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When Brand Activism Advertising Campaign Goes Viral: An Analysis of Always #LikeAGirl Video Networks on YouTube

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Abstract

As one of the successful brand activism ad campaigns in recent years, the current study focuses on the Always #LikeAGirl campaign that took on the issue of girls and female empowerment. As a viral video marketing campaign with YouTube as their main vehicle for campaign dissemination, this study examined how Always brand activism campaigns spread on YouTube by conducting a network analysis of YouTube video networks generated by the #LikeAGirl campaign spanning across five campaign periods. Quantifiable data (i.e., views, comments, likes, dislikes, user-generated videos) and structural network patterns show that the Always #LikeAGirl campaign was successful by both standards. Although the follow-up campaign periods were not as successful as the initial campaign, the substantial amount of views, comments, likes, and user-generated content showed that the consecutive campaigns still had impact. As shown through the network patterns, the main campaign ads were central in the diffusion of the campaign during the earlier periods but that role was passed onto the user-generated contents in the later periods. Implications of the findings and future social network analysis studies in brand advertising and brand activism campaigns are further discussed.

Keywords: *Social network analysis, YouTube, User-generated content, Viral marketing campaign, Brand activism*

1. Introduction

Social media has been widely used as one of the major tools for marketing communication campaigns in the last decade [1]. In 2018, 496 companies of the Fortune 500 companies used at least one of the social media platforms [2]. With its easy access and popularity over the world, companies are increasingly using social media for corporate social responsibility (CSR) efforts [3]. According to the 6th Annual Social Media Sustainability Index [4], among 475 global companies, the number of companies engaging in CSR using social media increased from 120 companies in 2011 to 283 companies in 2015. The increasing use of social media for CSR efforts calls for a need to examine conversations and engagement of viral marketing campaigns to gauge their social impact.

Values-driven brand activism is on the rise as consumers vote with their wallets supporting companies and brands that operate with a set of values that are working as authentic forces for good [5, 6, 7]. P&G's Always took on that role in launching a #LikeAGirl brand activism viral marketing campaign that advocated for empowerment and raising self-esteem for girls. With five major ads in a span of four years, the #LikeAGirl

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campaign has been regarded as highly successful in salience and visibility on social media but also in starting a social movement for positive change [8]. As a viral video marketing campaign with YouTube as their main vehicle for campaign dissemination, the current study used social network analysis to observe how the campaign spread, how it was received, and the user-generated content it inspired. The network patterns of the campaign periods were also observed to cross-compare differences and recognize which videos played a key role in the campaign diffusion. Social network analysis has been a popular method of research in social sciences in various disciplines including communications in the digital age (e.g., [9]) but there has been a noticeable absence of brand advertising campaign studies employing this strategy to examine how viral marketing campaigns spread on social media. As social media advertising, hashtag (#) advertising, online video advertising, and digital brand activism campaigns are amongst the most popular advertising venues in the digital age, the current study employed this strategy to observe the diffusion, providing a macro view of the flow of information and its impact, of the Always #LikeAGirl campaign on YouTube.

The purpose of this paper is to examine the social impact of Always #LikeAGirl YouTube videos in terms of quantitative responses and the network patterns of campaign-related YouTube videos. The current paper conducted a network analysis of a highly successful brand activism advertising campaign on YouTube. By doing so, it uncovered longitudinal engagement patterns by both the brand and social media users over five campaign periods. The next section describes brand activism in the social media context and proposes the social network analysis approach to examine the impact of the viral marketing campaign.

