$, 95% CI [.154, .159]), and those who do not follow the seed user ($B = -.354$, $p < .01$, 95% CI [−.360, −.347]). Furthermore, users who are closely connected with other retweeters are less inclined to retweet cross-ideological messages ($B = -.278$, $p < .01$, 95% CI [−.287, −.268]), and users who follow the seed users are also less likely to retweet cross-ideological messages ($B = -.154$, $p < .01$, 95% CI [−.161, −.147]), after controlling for other variables.

Second, the mediation and suppression effects were estimated explicitly (they are reported in Table 1). The indirect effect of cascade depth on cross-ideological sharing via following is positive ($B = .054$, $p < .01$, 95% CI [.052, .057]), which could be a mediation or confounding effect. The indirect effect of depth via connectedness is negative ($B = -.044$, $p < .01$, 95% CI [−.045, −.042]), which indicates a suppression effect. The total effect of depth ($B = .051$, $p < .01$, 95% CI [.044, .059]) is the sum of the direct effect (.040), mediation effect via following (.054), and the suppression effect via connectedness (−.044). When controlling for connectedness, the total effect of depth on cross-ideological sharing becomes even stronger ($B = .040 + .054 = .094$). The probability of cross-ideological sharing increases by 2.3% for each additional step in cascade depth. The mediation parameter in Table 1 indicates that 57.5% (95% CI [52.2%, 63.4%]) of this effect is mediated by following. The suppression effect means that without considering connectedness, the total effect decreases by 45.9% (i.e., from .094 to .051). Therefore, H2 is supported.

In addition, Table 1 shows that the negative relationship between time order and cross-ideological sharing is mediated by connectedness (6.6%) and suppressed by following the seed user (51.7%). These findings suggest that the temporal order of retweeting and cascade depth influenced the probability of cross-ideological sharing in different ways.

Finally, to test the impact of data collection time (evolving following networks) on the above findings, the estimated indirect and total effects for the 12 sub-datasets in 2016 were reported in the Appendix. In general, the estimates are qualitatively consistent over time. Yet, quantitative variations are observed. All indirect effects of depth through following are significantly positive, and all indirect effects of depth through connectedness are negative. These findings further confirm H2. Although the total effects of time order are not negative in the last four months, the direct effects are consistently negative.

Discussion

In summary, selective sharing is the predominant mechanism for spreading political messages. Individuals are more inclined to share messages posted or retweeted by users who share their ideology. Nevertheless, this study also found a significant proportion of cross-ideological sharing (more than 11%). These findings are generally consistent with results regarding selective sharing obtained by other researchers (An et al., 2014; Barberá et al., 2015; Coppini et al., 2017; Shin & Thorson, 2017). In addition, the study has explicitly distinguished between selective exposure and selective sharing. Social media users are exposed to content shared by their networked friends. If users only share ideologically congenial messages, and users are inclined to follow ideologically similar users, these users will be more likely to be exposed to ideologically similar content. Over time, this tendency will lead to the decline of political diversity.

A major contribution of this study is that it suggests that the structure of diffusion patterns can influence the degree of selective sharing. The study found that cascade depth, which is a primary indicator of viral diffusion, is positively correlated with the probability of cross-ideological sharing. This means that if the cascade spreads more deeply with multiple steps, a greater proportion of cross-ideological sharing is expected. As Figure 3B shows, the cross-ideological percentage at step 7 is double that found at step 1. Even though that proportion begins to decline from step 8, very few cascades actually reach that level of depth.

However, this effect does not mean that the proportion of cross-ideological sharing is increasing over time or that larger cascades with more retweets have higher proportions of cross-ideological sharing. On the contrary, the present study found that the temporal order of retweeting is negatively associated with the likelihood of cross-ideological sharing. The time order being equal to the number of retweets indicates that the percentage of cross-ideological retweets is smaller in larger information cascades with more retweets. Users who have the same ideology as that of the seed user may perceive a more congenial opinion climate in the diffusion cascade with a large number of retweets, because users may estimate opinion climate from the existing number of retweets before retweeting. Therefore, larger cascades are more likely to attract similar retweeters, so political diversity declines over time.

Furthermore, this study proposed that community structure is among the major reasons for the positive relationship between cascade depth and cross-ideological sharing. The rationale is that retweeters at deeper generations are more likely to come from different communities, and thus are more inclined to retweet messages from different ideological groups. This study used two indicators to measure community structure: connectedness and following the seed user. The findings are not consistent on the surface; cascade depth is positively associated with connectedness and is negatively associated with following. As shown in Table 1, the positive relationship between cascade depth and the probability of cross-ideological sharing is only mediated by following, while it is suppressed by connectedness. This indicates that a truly viral diffusion cascade may consist of sharers from a densely-connected community whose members are not directly following the seed user.

