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Hashtag homophily in twitter network: Examining a controversial cause-related marketing campaign

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ABSTRACT

Social media such as Twitter generate vibrant discussions related to key sociopolitical issues and have great ability to project various discourses into public arena. Yet, these discourses can be overwhelming and heated, in particular when controversial events happen. In this study, we performed topic modeling on more than 100,000 original tweets to examine Twitter discourses around Gillette's controversial cause-related marketing in 2019 and conducted network analysis through exponential random graph models (ERGM) to investigate the homophily tendency of users who used certain hashtags. Results show that users' discourses were mostly within the message frameworks of the campaign but users strongly reacted to others and top influencers in their online discussions. In addition, the mention network of these users showed homophily tendency based on hashtags. Homophily in this study was distinguished based on attraction of common users (i.e. increased chance of ties for users who both engage the hashtag) and alienation of nonusers (i.e. decreased chance of ties for users neither of whom engages the hashtag), and the comparison between ideological hashtags and conceptual hashtags revealed that homophily only manifested through ideological hashtags.

There is a growing trend of social movements using social media to organize and mobilize publics (Bonilla & Rosa, 2015; Dahlberg, 2001). In particular, Twitter has been noted by scholars as a vibrant place where users engage each other to discuss key sociopolitical topics (Park, 2013; Yu, 2016), and the platform has the power to elevate marginalized discourses to gain prominence (DeLuca, Lawson, & Sun, 2012; Penney & Dadas, 2014). Existing research generally concludes that despite some potential drawbacks of the platform such as misinformation and bullying, social media such as Twitter play an instrumental role in directing and shaping discourses (Dijck, 2011). Social media collapse multiple contexts, which makes discourses seemingly chaotic and amorphous (Boyd & Ellison, 2007). Yet, it is the collapsed contexts that provide ability for social media users to navigate various identities and contribute their personal experiences to negotiating a coalesced voice and representation (Kuo, 2018). Therefore, social media provide an ideal place to study how discourses manifest.

On the other hand, despite the efforts of companies and organizations to establish their corporate social responsibility through various cause-related marketing (CRM) campaigns (Barone, Miyazaki, & Taylor, 2000), cause-related marketing is one that comes with risks. Consumers' response to cause-related marketing range from skeptics to showing full support (Webb & Mohr, 1998). Yet, how publics respond to a controversial CRM campaign has not been adequately answered, particularly in the context of social media where discussions can be heated, multifaceted and volatile. Understanding the frameworks online users depend on to discuss a CRM campaign and the mechanisms through which discourses manifest is beneficial to theorizing socially mediated discourses, as well as to businesses and organizations that wish to find clarity in online clutters and noises.

There are unique functionalities associated with socially mediated discourses. Particularly, hashtags are used as ways to index and categorize content (Bonilla & Rosa, 2015). More importantly, these hashtags establish communities and discursive spaces for users to represent their voices and identify with other users (Jackson & Foucault Welles, 2015; Poell, 2014). Therefore, they serve as distilled versions of users' conceptual frameworks and viewpoints associated with issues. Coupled with the evidence that homophily, the phenomenon where people are more likely to form ties with ones who are similar to them, also exists in online networks (Boutyline & Willer, 2017; Centola, 2010; Colleoni, Rozza, & Arvidsson, 2014), we investigate whether homophily patterns based on hashtags exist in a Twitter mention network of a CRM campaign.

Big data analytic approaches such as topic modeling provide opportunities to utilize the enormous amount of user-generated content to

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understand the underlying frameworks and thematic structure. To that end, in this study, we performed topic modeling on more than 100,000 original tweets generated by Twitter users regarding a CRM campaign to analyze the prominent topic profiles. We also performed exponential random graph models (ERGMs) to test and examine social network ties based on users' engagement of certain hashtags.

In the following section, we first reviewed literature regarding cause-related marketing and Twitter as a social media platform that is vibrant in its nuanced discussions on social and political issues. Then we turned readers' attention to the role of hashtags in Twitter discourses and introduced the concept of homophily. Research question and hypotheses were developed and proposed through the literature review. In the next section, we discussed the data collection and processing procedures. Results were then reported, and discussions and implications were made regarding the characteristics of discourses on Twitter and homophily based on users' engagement with certain hashtags.

1. Cause-related marketing

Cause-related marketing is considered as a main component of a company's corporate social responsibility initiatives (Barone et al., 2000; He, Chao, & Zhu, 2019). It is a marketing strategy to promote sales and enhance companies' reputation by supporting charitable causes or donating money to nonprofit or charitable organizations (Varadarajan & Menon, 1988). In CRM research, a major focus has been on how these initiatives can help companies achieve desirable outcomes such as consumers' increased purchase intention (e.g., Nan & Heo, 2007; Yang & Yen, 2018) and employees' engagement (e.g., He et al., 2019). Following this line of research, several important factors are identified that determine how individuals perceive an organization's CRM, such as cause-brand fit (Gupta & Pirsch, 2006; Lafferty, 2007), consumers' identification or support of the cause itself (Sen & Bhattacharya, 2001), consumers' personality traits such as intrinsic or altruistic motivation (Basil & Weber, 2006; Bénabou & Tirole, 2010) and consumers' concerns over the company's ulterior motives and their skepticism (Menon & Kahn, 2003).

Despite the potential benefits, CRM campaigns are not ones without risks. Through analyzing 48 in-depth interviews with a diverse sample of consumers about their experiences and perceptions about companies' CRM campaigns, Webb and Mohr (1998) summarized four types of responses regarding companies' cause-related marketing campaigns: skeptics who generally have negative attitudes and show distrust towards companies; balancers who show generally positive attitudes towards companies' cause-related marketing campaigns but are not personally engaged in the causes; attribution-oriented consumers who care more about a company's motives; and socially concerned consumers who care deeply about the causes and show general support to the company-initiated programs. Therefore, the cause that a company supports through its CRM and the perceived motives to a large degree determine reactions.

Discourse analysis on ways consumers react to or respond to a CRM campaign is limited. Do they focus on the amount of donations? Do they debate about the cause? Are they skeptical about the organization's motives? Do they defend the organization? The potentially mixed responses to CRM campaigns highlight the challenges and difficulties a company faces, and such responses may become more prevalent and fluid on social media. This further necessitates discourse analysis on how consumers discuss CRM campaigns, particularly in a participatory and collaborative online environment such as Twitter that allows users to contribute to and shape the discourses around a topic (Ifukor, 2010; Papacharissi & de Fatima Oliveira, 2012).

2. Twitter as a discursive space

Even though the role of new media in modern democracy and political participation is not definitively established (Albrecht, 2006; Guillén & Suárez, 2005; Weber, Loumakis, & Bergman, 2003), scholars emphasize the abilities of social media platforms such as Twitter to enable collective mobilization and challenge mainstream narratives, which is foundational to a social movement (Obar, Zube, & Lampe, 2012; Poell, 2014; Segerberg & Bennett, 2011). For example, examining the role of Twitter along with face-to-face communication in organizing Occupy Wall Street protests, Penney and Dadas (2014) concluded that Twitter is instrumental to disseminating information to networked counterpublics and sustaining the connections in virtual networks that are geographically dispersed. They also noted that activists are able to articulate counter-discourses to which the mainstream media are unfamiliar and even hostile.

Indeed, emerging research on online discourses acknowledges the significant value and contributions of the numerous connections embedded in social media networks to critique power and create a community that values experiences associated with marginalized identities (Bonilla & Rosa, 2015; Jackson, Bailey, & Foucault Welles, 2018). Conceptually, even though the inequitable access to digital media, cyberbullying and misinformation spread on social media platforms may pose risks and challenges for users to engage in genuine dialogues, it is evident that users on platforms such as Twitter do engage in vibrant exchanges of information and thoughtful critique of power structure (Dahlberg, 2001). Such debates are paramount to projecting discourses of resistance into a public arena that used to be inaccessible to marginalized experiences (DeLuca et al., 2012; Penney & Dadas, 2014). In short, social media are able to elevate discourses into their prominence and the exchanges on these platforms can be powerful, constructive and meaningful.