2. Literature review

2.1. Values-driven brand activism: taking a stand

Since the 1950's, businesses have believed that they should be responsible and do good for the society while making a profit. Corporate social responsibility (CSR) practices have evolved from CSR as a side operation to CSR as the center of a company's strategic focus [10]. While previous efforts were seen as marketing-driven (e.g., cause-promotion and cause-related marketing) and corporate-driven (e.g., corporate philanthropy, workforce volunteering), more recent changes show companies engaging in values-driven brand activism, where the company's businesses and operations center around a core set of values, whether that's social, economic, or environmental [6]. Consumers welcome this progress as they want companies to be an authentic force for good and have values they can align themselves with. Out of 14,000 consumers surveyed in 14 countries, 57% said they would buy or avoid brands based on its stance on social or political issues [5]. Millennials and Generation Z, with unprecedented access to information and social activism tools, demand companies to be value-driven [7]. To satisfy social media-savvy consumers' demand on value-driven brand activism, social media and hashtag (#) campaigns are actively pursued by marketers and is considered to be a highly recommended strategy. Various reputable industry websites and trade publications give tips on how to conduct effective hashtag campaigns on social media (e.g., semrush.com, sproutsocial.com, adweek.com, digitalmarketinginstitute.com). Campaigns such as Coke's #ShareACoke, Always #LikeAGirl, ALS Association's #IceBucketChallenge, and KFC's #NationalFriedChickenDay were successful in building awareness, increasing consumer engagement, and leading to action [11]. As one of the successful brand activism viral marketing campaigns utilizing social media in recent years, the current study focuses on the Always #LikeAGirl campaign that took on the issue of girl empowerment.

2.2. #LikeAGirl Always viral marketing campaign

The first #LikeAGirl Always ad aired on YouTube in June 2014. The video showed a series of teenage or older individuals being asked to throw, run, and fight 'like a girl.' Everyone acted in a mocking manner, showing that girls are weak and incapable of engaging in such acts effectively. Then, young girls were brought in to throw, run, and fight 'like a girl.' These girls gave their best, showing no signs of weakness. The ad addresses that girls' confidence plummet during puberty and phrases such as 'like a girl' should not be used as insults but as compliments. Girl empowerment and championing for girls is the social issue that Always, a feminine hygiene product, took on, and their call to action to share #LikeAGirl stories of strong girls and women energized the public and started a social movement.

After the initial success of the ad, the 'Unstoppable #LikeAGirl,' '#LikeAGirl: Girl Emojis,' '#LikeAGirl: Keep Playing,' and 'Keep Going: #LikeAGirl' ads were launched consecutively, representing five periods of the campaign. Collectively, the videos uploaded on the Always official YouTube account generated about 132 million views. That does not account for all the views of shared videos or user-generated content. The videos were also released via Facebook, Instagram, and Twitter. This earned Always a 29th rank out of the 150 brands amongst millennials according to Enso's World Value Index. This was in contrast to the baby boomer's ranking of the brand, which was a much lower 99th [12].

As primarily a video viral marketing campaign, this paper focused on its YouTube campaign dissemination, which was their main campaign vehicle [8], to see how a successful brand activism campaign spread on social media. It did so by conducting a network analysis of the #LikeAGirl videos on YouTube. The following section discusses the basics of network analysis, the need for the current study, and addresses research questions.

2.3. Network analysis for a viral marketing campaign

Social network analysis is a study of individuals and groups and their network of social relationships they form [13]. It is a visualization of the macro network that is unobservable at the micro level but also is a study of "structural properties and their implications for social action ([13], p. 2)." Network theory has been used to explain phenomenon in a wide range of social sciences disciplines from psychology to economics [14] and have been studied with diverse topics such as public health to stop the spread of infectious diseases [15], understand terror networks [16], and conduct stakeholder analysis in natural resource management [17].

There has been a plethora of social network analysis studies in the communications discipline and many of them have turned to social media as a cultural and information diffusion platform in the Internet era (e.g., [9], [18, 19]). Network analysis observed a smoking cessation campaign on Twitter [20], tweets regarding Breast Cancer Awareness Month [21], retweeting behavior on breast cancer social networks [22], and information diffusion path of social media resources of organic products [23]. Although network analysis on health communication campaigns is easier to find (such as smoking cessation campaigns mentioned above), there has been a noticeable absence of network analysis studies on brand advertising campaigns. In the field of marketing, participants in a real-life word-of-mouth marketing (WOMM) campaign on a new Belgian-style beer were subjected to social network analysis and the findings gave way to a critique of standard WOMM campaign metrics [24]. Thus far, this seems to be the only social network analysis concerned with tracking a viral marketing campaign. This is surprising due to the fact that social media is increasingly used as one of the main channels for marketing campaigns. Social network analysis provides a fitting platform to understand the spread of viral marketing campaigns on social media.