The study clarifies that viral diffusion is a complex process. For users who are not following the seed users to retweet a message, it is necessary that either (a) those users had read a retweet from their followees, or (b) those users had read the messages from the platform itself, as with a trending topic suggested by Twitter. This study considered the second condition to be broadcast diffusion. According to our findings, successful viral diffusion requires sharers who are well connected with one another. Because these sharers are distant from seed users, they are more likely to retweet messages from the opposing viewpoint.

Overall, the impact of community structure on cross-ideological sharing presents a paradox. On the one hand, due to the close relationship among retweeters, cascade depth can decrease the likelihood of cross-ideological sharing. On the other hand, due to the significant distance between seed users and retweeters, cascade depth can also increase the likelihood of cross-ideological sharing. This study found that the mediation effect of following is stronger than the suppression effect of connectedness (difference = .098, 95% CI [.096, .100]). Therefore, the viral model leads to more cross-ideological sharing than the broadcast model.

Nevertheless, these relationships may only hold for political elites' sharing of messages. Tweets by ordinary users may be largely retweeted by their close friends. The (following) density among the sharers may be very high, which implies that homogenous sharing is dominant. The cascade depth can be very large, too, but the overall effect of depth may be negative due to a larger indirect effect through connectedness. To test this hypothesis, this study conducted a post hoc analysis by collecting a random sample of tweets containing the hashtags used in Conover et al. (2011; 43,906 retweets from 3,435 original tweets with no more than 100 retweets). The indirect effect of depth through following is .003 (95% CI [.002, .005]), whereas the indirect effect through connectedness is −.006 (95% CI [−.010, −.002]). The overall effect of depth is −.010 (95% CI [−.017, −.003]). The average density of following among sharers is .38 (compared to .21 in the Congress dataset). However, the relationships are far from conclusive. As discussed above, tweets including hashtags can cause addition biases. Future studies are needed to test the conditions and boundaries of these effects.

Alternative Explanations

The community structure explanation is largely consistent with previous explanations based on normative influence. Normative social influence occurs when individuals are motivated by their desire to conform to the positive expectations of other people (Price, Nir, & Cappella, 2006). In the current study, both indicators of community structure are negatively associated with cross-ideological sharing. According to Slater (2007), reinforcing spirals of selectivity are stronger among social groups that are more closed or susceptible to influence. Therefore, it is plausible that users from outside the community are less subject to any normative influence and that we can thus observe a higher probability of cross-ideological retweets.

Furthermore, there are different forms of normative influence. For example, according to the imagined audience theory (Marwick & boyd, 2011), people strive to socialize with their followers on social media platforms, and users are likely to share messages in which they think their followers would be interested (An et al., 2014). However, a post hoc analysis found that the number of followers who also retweeted a given message was negatively related to the likelihood of cross-ideological sharing ($B = -.208$, $SE = .004$, $p < .001$).

In addition to a purely normative influence, informational influence may also be at work. It is possible that users from outside the community who are willing to retweet a cross-ideological message are genuinely interested in that message; they find it informative and useful and agree with the opinions it expressed. Indeed, An et al. (2014) found that people who are interested in a given topic are more inclined to retweet items with which they disagree than those with which they agree.

Another plausible explanation is that the positive relationship between cascade depth and cross-ideological sharing is mediated by exposure to diverse followees, such that cross-ideological retweeters may come from the group of users who are exposed to diverse retweeters. A post hoc analysis found that exposure to diversity is positively associated with both the probability of cross-ideological sharing and cascade depth. The indirect effect is .021 ($SE = .001$, $p < .01$). Nevertheless, few users were exposed to multiple followees (4.8%), and exposure to diverse retweeters is more likely to be a consequence than a cause of information diffusion. Cascade depth can increase cross-ideological retweets and thus increase the chance of being exposed to diverse retweeters.

Theoretical implications

These findings contribute to the debate regarding whether social media is beneficial for political diversity and deliberative democracy. According to the present study, a viral diffusion model can increase cross-ideological sharing, which in turn can increase exposure to diversity though diffusion in networks. Given that sharing is a sender effect, sharing may also increase sharers' own deliberativeness (Pingree, 2007). In this sense, social media, which have been celebrated for facilitating person-to-person communications, are more capable of fostering political diversity than broadcast media. However, the reality is that most social media messages spread following the broadcast model; truly viral spreading is rare (over 99% of cascades terminated within a single generation on Twitter; Goel et al., 2016), which may limit the beneficial impact of social media. Future research into how to facilitate viral diffusion is needed.