So far, existing research has comprehensively examined the emergence of discourses on social media regarding large-scale social movements such as Occupy Wall Street, Arab Spring, the MeToo movement and Black Lives Matter (e.g., Bruns, Highfield, & Burgess, 2013; Ince, Rojas, & Davis, 2017; Kuo, 2018; Tremayne, 2014). These studies show that Twitter is nothing but a volatile environment. It provides opportunities for counterpublics and dissidents to organize and mobilize, but also a place where views and narratives clash. Social media aggravate collapsed contexts where the self is presented in multiple contexts, both private and public (Boyd & Ellison, 2007). A simple example is that private posts intended for friends or families are simultaneously on public display, which is a key logic of socially mediated publicness (Baym & Boyd, 2012). As a result, the collapsed contexts prone to social media make social media's ecology fluid and volatile, enabling seemingly chaotic yet multifaceted discourses to clash and emerge.

Given that CRM campaigns usually take on key social issues that can be controversial, it would not be surprising to see that a CRM campaign creates buzz yet polarized opinions on social media. Since consumers tend to display various responses to CRM campaigns based on their positions on the issue and perceptions of the organization's motives and brand-cause fit (Webb & Mohr, 1998), these responses may become more prominent in an online space, whose collapsed contexts and volatility intensify the interactions among multiple groups of people who have different viewpoints and understandings of the CRM campaign. It is unclear whether online users' discussions are more focused on the CRM campaign itself, the campaign messages, issues related to the cause, or the actual donation. Therefore, it is worth investigating how online users respond to a CRM campaign, so that marketing and public relations practitioners know what to prepare for when engaging social media users.

RQ1. In what ways do online users discuss a CRM campaign?

3. The role of hashtags

Twitter provides a medium where diverse interests shape social, political and cultural discourses (Dijck, 2011). Some of its platform functionalities are unique and enable various ways for users to establish connections and interact with each other. The very foundation of the platform allows Twitter users to follow other users freely. Unlike Facebook, such ties are not expected to be bi-directional. Furthermore, given each post's compressed short format, users can freely express their opinions and engage with others on quick discussions and conversations. Another prominent feature of Twitter that facilitates users' discussions and conversations on specific topics is hashtags (Bruns & Burgess, 2011).

Hashtags are often used to create discursive spaces for individuals to participate in cultural creations of meanings around a wide range of topics such as racial justice, gender equality, or health-related issues (Kuo, 2018). These discursive spaces enabled by hashtags do not require users following each other, separating the hashtag-based communities from the previously established following-follower networks (Bruns & Burgess, 2011). These hashtag communities have tremendous power to shape conversations and mobilize users. For example, Blevins, Lee, McCabe, and Edgerton (in press) examined the hashtags used by twitter users during the Ferguson protest of the killing of Michael Brown and found that twitter users use hashtags such as #IfTheyGunnedMeDown to collectively construct the meaning of being Black in America and build narratives around experiences of police brutality. These stories are diverse and multifaceted, each contributing to the traction of a social movement, and they are organized, stored, and archived through keywords-based hashtags.

In this sense, Twitter hashtags can be approached as indicators of ad-hoc publics around issues (Bruns & Burgess, 2015). These hashtag publics are aggregated groups of people in reaction to prominent social, political events or pivotal moments such as breaking news and natural disasters (Bruns, Moon, Paul, & Münch, 2016). Often times, these hashtags can even become stable sub-groups where users create spaces to discuss particular issues. For example, online support groups become a convenient and affordable platform for cancer survivors to support each other and share useful information (Chung, 2014). A well-known tweet chat around #BCSM (breast cancer social media) becomes a prominent place for breast cancer survivors to give each other emotional support and discuss a wide range of topics such as recent research breakthrough, living with cancer and tips for family members to overcome the emotional burden. These hashtags-enabled communities usually contain regular users presenting themselves as important groups of people who show care and attention to the issues.

Finally, hashtags can also be used as ideological markers to indicate a person's particular position, belief and identity within the discursive space (Blevins et al., 2019). For example, the use of either #BlackLivesMatter or #AllLivesMatter to a large degree reveals an individual's ideological position in social justice issues. These markers can be used to express self-identity and help users connect and identify with members in a broader community. As demonstrated through the development of user classification algorithms for twitter users, hashtags are often used as an important piece of information to identify users' political ideology (Conover, Goncalves, Ratkiewicz, Flammini, & Menczer, 2011; Pennacchiotti & Popescu, 2011). For instance, #tcot (top conservatives on twitter) is usually used to show someone's conservative identity. #P2 (Progressive 2.0) is used in opposition to #tcot to indicate someone's progressive political identity. This line of research on the other hand shows the users' tendency to use certain hashtags to express personal identity and connect with similar users.

Similarly, separate research has shown the ability of hashtags to establish coalesced, shared identity (Jackson & Foucault Welles, 2015; Kuo, 2018). People who are marginalized by the existing social structure have more chance to engage in community-specific (and identity-specific) self-representation (Jackson & Foucault Welles, 2015; Poell, 2014). These users utilize the technical architecture of social media platforms such as Twitter to connect to a broader discourse community (Bonilla & Rosa, 2015). At the same time, the communities enabled by specific hashtags become main ways for Twitter users to navigate and actively participate in online discourses to co-construct meanings around particular identities, and therefore collectively shape, define and redefine a coalesced identity (Kuo, 2018). In short, hashtags open up discursive spaces that connect like-minded people.

It is evident that homophily, a social network concept indicating the higher likelihood of individuals forming ties based on similar characteristics (McPherson, Smith-Lovin, & Cook, 2001), drives the formation of ties in online social networks (e.g., Centola, 2010; Colleoni et al., 2014). Simply put, people like to establish connections with people exhibit similarities such as status and cohort. In fact, the homophily tendency on Twitter is believed to create the echo chamber effect on online discussions about political issues (Boutyline & Willer, 2017), where users who share similar political beliefs tend to follow each other. In addition, Aiello et al. (2012) demonstrate that topical similarity on social media predicts friendship networks and Conover, Goncalves, et al. (2011) and Conover, Ratkiewicz, et al. (2011) show that the retweet network during the 2010 congressional elections indicates that Twitter users are more likely to retweet like-minded information. These studies provide convincing evidence that homophily in online networks manifests through users following those who share similar ideology and topical content. Given the major functionalities of hashtags reviewed above of serving as ideological markers (Blevins et al., 2019; Jackson & Foucault Welles, 2015) and creating topical discursive spaces (Bruns & Burgess, 2015; Bruns et al., 2016; Kuo, 2018), we expect that homophily patterns also manifest in ways Twitter users use hashtags when discussing a CRM campaign.

Furthermore, following Blevins et al.'s suit, we believe it is worth distinguishing the role between ideological hashtags and conceptual hashtags. In their study on the Ferguson protest for racial justice, Blevins et al. traced the emergence of hashtags at two critical moments of the protest and found that some hashtags are ideologically based such as #BlackLivesMatter and #JusticeforMichaelBrown and some hashtags are conceptually based such as #ICantBreathe and #IfIWasGunnedDown. Hashtags as conceptual markers are used as personal conceptualizations of or personal references to the story (Blevins et al., 2019). We would expect that online discourses around a CRM campaign that deals with a potentially controversial topic will see both ideological hashtags and conceptual hashtags. In the CRM context, ideological markers reveal users' sociopolitical stance and position and conceptual markers are used as references to discuss the CRM campaign. We speculate that ideological markers, compared to conceptual markers, play a pivotal role in driving formation of ties, because these hashtags are more related to person's identity (Jackson & Foucault Welles, 2015; Kuo, 2018).

Homophily through hashtags, however, can manifest in different patterns. On one hand, hashtag homophily is established when users are more likely to form ties when they use the same hashtag. On the other hand, a pattern where users who do not use the same hashtag have a lower likelihood of forming ties can be also considered as homophily. The strongest homophily effect of a hashtag is then a decreased likelihood of having ties when neither users engage the hashtag while having an increased likelihood of forming ties when both users engage the hashtag. Given the nuances of the different homophily patterns, we ask whether ideological hashtags and conceptual hashtags exhibit different homophily patterns. To summarize, we propose the following research question and hypotheses:

RQ2. Does ties formation based on ideological hashtags vs. conceptual hashtags differ?