YouTube is a video-sharing social media site, where you can post, subscribe, share, like, dislike, and comment on the videos [25, 26]. In relation to the hierarchy of effects models of advertising [27], seeing a YouTube video could be considered the cognitive stage (i.e., awareness and learning), clicking a like or dislike button could be construed as showing your affect reaction to the video, commenting could be considered either cognitive or affective, and uploading user-generated content, sharing, subscribing, or purchasing the brand could be construed as the action stage. It is important to observe all cognitive, emotional, and behavioral reactions to the campaign and network analysis to a certain extent allows all three. In a YouTube video network analysis, each node could represent the video, users, or commenters, and these nodes would be linked in the network, representing the flow of information and the connection in between [28]. In a study of YouTube Jihadists, Klausen et al. [28] designated channels and accounts as 'nodes' and subscriber links between the channels as 'edges.' O'Callaghan et al. [29] tracked spam campaigns on YouTube by tracking spam user accounts and videos they comment on. Xu, Park, and Park [19] observed commenter networks semantics in commenter evaluations for a K-pop video on YouTube while their more recent paper [30] observed the temporal changes of commenter characteristics and network patterns. As the #LikeAGirl campaign had five separate periods demarcated with the five video ads, this study takes a similar approach to Xu et al. [30] by observing the temporal network pattern differences in the diffusion of information. Unlike the aforementioned studies on YouTube, the current study designated the videos as the nodes of the network as they are the key elements of the advertising campaign.

With the initial success of the first #LikeAGirl ad campaign, it is likely that the presence of cognitive, attitudinal, and behavioral effects of the campaign [27] would be substantial as evidenced by the number of user-generated content, views, comments, likes, and dislikes of all videos during the first campaign period. However, as this initial splash 'drove unprecedented earned media coverage' along with a spike in positive attitude and Always social media following [8], it would be an interesting line of inquiry to observe how much of this success was sustained throughout the five campaign periods. Diffusion of innovation theory [31] contends that something novel such as an innovation, idea, or technology is introduced by promoters and spreads through early adopters, early majority, late majority, and then laggards. The number of adoptions peak through early majority and late majority stages and eventually tapers off during the laggard adoption stage [31]. The 'contagion' of adoption is first introduced through a representation (e.g., advertisement) and spreads through communication channels such as mass media, word-of-mouth, and personal contact [32]. Most innovations fail to diffuse [33] but 'bursty topics' take off when adopters find that the innovation provides a solution to particular needs [32, 34].

With greater acknowledgement and accumulation of evidence that self-esteem and self-confidence drop at an alarmingly faster rate for girls than boys as they age (e.g., [35]), Always #LikeAGirl campaign was the first corporate advertising campaign that took on the cause in 2014 and filled a void, making it a potential 'bursty topic' for adoption. Although there were five stages to the campaign, as they operated under the one umbrella movement of #LikeAGirl and girl empowerment, the five separate ads could be seen as an extension of the initial campaign that started in 2014. Thus, it could be predicted that, just as the diffusion of innovation graph predicts, the initial adoption and response to the campaign could see a huge spike but the gradual adoption should reach a peak and die down in the later stages of the campaign. The following research question sets out to observe the extent of the above predictions:

RQ1. Across each campaign period, what were the trends in related videos posted, number of views, comments, likes, and dislikes of the videos?

Observing the pattern of the network structures allows you to see how large the size of the network is, whether a structure is highly centralized or decentralized, how densely the nodes are connected in the network, the identity and location of the central players of the network (e.g., Always ads or user-generated content videos), and ultimately in what pattern the network spread (e.g., [14, 36]).