The implications could go beyond political communication and contribute to the literature on information diffusion in general. First, although researchers have argued that the boundary between mass and interpersonal communication is blurring on social media (Walther & Valkenburg, 2017), the present study demonstrated that they still have different mechanisms and effects. Viral diffusion usually occurred among individuals in well-connected communities. Yet, the viral structure has advantages in terms of involving individuals with diverse backgrounds. Second, the structure of social networks is important for information diffusion, serving as an information conduit. In the current study, the impact of community structure on cross-ideological sharing presents a paradox. The emergence of viral or broadcast diffusion depends on the community structure. Well-connected networks can facilitate the emergence of viral diffusion, but decrease the indirect effect of cascade depth on selective sharing through social distances. Finally, information diffusion within homogenous communities might be considered less beneficial in many communication contexts, such as strategic communication. The present study suggests that the broadcast model is effective at spreading information widely, but among homogenous individuals. The viral diffusion model, on the other hand, can spread information widely across individuals with diverse backgrounds. In this sense, it is more appropriate to use the broadcast model to spread information within existing audiences and the viral model to attract new audiences.

Limitations and future studies

Using Twitter data is a distinctive way to trace the complete diffusion process and makes it possible to investigate diffusion structures in detail. However, it does have limitations. First, although this study constructed complete Twitter-specific information cascades based on the official retweeting function, this does not mean that those cascades are truly complete in a broader sense. The same content can spread in multiple paths from different seed users. It is difficult to combine all the paths because the various seed messages may use very different words to express the same idea. In addition, messages could spread through unofficial retweets, which were not considered in this study. Missing unofficial retweets may not influence the inference of diffusion paths via official retweets; this decreases the estimation of the cascade size at each step. However, the diffusion patterns may differ between official and unofficial retweets. Furthermore, the estimation of diffusion paths inevitably has errors, especially when users are exposed to multiple retweets. Different estimation methods can influence the estimation of cascade depth (Dow et al., 2013). Finally, the current study examined only a single platform; in actuality, messages can and do spread through a wide variety of means across platforms. Even though Twitter is primarily designed for information diffusion, sharing messages on Facebook is common. Theoretically, diffusion cascades on Facebook could be constructed using the same method. However, Facebook's following relationships among users are unavailable for researchers. Future studies may combine online survey and big data approaches to collect data across platforms. Besides, the messages selected in this study are biased. Tweets from Congress members cannot represent all social media messages. As suggested by the post hoc analysis, messages from ordinary users may present different patterns. Future studies are needed to test the theory in other communication contexts.

Second, there are potential measurement errors in the current study. For instance, ideology was estimated statistically. Although this method has been validated empirically, the results would be more accurate if actual party affiliations were available. In addition, the study used a binary variable (following or not following the seed user) to measure the social distance between retweeters and seed users. If researchers could obtain complete following networks directly from Twitter, distance measures could be calculated with greater accuracy. Further, the evolution of following networks, though it may not have influenced the main conclusions in this study, did produce estimation errors, as presented in the Appendix. In addition, selective sharing should be measured with respect to multiple dimensions, such as demographics, attitudes, and behaviors, in addition to political ideology.

Finally, the present study adopted a structural explanation of selective sharing, the relationship between cascade depth, and the degree of selective sharing. Previous studies have generally adopted a psychological approach to this phenomenon (e.g., An et al., 2014; Coppini et al., 2017), so future studies may incorporate the two approaches. In addition, while this study has noted the relationships between selective exposure, selective sharing, and the dynamic process that leads to societal-level consequences, such as echo chambers and filter bubbles, it did not provide any direct evidence in this regard. Future empirical studies could offer valuable insights on these topics.

Conclusion

Although the broadcast model (one-to-many) and selective sharing remain predominant in online information diffusion, the present study demonstrated that viral spreading (person-to-person) can decrease the degree of selective sharing, and thus increase the overall diversity of sharers and potential audiences in the diffusion process. By contrast, broadcast diffusion is associated with declining diversity over time. This means that person-to-person diffusion can involve more diverse participants and audiences than the broadcast model. However, this effect might be conditional on social network structures. Individuals in well-connected networks are likely to create long-chain cascades; in this situation, the positive effect of cascade depth on selective sharing via connectedness might be stronger than the negative effect via social distance between originators and sharers, which can lead to declining diversity over cascade depth. Nevertheless, this study clearly demonstrated that the structure of diffusion patterns can influence the degree of selective sharing and audience diversity. Even though mass and interpersonal communication processes are mixed on social media platforms, there are important differences of mechanism and effect between them.

Supplementary Material

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

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