H1. Ideological hashtags have homophily effects among social media users who discuss a CRM campaign.

H2. Ideological hashtags have greater ability to predict homophily than conceptual hashtags do.

4. Method

We used Gillette's CRM campaign "The Best Men Can Be" to answer the research questions and test the hypotheses. The campaign soon became a trending topic on Twitter when the campaign video rolled out. This CRM campaign of Gillette's, a razor brand affiliated to Procter & Gamble, claimed to tackle issues related to toxic masculinity and promote a healthier role model for younger generations (Dreyfuss, 2019). Gillette also pledged to donate 1 million dollars to relevant nonprofit organizations for the next three years. These components make it a typical CRM campaign. The ad received positive feedback given its positive messages of gender and its redefinition of masculinity (McCluskey, 2019), but also significant backlash from consumers (Smith, 2019). Given the high profile of the brand and the significant amount of discussion taking place on Twitter, this CRM campaign provides a great opportunity to examine the ways social media users interact with each other and react to CRM.

4.1. Data collection

Tweets were collected using R package *rtweet* over the span of 11 days following Gillette's release of its advertisement "The Best Man Can Be" on twitter from January 18, 2019 to January 28, 2019. Tweets were collected through Twitter's standard REST API with the mention of keyword "Gillette." Only original tweets (i.e. tweets that have any original content, including tweets that quoted other tweets) were collected. The data collection process resulted in a total of 109,496 tweets. An initial examination of the tweets indicated that some tweets mentioned "Gillette Stadium," New England Patriots' home football stadium, which is not related to Gillette's CRM campaign. After deleting those irrelevant tweets, the final dataset contained 107,641 tweets from 75,302 unique twitter users. See Fig. 1 of the frequency of the data on each hour. The number of words of all the tweets in the dataset ranged from 1 to 123, with the median of 17 words and average of 21.94 words.

4.2. Data analysis procedures

Topic Modeling. To answer the first research question, we conducted topic modeling. Topic modeling is a machine learning method that typically uses the Latent Dirichlet Allocation approach that treats topics as hidden structure of the documents of words (Blei, Ng, & Jordan, 2003). Essentially, the algorithm models words in a collection (a document) as a random mixture of a set of topics $P(Token|Topic)$, and the set of topics is modeled as an infinite mixture on the probabilities of the words $P(Topic|Tokens)$ (Darling, 2011). Topic modeling also returns the posterior proportions of topics for each document $P(Topic|Document)$.

We pre-processed the words in the dataset by deleting all the stopwords, all the punctuations and all the links. When constructing corpus, we deleted rare words that appeared in the dataset less than five times. As a result, the entire corpus contained 15,699 terms. It should be noted that LDA-based topic modeling is based on topic co-occurrence, and researchers need to specify the number of topics *a priori*. Challenges exist in specifying the "appropriate" number of topics.

There are existing statistical indices designed to help researchers decide the appropriate number of topics (e.g., Arun, Suresh, Madhavan, & Murthy, 2010; Cao, Xia, Li, Zhang, & Tang, 2009; Deveaud, SanJuan, & Bellot, 2014). Cao et al.'s and Devaud et al.'s indices indicate the difference of each pairs of the topics. In addition to maximizing the distance or the difference of each pairs of the topics, another important criterion is topic coherence (Mimno, Wallach, Talley, Leenders, & McCallum, 2011; Roberts et al., 2014). Yet, even though the advancement of these statistical indices can approximate the number of topics in a corpus of texts, a gold standard barely exists and human interpretations of the topics through unsupervised methods are still needed (Chang, Gerrish, Wang, Boyd-graber, & Blei, 2009). In particular, the performances of these metrics for documents with small number of words such as a tweet have not been well studied.

As a result, topic modeling in this study was done multiple times with several prior numbers of topics ranging from 5 to 20. Then we examined each topic retrieved through unsupervised machine learning. Finally, we settled down with nine topics in the dataset and calculated

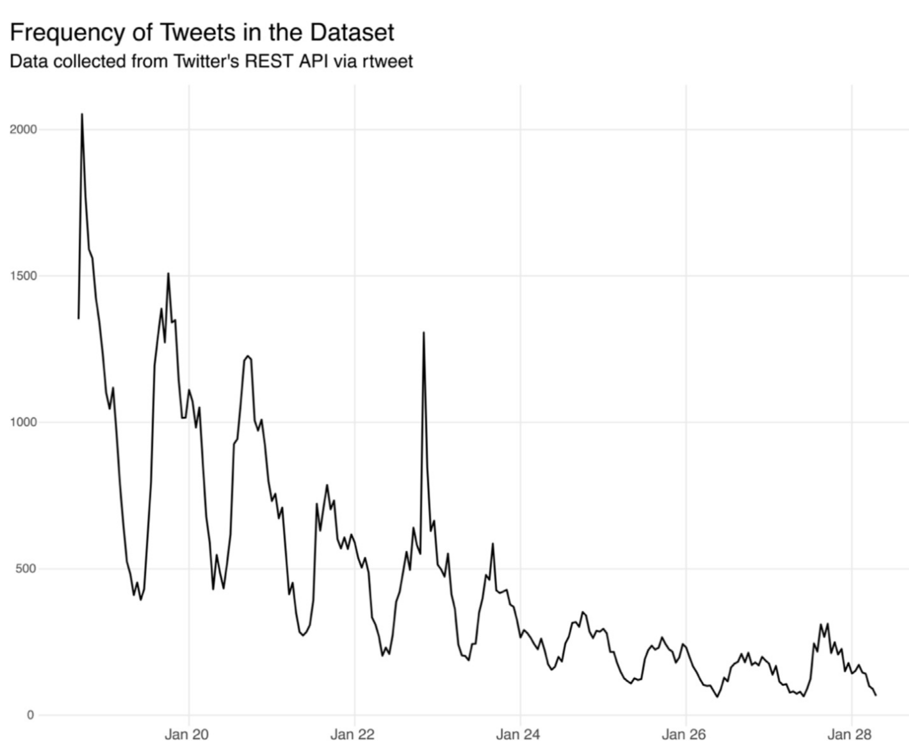

Fig. 1. Frequency of tweets in the dataset.

within-topic coherence following Mimno et al. (2011) and between-topic difference using Jensen-Shannon divergence (Puranam, Narayan, & Kadiyali, 2017; Steyvers & Griffiths, 2007) to confirm the quality of the topics.

The topic coherence was calculated following Mimno et al. (2011). In this approach, a topic is considered coherent when top words in a topic profile are more likely to co-occur in the same document. The coherence is calculated as follows (Mimno et al., 2011):

$$C(t; v^{(t)}) = \sum_{m=2}^{M} \sum_{l=1}^{m-1} log \frac{D(v_m^{(t)}, v_l^{(t)}) + 1}{D(v_l^{(t)})}$$

where *D(v)* represents the document frequency of word *v*, *D*(*v*, *v'*) indicates the co-document frequency of words *v* and *v'*, and $V^{(t)}$ is a list of *M* most probable words in Topic *t*. Evidence exists in showing that the closer the score is to zero, the more interpretable the topic model is (Puranam et al., 2017).

ERGM. To test the hypotheses and answer the second research question in this study. Exponential random graph models were used. In ERMGs, predictors are network statistics such as triangles and ties of nodes at the same grade that occur more frequently than expected by chance (Morris, Handcock, & Hunter, 2008). Exponential random graph models (ERGMs) are a series of generative models that infer underlying configurations of network structures (Lusher, Koskinen, & Robins, 2013). ERGMs statistically model the presence and absence of ties based on the network's local and structural factors, and have long been used to analyze observed social networks in management, communication, and social media settings (Gonzalez-Bailon, 2009; Robins, Pattison, Kalish, & Lusher, 2007; Saffer, Yang, & Taylor, 2018). Such network analysis is uniquely suited to explain the structure of a social media network where nodal attributes and link formation are observed (Getchell & Sellnow, 2016; Park & Kaye, 2017; Song, 2015). We used R packages *statnet* and *ergm* to fit the model in this study.