In addition, one of the benefits of social network analysis is that it allows identification of key entities that played a role in the dissemination of information [37]. The uploaded videos that are at the center of a network play a vital role in furthering the network of videos [29]. High video views do not necessarily translate to being a key influencer in the network [38]. How much an entity plays a central role in the network can be ascertained by the 'centrality measure' [38]. This helps understand the information flow and the major influencers. Xu et al. [19] observed YouTube users who were involved in the early diffusion of a K-pop video while Chung [20] looked for the users who played a central role in the tweet-and-retweet network on Twitter for smoking cessation campaign. The current study predicts that the five original #LikeAGirl video advertisements uploaded by Always will be at the center of different networks but as this was a brand activism campaign that had a call to action, it can be foreseen that some user-generated content videos might also have a significant influence on the campaign dissemination. The two-step theory of information flow posits that the information flows out of mass media and through the opinion leaders, delivered to the individuals in the public [39]. The opinion leaders consist of well-connected and active individuals who further disseminate information to lesser active individuals. In the Internet and social media era, the strict interpretation of the traditional two-step model would be less applicable as many individuals are well-connected and often receive information directly from the source [40]. However, there exists clear opinion leaders (e.g., influencers) and more active users that devote greater time and effort than others in the creation, dissemination, and sharing of content and information on social media [41, 42]. Thus, less active users are likely to be exposed to information from mass media directly but also through opinion leaders. As aforementioned, given that the campaign had a call to action to share information via #LikeAGirl, it is likely that the pattern of centrality could shift from Always as the initial mass media launch of information to user-generated content by opinion leaders and other individual users. Thus, the following questions regarding network structures and centrality of videos are asked:

RQ2. Across the five campaign periods, are there differences in the network structures?
RQ3. Which videos played the central role in the network?

3. Method

3.1. Data collection

To examine how #LikeAGirl campaign related videos were spread on YouTube, we imported #LikeAGirl related YouTube videos using NodeXL, a social media network data collection and analysis program. NodeXL allows researchers to import videos with title, keywords, description, categories, or username containing the keyword. Data collection was performed on June 12, 2018. We entered #LikeAGirl as the keyword and gathered a total of 453 videos. After deletion of 60 irrelevant videos and 21 videos that were published prior to the first #LikeAGirl ad campaign (June 26, 2014), 372 videos remained for the analysis.

3.2. Campaign period

The first video regarding the #LikeAGirl campaign was posted on June 26, 2014. Based on the dates of the videos uploaded on the Always official YouTube account, five campaign periods were determined: (1) ‘#LikeAGirl’ (3m 18s) and ‘#LikeAGirl-youtube’ (60s), 2014/6/26-2015/7/6, (2) ‘Unstoppable’ (2m 44s), 2015/7/7-2016/3/1, (3) ‘Girl Emojis’ (2m 10s), 2016/3/2-2016/6/27, (4) ‘Keep Playing’ (1m), 2016/6/28-2017/8/15, (5) ‘Keep Going’ (1m 20s), 2017/8/16-2018/6/12.

3.3. Analysis plan

RQ1, concerning trends across each campaign period, was examined by performing a longitudinal analysis of views, comments, likes, and dislikes of videos for each campaign period. To examine RQ2 and RQ3 concerning the structure of the network and the videos playing central roles in the network, network analysis was performed. First, using NodeXL, a video network of nodes and edges was created. In video networks, each video represented a node (vertex) on the network graph and the link (edge, tie) between the nodes represented the relationship between the nodes. NodeXL allows YouTube video network import with edge lists consisting of pair of videos that was commented by the same user. This means that the network shows the connections of videos that attract common attention and action from a group of users. Second, overall network metrics (size, connected components, graph density) and centrality measures (degree and betweenness centrality) were calculated using NodeXL. The number of total vertices and unique edges determine the size of the network. Connected components refer to the number of clusters of vertices that are connected to each other. The density score is calculated by dividing the total number of edges by the number of maximum possible edges (score range: between 0 and 1). Degree refers to the number of unique edges that are connected to the node. Betweenness centrality was calculated as the frequency of a node that lies on the shortest paths between two other nodes [38].