First, since some users tweeted more than once, we combined all the tweets based on user ids. Next we extracted all the hashtags that were used by each user. The frequencies of hashtags were shown in Fig. 2. Based on the definition of ideological markers and conceptual markers provided by Blevins et al., we examined and categorized top hashtags as either ideological markers or conceptual markers, and then tagged the users accordingly as whether the user used a particular hashtag. Then we extracted the mention (@user in each tweet) network and the tags were passed along as nodal attributes for statistical modeling. For users who were mentioned but did not have any actual content in the dataset for us to judge whether the nodes used certain hashtags or not, their nodal attributes were coded as missing data.

Mention networks and retweet networks are two most common types of conversational networks formed by Twitter users (Jackson & Foucault Welles, 2015). However, it should be noted here that these two types of networks also differ from each other, with the former ones more significant in ways how users interact (Conover et al., 2011). We chose to focus on the mention network because that is how conversations emerge, through the actual *exchange* of information and active contributions to dialogues, not simply relaying what others have said.

5. Results

5.1. Topic modeling analysis

For these 9 topics, the Jensen-Shannon divergence metrics (Puranam et al., 2017; Steyvers & Griffiths, 2007) of each pair of topics indicated that all pairs of topics were indeed very different from each other. Jensen-Shannon divergence is symmetrical and represents the distance of two probability distributions. We present Jensen-Shannon divergences for each pair in Table 1. The top three words that appeared in each topic model were used to calculate each topic's semantic coherence. All the topics achieved great coherence scores. The coherence scores are reported in Table 2 along with the top words in each topic

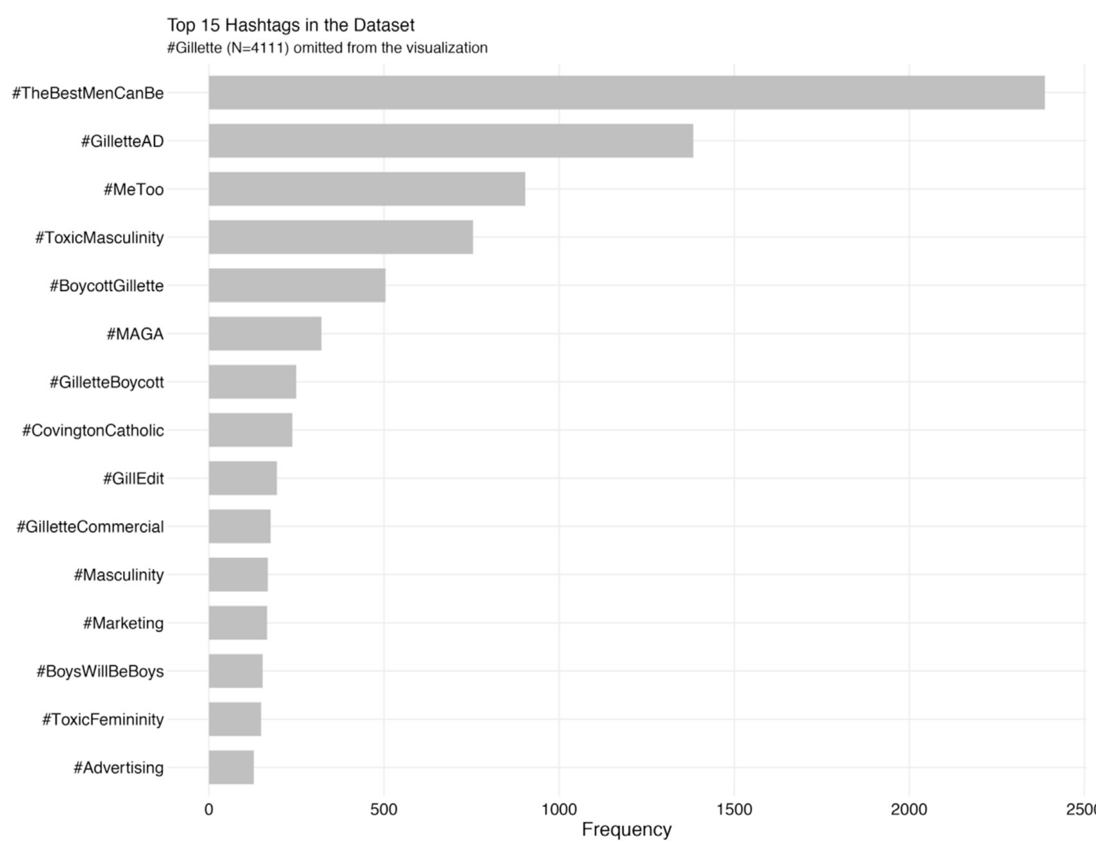

Fig. 2. Top 15 hashtags in the dataset.

Table 1
Jensen-Shannon divergence for each pair of the topic profiles.

Topics	1	2	3	4	5	6	7	8
2	0.866							
3	0.914	0.843						
4	0.894	0.779	0.837					
5	0.864	0.791	0.866	0.812				
6	0.864	0.786	0.866	0.836	0.778			
7	0.965	0.912	0.886	0.795	0.884	0.916		
8	0.962	0.902	0.855	0.896	0.891	0.936	0.867	
9	0.814	0.775	0.854	0.822	0.742	0.761	0.905	0.944

Note. The higher the number, the more distanced each pair of topics is.

model.

Among the nine topic models, Topics 1, 4 and 6 were about the actual CRM campaign messages such as "toxic masculinity" and "boys will be boys." Topic 4 was particularly about Gillette's stand on #metoo movement. Topic 2, combined with the hashtag analysis in the next section, revealed that the topic was about Covington Catholic High School students' clash with a Native American elder in Washington D.C. The incident happened around the same time when Gillette's ad rolled out. Topic 3 involved twitter users' discussion on Gillette's products and framed this CRM campaign as the company's marketing technique. Topic 5 involved Tomi Lahren's tweet that mentioned Cardi B and Stormy Daniels. They were also highly visible based on the frequency of the words in the last section. Reactions to this single tweet become a prominent topic profile. Topic 7 was based on twitter users' reaction and response to the actual Youtube video. Topic 8 is best described as twitter users' reactions to some others' reactions regarding the CRM campaign—particularly those who felt offended. Finally, Topic 9 was best described as twitter users' discussion on gender issues.

Based on such results, twitter users' discussions on this CRM campaign are categorized in four major themes: (1) discussions on the campaign itself, including the campaign's slogans and key messages, as well as the campaign itself as a marketing technique; (2) reactions to key influencers who discussed the campaign, even though the actual message might not be highly relevant to the overall campaign; (3) discussions on breaking news or prominent events during the same time related to the cause in the CRM campaign; and (4) general discussions on the cause-related issue itself. Topic 2 as a key topic among twitter users' discussions on the CRM campaign and the presence of MeToo and MAGA as top words in two separate topics demonstrate that twitter is indeed a volatile environment where collapsed contexts disperse discussions on a specific CRM campaign.

5.2. ERGM

The mention network (directed) in the dataset contained 63,901 nodes and 110,068 edges. The diameter of the network (the longest distance between two nodes) was 19. The directed mean distance was 6.91. In this mention network, 4.39 percent of the total edges were reciprocated (*Reciprocity* = 0.0439).

We chose four most frequently used yet distinct hashtags in this dataset to test the homophily hypotheses in this study, #MAGA, #MeToo, #ToxicMasculinity and #TheBestMenCanBe. #Metoo and #MAGA were ideological markers because they were likely to indicate users' sociopolitical stance. In comparison, #ToxicMasculinity and #TheBestMenCanBe were conceptual markers, as they were directly related to the slogan and key messages in the campaign.

We specified an ERGM model with a basic term *edges*, which controls the overall probability of a link (Morris et al., 2008), main effects of the covariates and differential homophily as the interaction effect of the covariates. The coefficient results are shown in Table 3. As the results show, for ideological hashtags #MeToo and #MAGA, differential homophily showed that when neither users engaged #MeToo, they had a slightly decreased chance of forming a tie, but when both users engaged #MeToo, their likelihood of forming a tie significantly increased. For #MAGA, when neither users engaged the hashtag, their chance of having a tie significantly decreased, but both users' engagement with the hashtag did not have a significant effect. Therefore, we can arrive at the conclusion that homophily effects did exist for both hashtags, but they worked in a different pattern, with #MeToo driving homophily by attraction of common users (increased chance of ties for users who both engage the hashtag) and #MAGA driving homophily by alienating nonusers (decreased chance of ties for users neither of whom engages the hashtag).

In comparison, for conceptual hashtags #ToxicMasculinity and #TheBestMenCanBe, neither of the homophily patterns existed. In fact, for users who both engaged #TheBestMenCanBe, their chance of forming a tie significantly decreased; and for users neither of whom engaged the hashtag, their chance of forming a tie significantly increased. This is opposite to homophily. In short, ideological hashtags drove homophily of network formation, though the patterns differ. Conceptual hashtags, in comparison, did not have homophily effects on network formation. H1 and H2 were supported. The results also showed that the use of hashtags lowered users' chance of receiving ties and that users who used hashtags were likely to send out more ties in this mention network. We present these coefficients in a bar graph with 95% confidence interval in Fig. 3 to give readers a more straightforward look.

6. Discussion and implications

In this section, we first discuss the topic modeling of Gillette's CRM campaign and its implications on CRM literature. Then we discuss the implications of the homophily effects of hashtags in the mention network.

6.1. Online discourses of CRM

Online discourses based on topic modeling analysis show that the discussions around CRM campaign are not only focused on the CRM

Table 2
Topics, semantic coherence and top words in topics.

Topic	Label	Coherence	Top 12 Words
1	Campaign Message: Boys Will Be Boys	−7.728	gillette boys commercial great time ads today day week show boy work
2	Current Event	−11.592	gillette white kids maga hate news real trump media face school left
3	Products/Marketing	−9.643	gillette razors razor shave products buy shaving make marketing brand years social
4	Reaction to the Company's Stance	−7.545	gillette ad company love gillettead stand put anti metoo feminist wrong toxicmasculinity
5	Influencers	−6.826	gillette tomilahren iamcardib stormydaniels realjameswoods guy lol guess back woman oldcheapwine nice
6	Campaign Message: Toxic Masculinity	−3.048	ad toxic masculinity gillette proctergamble thebestmencanbe taking end super bowl action challenging
7	Campaign Video	−5.653	gillette man youtube video response watch film parody short woke egard reaction
8	Reaction to Other Users	−8.267	commercial people good offended message thing made problem advert point feel guys
9	Gender Issue	−7.278	men women bad hey stop male good real behavior bullying things gender

Note. Higher coherence score indicates more semantically coherent topic profile.

Table 3
ERGM estimates.

	Estimate	*SE*	Estimate/SE	*p*	
Constant (edges)	−10.484	0.0043	−2462.651	< .001	***
Neither engaged #MeToo	−0.035	0.0463	−0.756	0.450	
Both engaged #MeToo	2.138	0.1561	13.695	< .001	***
Neither engaged #MAGA	−0.359	0.0505	−7.097	< .001	***
Both engaged #MAGA	−0.051	0.5808	−0.087	0.930	
Neithr engaged #ToxicMasculinity	−0.069	0.0441	−1.570	0.117	
Both engaged #ToxicMasculinity	0.307	0.2818	1.091	0.275	
Neither engaged #TheBestMenCanBe	0.409	0.0276	14.828	< .001	***
Both engaged #TheBestMenCanBe	−0.878	0.2908	−3.021	0.003	**
Indegree main effect of #MeToo	−0.390	0.0535	−7.280	< .001	***
Outdegree main effect of #MeToo	0.229	0.0440	5.198	< .001	***
Indegree main effect of #MAGA	−0.047	0.0583	−0.814	0.415	
Outdegree main effect of #MAGA	0.282	0.0525	5.359	< .001	***
Indegree main effect of #ToxicMasculinity	−0.173	0.0484	−3.571	< .001	***
Outdegree main effect of #ToxicMasculinity	0.386	0.0410	9.401	< .001	***
Indegree main effect of #TheBestMenCanBe	−1.553	0.0442	−35.118	< .001	***
Outdegree main effect of #TheBestMenCanBe	0.492	0.0220	22.336	< .001	***

campaign key messages and the issue itself, but also consumers' general skepticism as they quickly acknowledge the campaign as a marketing technique. In addition, they react to top influencers/celebrities, especially controversial ones that may not have anything to do with the campaign itself, and they react to other users' reaction. Such vibrant and multifaceted discourses around a CRM campaign show further support that social media users are generally very active in expressing their opinions about issues (Ifukor, 2010; Papacharissi & de Fatima Oliveira, 2012).

Furthermore, social media collapse contexts in ways that private space and public space intersect and that the "conversational" environment is more volatile and malleable (Baym & Boyd, 2012; Boyd & Ellison, 2007). This study demonstrates that social media such as Twitter indeed can be a space filled with clutters and noises. The fact that reactions to an influencer's single tweet become a prominent topic profile in the dataset shows that conversations can grow disproportionally to their significance. In addition, Twitter is not only an echo chamber where selective exposure is prevalent (Boutyline & Willer, 2017; Colleoni et al., 2014; Garrett, 2009) but also a virtual reactive chamber where people eagerly react to influencers and controversies as well as to each other and current events.

Past research indicates that social media is instrumental to projecting marginalized voices into the public arena (Bruns et al., 2013; DeLuca et al., 2012; Ince et al., 2017; Jackson et al., 2018; Obar et al., 2012) and that people engage in thoughtful articulation of their experiences and critique of power (Bonilla & Rosa, 2015). Indeed, social media users also use the opportunity of the CRM campaign to engage in discussions about gender-related issues, evidenced by multiple topic

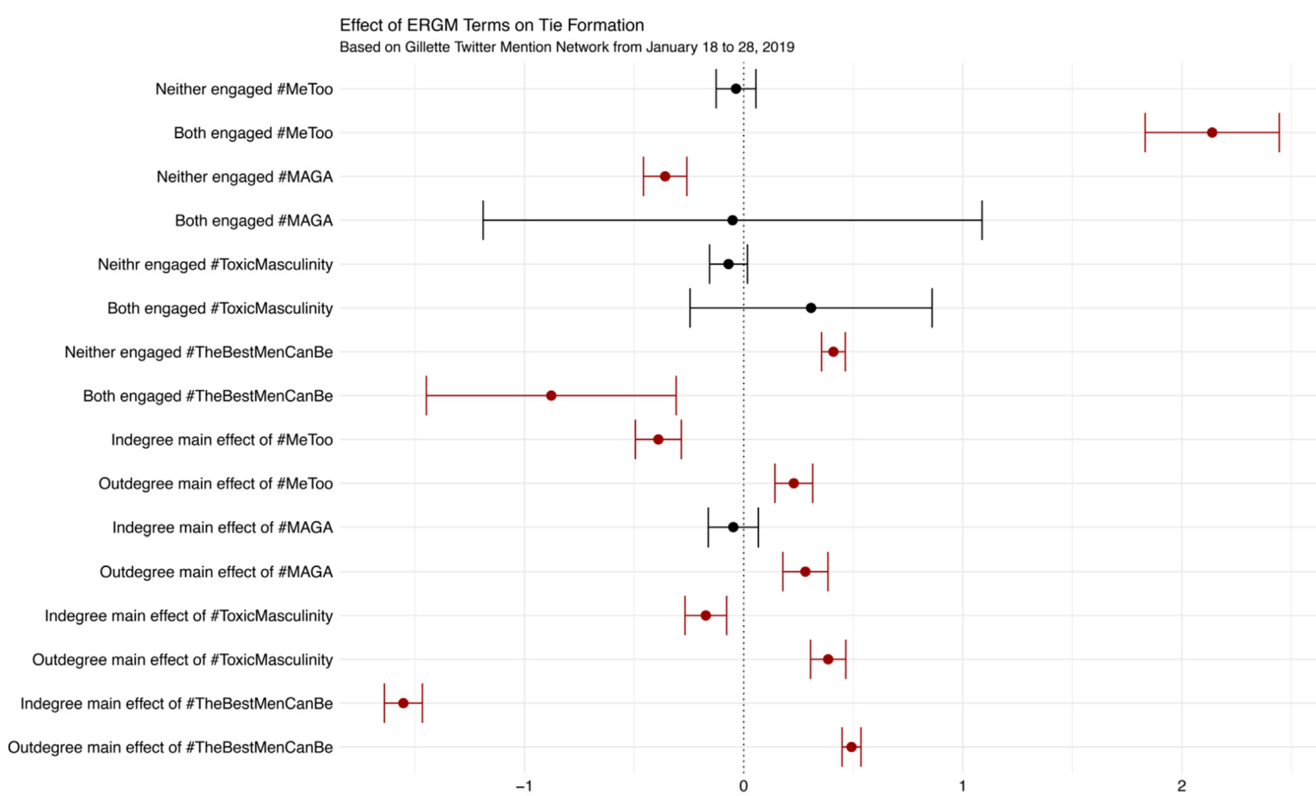

Fig. 3. ERGM coefficients shown in 95% confidence interval.