4. Results

For RQ1, longitudinal analysis of views, comments, likes, and dislikes of videos for each campaign period was performed. As shown in Figure 1 and Table 1, the highest number of campaign related videos (n=146) were uploaded on YouTube during the first campaign period. The number of videos gradually decreased over the second (n=57) and third (n=32) periods and increased again during the fourth period (n=102), to drop again in the last period (n=35). The number of views for each period showed a pattern similar to the number of videos (Figure 2 and Table 1). Interestingly, the percentage of user-generated videos was highest in Period 1 (n=139, 95.2%) whereas the percentage of Always-posted videos peaked at Period 4 (n=33, 32.4%). Videos generated by users were the highest during the first campaign period, which indicates the initial success of the first campaign inspiring user-generated content. Moreover, videos uploaded during the first period generated the greatest number of comments and likes (Figure 3 and Table 1). The amount of buzz diminished over the campaign periods, while positive reaction in terms of proportion of likes to overall ratings was the lowest during Period 3 (40.9%). The attempt by Always to revitalize the campaign by posting a series of videos titled 'Keep Playing' seemed successful, which generated the second largest number of user-generated videos (n=69, 67.6%). However, the success did not last. During Period 5, the number of views, comments, and likes were the lowest and proportion of likes to overall ratings once again dipped.

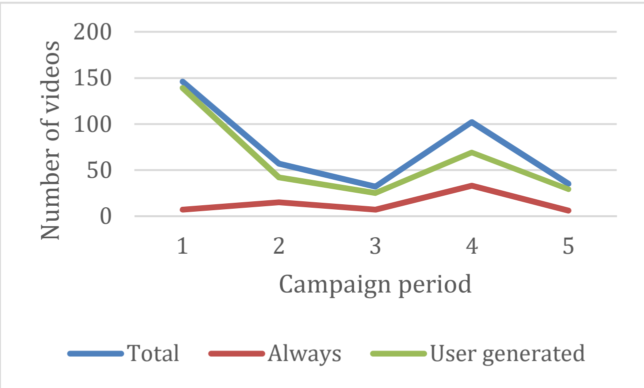

Figure 1. Number of videos by campaign period

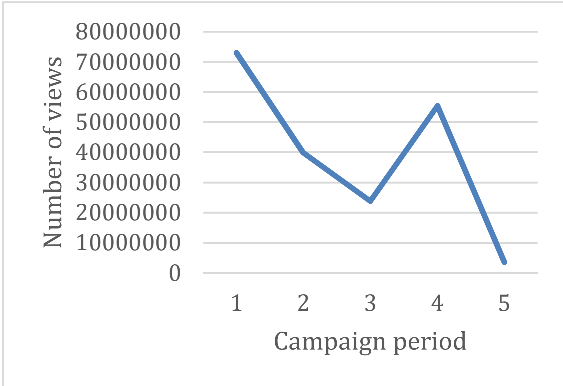

Figure 2. Number of views by campaign period

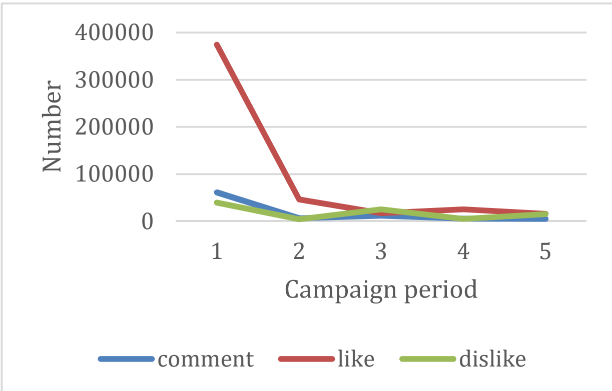

Figure 3. Number of comments, likes, and dislikes by campaign period

Table 1. Number of videos, views, comments, likes, and dislikes by campaign period