profiles that have the key campaign messages as underlying frameworks. From this perspective, CRM can be useful to generate conversations and debates by making language and frameworks readily available to a larger audience.

Finally, the observation on these topic profiles revealed that the online discussions overlook donations. Commitment to donating money to charitable or nonprofit organizations is a primary feature of CRM (Barone et al., 2000; Varadarajan & Menon, 1988). Yet, the discussion on the charity nature of Gillette's CRM campaign and donations committed by the company was absent. This absence demonstrates that online users tend to overlook the charitable aspect of CRM. Instead, they are more reactive to other users and more focused on the key campaign messages and the controversy. Future studies can pay attention to the charitable donations' effects, or lack thereof, on consumers' or social media users' perceptions, discussions and acceptance of a cause-related marketing.

6.2. Hashtag homophily

Hashtags are widely used by Twitter users to serve multiple purposes. Hashtags first and foremost create discursive spaces where conversations around a particular topic, event, incident or perspective happen (Jackson et al., 2018; Kuo, 2018). The aggregated conversations in discursive spaces created and enabled by hashtags play a significant role in creating online ad-hoc publics who mobilize quickly based on shared interests and concerns (Bruns & Burgess, 2011; Bruns et al., 2016).

The homophily effects of ideological hashtags found in this study demonstrate that hashtag usage predicts tie formations. Such homophily effects through hashtags, where users who both engage in certain hashtag have higher chance of forming ties together, confirm to the broader function of hashtags to maintain communities and self-representation (Jackson & Foucault Welles, 2015). Hashtags, in this case of a controversial CRM campaign, are used as ways to express ideological positions and identify with similar users.

Previous studies have shown that homophily exists in online networks (Colleoni et al., 2014) and users are more likely to establish networks with people who are similar to them. Similarity in an online network can have multiple layers. On one hand, similarity can be about personal traits such as gender or political ideology that are more or less evident. On the other hand, research shows that content similarity can be also a driven force of homophily ties (Aiello et al., 2012; Conover et al., 2011), particularly in Twitter where user content is more visible than the user profile and users are more likely to interact with content than only with friends or followers. This study adds to the existing research by providing additional evidence that hashtags, as condensed indices of user content to connect with other users (Bonilla & Rosa, 2015), are significant predictors of homophilous tie formations.

It is worth noting that the homophily effects of hashtags are not the same for all hashtags. Blevins et al., 2019 noted that hashtags in a racial justice protest generally can be categorized as ideological markers and conceptual markers. Ideological markers indicate identity or identification, position and/or viewpoints, whereas conceptual markers are used as personal references to stories or personal conceptualizations of the events. Results of this study indicate that homophily effects are only present for ideological hashtags. Yet, ideological hashtags can also differ in their homophily patterns. A hashtag can drive homophily by attracting common users, alienating non-users, or both. In our study, one hashtag (#MeToo) mainly worked through attraction and the other hashtag (#MAGA) worked through alienation. Given these promising yet preliminary results, future studies should further validate the results in different contexts and continue to examine the homophily tendency exhibited through users' engagement with certain hashtags.

Finally, results of this study highlight another phenomenon. The use of either hashtags had a negative indegree main effect and a positive outdegree main effect, meaning that users who engaged hashtags were less likely to receive ties even though they were more likely to send out ties in this mention network. So far there has not been enough research on this aspect, but we speculate that Twitter users who use hashtags are more active in their discussions, therefore leading to higher outdegrees. Yet, given that hashtags reveal users' ideology, they may increase tie formations among like-minded people, but in the same time alienate other users and therefore reduce the overall likelihood of receiving ties. The consistent pattern shown in this study on four different hashtags indicates a promising path for future studies to investigate and theorize the functionalities of hashtags in online networks, in particular areas related to the different motives of users engaging certain types of hashtags and users' reactions to messages containing ideological vs. conceptual hashtags.

6.3. Limitations

A major limitation of the current study is that the study was based on one cause-related marketing event. Results of this study may not be generalizable to other contexts. Future studies can continue this line of research by investigating social media users' networks in other cause-related marketing events. In addition, this study modeled the effect of homophily using ERGM, while other alternative methodological approaches could be tested, for example by using clustering coefficient and polarization index (Morales, Borondo, Losada, & Benito, 2015; Primario et al., 2015). Future studies combining ERGM and these indices may provide greater insights on users' discussions on social media.

7. Conclusion

Despite the limitations, this study provides valuable insights regarding discourses around cause-related marketing and these conversational ties. The first research question of this study seeks to understand how these conversations emerge on social media. Topic modeling of the online discussions on Twitter point out that users depend upon established frameworks in the campaign to discuss key issues. Users also react enthusiastically to influencers and other users' viewpoints, indicating the reactive nature of these online discussions. Related to the first research question, the second research question seeks to further understand how the networks of conversational ties further propel the users' reactions and discourses. As a result, ideological hashtags serve as indicators of homophily tie formation but conceptual hashtags do not, pointing to the different purposes ideological vs. conceptual hashtags serve. This homophily tendency exhibited through users' usage of certain ideological hashtags also gives further evidence that these hashtags create discursive spaces where users construct meaning, vie for representation and foster identification with other users.

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References

Aiello, L. M., Barrat, A., Schifanella, R., Cattuto, C., Markines, B., & Menczer, F. (2012). Friendship prediction and homophily in social media. *ACM Transactions on the Web, 6*(2), 1–33. https://doi.org/10.1145/2180861.2180866.

Albrecht, S. (2006). Whose voice is heard in online deliberation? A study of participation and representation in political debates on the internet. *Information, Community and Society, 9*(1), 62–82. https://doi.org/10.1080/13691180500519548.

Arun, R., Suresh, V., Madhavan, C. V., & Murthy, M. N. (2010). On finding the natural number of topics with latent dirichlet allocation: Some observations. In M. J. Zaki, J. X. Yu, B. Ravindran, & V. Pudi (Eds.). *Advances in knowledge discovery and data mining: 14th Pacific-Asia conference, PAKDD 2010. Hyderabad, India, June 21-24, 2010* *proceedings Part I* (pp. 391–402). New York, NY: Springer.

Barone, M. J., Miyazaki, A. D., & Taylor, K. A. (2000). The influence of cause-related marketing on consumer choice: Does one good turn deserve another? *Journal of the Academy of Marketing Science, 28*(2), 248–262. https://doi.org/10.1177/0092070300282006.

Basil, D. Z., & Weber, D. (2006). Values motivation and concern for appearances: The effect of personality traits on responses to corporate social responsibility. *International Journal of Nonprofit and Voluntary Sector Marketing, 11*(1), 61–72. https://doi.org/10.1002/nvsm.38.

Baym, N. K., & Boyd, D. (2012). Socially mediated publicness: An introduction. *Journal of Broadcasting & Electronic Media, 56*(3), 320–329. https://doi.org/10.1080/08838151.2012.705200.

Bénabou, R., & Tirole, J. (2010). Individual and corporate social responsibility. *Economica, 77*(305), 1–19. https://doi.org/10.1111/j.1468-0335.2009.00843.x.

Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent dirichlet allocation. *Journal of Machine Learning Research, 3*, 993–1022.

Blevins, J. L., Lee, J. J., McCabe, E. E., & Edgerton, E. (2019). *Tweeting for social justice in #Ferguson: Affective discourse in Twitter hashtags.* New Media & Societyhttps://doi.org/10.1177/1461444819827030 (in press).

Bonilla, Y., & Rosa, J. (2015). #Ferguson: Digital protest, hashtag ethnography, and the racial politics of social media in the United States: #Ferguson. *American Ethnologist, 42*(1), 4–17. https://doi.org/10.1111/amet.12112.

Boutyline, A., & Willer, R. (2017). The social structure of political echo chambers: Variation in ideological homophily in online networks. *Political Psychology, 38*(3), 551–569. https://doi.org/10.1111/pops.12337.

Boyd, D. M., & Ellison, N. B. (2007). Social network sites: Definition, history, and scholarship. *Journal of Computer-Mediated Communication, 13*(1), 210–230. https://doi.org/10.1111/j.1083-6101.2007.00393.x.

Bruns, A., & Burgess, J. E. (2011). The use of Twitter hashtags in the formation of ad hoc publics. August *Proceedings of the 6th European consortium for political research (ECPR) general conference 2011*. Retrieved from https://eprints.qut.edu.au/46515/1/The_Use_of_Twitter_Hashtags_in_the_Formation_of_Ad_Hoc_Publics_(final).pdf.

Bruns, A., & Burgess, J. (2015). Twitter hashtags from ad hoc to calculated publics. In N. Rambukkana (Ed.). *Hashtag publics: The power and politics of discursive networks* (pp. 13–28). New York, NY: Peter Lang.

Bruns, A., Highfield, T., & Burgess, J. (2013). The Arab spring and social media audiences: English and Arabic twitter users and their networks. *American Behavioral Scientist, 57*(7), 871–898. https://doi.org/10.1177/0002764213479374.

Bruns, A., Moon, B., Paul, A., & Münch, F. (2016). Towards a typology of hashtag publics: A large-scale comparative study of user engagement across trending topics. *Communication Research and Practice, 2*(1), 20–46. https://doi.org/10.1080/22041451.2016.1155328.

Cao, J., Xia, T., Li, J., Zhang, Y., & Tang, S. (2009). A density-based method for adaptive LDA model selection. *Neurocomputing, 72*(7–9), 1775–1781. https://doi.org/10.1016/j.neucom.2008.06.011.

Centola, D. (2010). The spread of behavior in an online social network experiment. *Science, 329*(5996), 1194–1197. https://doi.org/10.1126/science.1185231.

Chang, J., Gerrish, S., Wang, C., Boyd-graber, J. L., & Blei, D. M. (2009). Reading Tea Leaves: How Humans Interpret Topic Models. *Proceedings of the Advances in Neural Information Processing Systems Conference* (pp. 288–296). Vancouver, Canada.

Chung, J. E. (2014). Social networking in online support groups for health: How online social networking benefits patients. *Journal of Health Communication, 19*(6), 639–659. https://doi.org/10.1080/10810730.2012.757396.

Colleoni, E., Rozza, A., & Arvidsson, A. (2014). Echo chamber or public sphere? Predicting political orientation and measuring political homophily in twitter using big data: Political homophily on twitter. *Journal of Communication, 64*(2), 317–332. https://doi.org/10.1111/jcom.12084.

Conover, M. D., Goncalves, B., Ratkiewicz, J., Flammini, A., & Menczer, F. (2011). Predicting the political alignment of twitter users. *2011 IEEE third int'l Conference on privacy, security, Risk and Trust and 2011 IEEE third int'l Conference on social computing* (pp. 192–199). . https://doi.org/10.1109/PASSAT/SocialCom.2011.34.

Conover, M. D., Ratkiewicz, J., Francisco, M., Gonçalves, B., Menczer, F., & Flammini, A. (2011). Political polarization on twitter. *Fifth international AAAI conference on weblogs and social media* July.

Dahlberg, L. (2001). Computer-mediated communication and the public sphere: A critical analysis. *Journal of Computer-Mediated Communication, 7*(1), Online. Retrieved from https://academic.oup.com/jcmc/article/7/1/JCMC714/4584246.

Darling, W. M. (2011). A theoretical and practical implementation tutorial on topic modeling and gibbs sampling. *Proceedings of the 49th annual meeting of the association for computational linguistics: Human language technologies* (pp. 642–647). December.

DeLuca, K. M., Lawson, S., & Sun, Y. (2012). Occupy Wall Street on the public screens of social media: The many framings of the birth of a protest movement. *Communication. Cultural Critique, 5*(4), 483–509. https://doi.org/10.1111/j.1753-9137.2012.01141.x.

Deveaud, R., SanJuan, E., & Bellot, P. (2014). Accurate and effective latent concept modeling for ad hoc information retrieval. *Document Numérique, 17*(1), 61–84. https://doi.org/10.3166/DN.17.1.61-84.

Dijck, J. V. (2011). Tracing Twitter: The rise of a microblogging platform. *International Journal of Media and Cultural Politics, 7*(3), 333–348. https://doi.org/10.1386/macp.7.3.333_1.

Dreyfuss, E. (2019). Gillette's ad proves the definition of a good man has changed. January 16, Wired. Retrieved from https://www.wired.com/story/gillette-we-believe-ad-men-backlash/.

Garrett, R. K. (2009). Echo chambers online? Politically motivated selective exposure among internet news users. *Journal of Computer-Mediated Communication, 14*(2), 265–285. https://doi.org/10.1111/j.1083-6101.2009.01440.x.

Getchell, M. C., & Sellnow, T. L. (2016). A network analysis of official Twitter accounts during the West Virginia water crisis. *Computers in Human Behavior, 54*, 597–606. https://doi.org/10.1016/j.chb.2015.06.044.

Gonzalez-Bailon, S. (2009). Opening the black box of link formation: Social factors underlying the structure of the web. *Social Networks, 31*(4), 271–280. https://doi.org/10.1016/j.socnet.2009.07.003.

Guillén, M. F., & Suárez, S. L. (2005). Explaining the global digital divide: Economic, political and sociological drivers of cross-national Internet use. *Social Forces, 84*(2), 681–708. https://doi.org/10.1353/sof.2006.0015.

Gupta, S., & Pirsch, J. (2006). The company-cause-customer fit decision in cause-related marketing. *Journal of Consumer Marketing, 23*(6), 314–326. https://doi.org/10.1108/07363760610701850.

He, H., Chao, M. M., & Zhu, W. (2019). Cause-related marketing and employee engagement: The roles of admiration, implicit morality beliefs, and moral identity. *Journal of Business Research, 95*, 83–92. https://doi.org/10.1016/j.jbusres.2018.10.013.

Ifukor, P. (2010). 'Elections' or 'selections'? Blogging and twittering the Nigerian 2007 general elections. *Bulletin of Science, Technology & Society, 30*(6), 398–414. https://doi.org/10.1177/0270467610380008.

Ince, J., Rojas, F., & Davis, C. A. (2017). The social media response to black Lives matter: How twitter users interact with black Lives matter through hashtag use. *Ethnic and Racial Studies, 40*(11), 1814–1830. https://doi.org/10.1080/01419870.2017.1334931.

Jackson, S. J., Bailey, M., & Foucault Welles, B. (2018). #GirlsLikeUs: Trans advocacy and community building online. *New Media & Society, 20*(5), 1868–1888. https://doi.org/10.1177/1461444817709276.

Jackson, S. J., & Foucault Welles, B. (2015). Hijacking #myNYPD: Social media dissent and networked counterpublics: Hijacking #myNYPD. *Journal of Communication, 65*(6), 932–952. https://doi.org/10.1111/jcom.12185.

Kuo, R. (2018). Racial justice activist hashtags: Counterpublics and discourse circulation. *New Media & Society, 20*(2), 495–514. https://doi.org/10.1177/1461444816663485.