	Total	1st	2nd	3rd	4th	5th
Videos	372	146	57	32	102	35
Always posted videos	68	7	15	7	33	6
User-generated videos	304	139	42	25	69	29
Views	195,615,214	73,005,250	39,833,759	23,826,036	55,397,155	3,553,014
Comments	88,787	61,325	6,457	11,262	5,156	4,587
Likes	478,718	374,480	46,111	17,299	25,048	15,780

Dislikes	88,669	39,616	4,368	24,982	4,605	15,098
Proportion of likes to overall ratings (Likes+Dislikes)	84.3%	90.4%	91.3%	40.9%	84.5%	51.1%

To examine RQ2 and RQ3, a NodeXL map was created based on degree and betweenness centrality of videos for each period (See Figure 4). In the map, five distinct subgraphs were presented in the order of network size. Overall graph metrics for each period were presented in Table 2. The network graph for campaign Period 1 presents the largest network with 146 nodes, followed by campaign Period 4 with 102 nodes. The network graph for campaign Period 4 had a larger number of edges between nodes with fewer subcomponents than Period 1, which means that there were more connections between the videos in the graph for campaign Period 4. The density scores were relatively low for all five periods, implying that users' attention and commenting behaviors focused on only a few sets of videos.

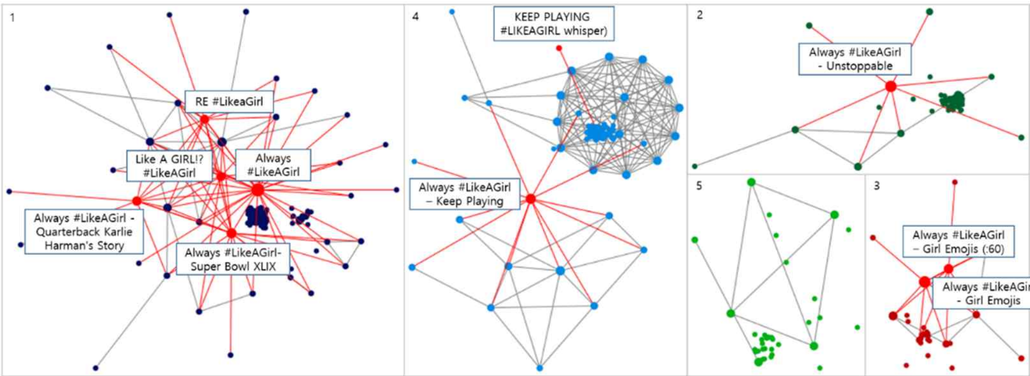

Figure 4. NodeXL map with vertex size mapped to degree
Note: Highlighted videos represent the top 10 highest betweenness centrality score

Table 2. Overall graph metrics

Metric	Total	Period 1	Period 2	Period 3	Period 4	Period 5
Vertices (node)	372	146	57	32	102	35
Unique edges (link)	555	99	12	19	126	7
Connected components	272	110	49	23	73	31
Maximum geodesic distance (Diameter)	5	4	3	3	4	1
Average geodesic distance	2.086	2.058	1.580	1.500	1.379	0.700
Graph density	0.008	0.009	0.008	0.038	0.024	0.012