Lafferty, B. A. (2007). The relevance of fit in a cause–brand alliance when consumers evaluate corporate credibility. *Journal of Business Research, 60*(5), 447–453. https://doi.org/10.1016/j.jbusres.2006.09.030.

Lusher, D., Koskinen, J., & Robins, G. (2013). *Exponential random graph models for social networks: Theory, methods, and applications.* New York, NY: Cambridge University Presshttps://doi.org/10.1017/CBO9780511894701.

McCluskey, M. (2019). Gillette makes waves with controversial new commercial. *Time*. January, Retrieved from http://time.com/5503156/gillette-razors-toxic-masculinity/.

McPherson, M., Smith-Lovin, L., & Cook, J. M. (2001). Birds of a feather: Homophily in social networks. *Annual Review of Sociology, 27*(1), 415–444. https://doi.org/10.1146/annurev.soc.27.1.415.

Menon, S., & Kahn, B. E. (2003). Corporate sponsorships of philanthropic activities: When do they impact perception of sponsor brand? *Journal of Consumer Psychology, 13*(3), 316–327. https://doi.org/10.1207/S15327663JCP1303_12.

Mimno, D., Wallach, H. M., Talley, E., Leenders, M., & McCallum, A. (2011). Optimizing semantic coherence in topic models. *Proceedings of the conference on empirical methods in natural language processing* (pp. 262–272). Stroudsburg, PA: Association for Computational Linguistics July.

Morales, A. J., Borondo, J., Losada, J. C., & Benito, R. M. (2015). Measuring political polarization: Twitter shows the two sides of Venezuela. *Chaos: An Interdisciplinary Journal of Nonlinear Science, 25*(3), 033114.

Morris, M., Handcock, M. S., & Hunter, D. R. (2008). Specification of exponential-family random graph models: Terms and computational aspects. *Journal of Statistical Software, 24*(4), https://doi.org/10.18637/jss.v024.i04.

Nan, X., & Heo, K. (2007). Consumer responses to corporate social responsibility (CSR) initiatives: Examining the role of brand-cause fit in cause-related marketing. *Journal of Advertising, 36*(2), 63–74.

Obar, J. A., Zube, P., & Lampe, C. (2012). Advocacy 2.0: An analysis of how advocacy groups in the United States perceive and use social media as tools for facilitating civic engagement and collective action. *Journal of Information Policy, 2*, 1–25. https://doi.org/10.5325/jinfopoli.2.2012.0001.

Papacharissi, Z., & de Fatima Oliveira, M. (2012). Affective news and networked publics: The rhythms of news storytelling on# Egypt. *Journal of Communication, 62*(2), 266–282. https://doi.org/10.1111/j.1460-2466.2012.01630.x.

Park, C. S. (2013). Does twitter motivate involvement in politics? Tweeting, opinion leadership, and political engagement. *Computers in Human Behavior, 29*(4), 1641–1648. https://doi.org/10.1016/j.chb.2013.01.044.

Park, C. S., & Kaye, B. K. (2017). The tweet goes on: Interconnection of Twitter opinion leadership, network size, and civic engagement. *Computers in Human Behavior, 69*, 174–180. https://doi.org/10.1016/j.chb.2016.12.021.

Pennacchiotti, M., & Popescu, A. (2011). A machine learning approach to Twitter user classification. *Proceedings of the fifth international AAAI conference on weblogs and social media.*Association for the Advancement of Artificial Intelligence. Retrieved from https://www.aaai.org/ocs/index.php/ICWSM/ICWSM11/paper/view/2886/3262.

Penney, J., & Dadas, C. (2014). Re) Tweeting in the service of protest: Digital composition and circulation in the Occupy Wall Street movement. *New Media & Society, 16*(1), 74–90. https://doi.org/10.1177/1461444813479593.

Poell, T. (2014). Social media and the transformation of activist communication: Exploring the social media ecology of the 2010 toronto G20 protests. *Information, Communication & Society, 17*(6), 716–731. https://doi.org/10.1080/1369118X.2013.812674.

Primario, S., Borrelli, D., Iandoli, L., Zollo, G., & Lipizzi, C. (2017). Measuring polarization in Twitter Enabled in online political conversation: The case of 2016 US presidential election. *Proceedings of the 2017 IEEE international conference on information reuse and integration* (pp. 607–613). IEEE. San Diego, CA http://dx.doi.org/10.1109/

IRI.2017.73.

Puranam, D., Narayan, V., & Kadiyali, V. (2017). The effect of calorie posting regulation on consumer opinion: A flexible latent dirichlet allocation model with informative priors. *Marketing Science, 36*(5), 726–746. https://doi.org/10.1287/mksc.2017.1048.

Roberts, M. E., Stewart, B. M., Tingley, D., Lucas, C., Leder-Luis, J., Gadarian, S. K., et al. (2014). Structural topic models for open-ended survey responses: Structural topic models for SURVEY responses. *American Journal of Political Science, 58*(4), 1064–1082. https://doi.org/10.1111/ajps.12103.

Robins, G., Pattison, P., Kalish, Y., & Lusher, D. (2007). An introduction to exponential random graph (p*) models for social networks. *Social Networks, 29*(2), 173–191. https://doi.org/10.1016/j.socnet.2006.08.002.

Saffer, A. J., Yang, A., & Taylor, M. (2018). Reconsidering power in multistakeholder relationship management. *Management Communication Quarterly, 32*(1), 121–139. https://doi.org/10.1177/0893318917700510.

Segerberg, A., & Bennett, W. L. (2011). Social media and the organization of collective action: Using Twitter to explore the ecologies of two climate change protests. *The Communication Review, 14*(3), 197–215. https://doi.org/10.1080/10714421.2011.597250.

Sen, S., & Bhattacharya, C. B. (2001). Does doing good always lead to doing better? Consumer reactions to corporate social responsibility. *Journal of Marketing Research, 38*(2), 225–243. https://doi.org/10.1509/jmkr.38.2.225.18838.

Smith, T. (2019). Backlash erupts after gillette launches a new #MeToo-Inspired ad campaign. January 17, Retrieved March 22, 2019, from NPR.org website: https://www.npr.org/2019/01/17/685976624/backlash-erupts-after-gillette-launches-a-new-metoo-inspired-ad-campaign.

Song, H. (2015). Uncovering the structural underpinnings of political discussion networks: Evidence from an exponential random graph model. *Journal of Communication, 65*(1), 146–169. https://doi.org/10.1111/jcom.12140.

Steyvers, M., & Griffiths, T. (2007). Probabilistic topic models. In T. K. Landauer, D. S. McNamara, S. Dennis, & W. Kintsh (Eds.). *Handbook of latent semantic analysis* (pp. 427–448). New York, NY: Routledge.

Tremayne, M. (2014). Anatomy of protest in the digital era: A network analysis of twitter and Occupy Wall Street. *Social Movement Studies, 13*(1), 110–126. https://doi.org/10.1080/14742837.2013.830969.

Varadarajan, P. R., & Menon, A. (1988). Cause-related marketing: A coalignment of marketing strategy and corporate philanthropy. *Journal of Marketing, 52*(3), 58–74.

Webb, D. J., & Mohr, L. A. (1998). A typology of consumer responses to cause-related marketing: From skeptics to socially concerned. *Journal of Public Policy and Marketing, 17*(2), 226–238. https://doi.org/10.1177/074391569801700207.

Weber, L. M., Loumakis, A., & Bergman, J. (2003). Who participates and why? An analysis of citizens on the internet and the mass public. *Social Science Computer Review, 21*(1), 26–42. https://doi.org/10.1177/0894439302238969.

Yang, H. T., & Yen, G. F. (2018). Consumer responses to corporate cause-related marketing: A serial multiple mediator model of self-construal, empathy and moral identity. *European Journal of Marketing, 52*(9/10), 2105–2127. https://doi.org/10.1108/EJM-07-2017-0468.

Yu, R. P. (2016). The relationship between passive and active non-political social media use and political expression on Facebook and Twitter. *Computers in Human Behavior, 58*, 413–420. https://doi.org/10.1016/j.chb.2016.01.019.