Always' first #LikeAGirl ad had the highest degree and betweenness centrality scores of all campaign periods, as shown to be located in the middle of the graph for campaign Period 1 (See Figure 4). During campaign Period 1, among the seven videos uploaded by Always, five were in the top 10 degree and betweenness centrality scores (See Table 3), making them pivotal videos in the network. Three user-generated videos containing negative reactions toward the campaign also ranked high in terms of degree and betweenness centrality. During campaign Period 2, five videos out of 15 by Always ranked high in terms of degree and betweenness centrality scores. As shown in Figure 4, the second major ad 'Always #LikeAGirl – Unstoppable' played a central role in the network. During campaign Period 3, three videos out of seven uploaded by Always ranked high in terms of degree and betweenness centrality scores. Two user-generated videos with negative reactions also had high degree and betweenness centrality scores. As shown in Figure 4, the third major ad 'Always #LikeAGirl – Girl Emojis' was located at the center of the network and played the role of a bridge connecting other videos. During campaign Period 4, seven videos by Always (including Whisper Korea) out of 33 ranked high in terms of betweenness centrality scores. The subgraph for Period 4 (See Figure 4) had two major clusters. The circle represents mainly user-generated videos connected densely to each other. Another cluster consisted of Always ads. The fourth major ad 'Always #LikeAGirl – Keep Playing' was located in the middle of the network, connecting the two clusters. For campaign Period 5, one video out of six uploaded by Always ranked high in terms of degree and betweenness centrality scores. The subgraph for Period 5 (See Figure 4) had a large diamond cluster representing mainly user-generated videos. The fifth major ad 'Always #LikeAGirl – Keep Going' was located outside of the main cluster. The series of Always ads did not play central roles in the fifth network.

Table 3. Degree and betweenness centrality scores by campaign period

Campaign period	Title	Author	Degree	Betweenness centrality
1	Always #LikeAGirl	Always	61	1346.614
1	Always #LikeAGirl - Super Bowl XLIX	Always	31	177.841
1	Always #LikeAGirl - Quarterback Karlie Harman's Story	Always	25	194.500
1	RE #LikeaGirl	Thunderf00t	24	179.946
1	Like A GIRL!? #LikeAGirl	UhOhBro	24	148.344
1	The #LikeAGirl Lie	Amazing Atheist	24	72.698
1	Always #LikeAGirl – Interviewer Karlie with Sam Gordon	Always	19	29.595
1	Always #LikeAGirl - Meet the Director, Lauren Greenfield	Always	17	88.154
1	#LikeAGirl	Saphira Howell	10	9.210
1	#LikeAGirl Smashes Stereotypes	YouTube Nation	8	22.735
2	Always #LikeAGirl - Unstoppable	Always	42	405.938
2	#LIKEAGIRL: Katty Diaz BMX 2016	Katty Bmx	18	0.000
2	Being Unstoppable #LikeAGirl - A Film by Zuriel Oduwole	Always	14	2.816
2	Always #LikeAGirl – Behind the Scenes with Lauren Greenfield	Always	12	4.844
2	Always #LikeAGirl - Confidence Summit announcing partnership with TED	Always	11	80.376
2	Always #LikeAGirl - Unstoppable | Carissa Romero - Growing your Mind	Always	9	2.060
3	Always #LikeAGirl - Girl Emojis	Always	43	346.872
3	Always #LikeAGirl – Girl Emojis (:60)	Always	26	119.040
3	Always #LikeAGirl – Girl Emojis (Behind the Scenes with the Director)	Always	21	41.505
3	#LikeAGirl Girl Emojis!?! (Female Reaction)	Alien Queen Of Darkness	12	8.599
3	Why Feminism Gets No Respect: A Response to #LikeAGirl - Girl Emojis	Dr Shaym	11	12.896

4	Always #LikeAGirl – Keep Playing	Always	32	210.176
4	KEEP PLAYING #LIKEAGIRL whisper	Whisper Korea	3	158.000
4	HOW TO BE CONFIDENT! Puberty, Sports and Always #LikeAGirl	Hailey Sani	4	87.498
4	Always #LikeAGirl – Keep Playing (Extended Version)	Always	24	31.392
4	Always #LikeAGirl | Olympian Alex Morgan - The Power of Playing #LikeAGirl	Always	15	8.186
4	Always | Team Canada's Stephanie Labbe Keeps Playing #LikeAGirl	Always	13	4.792
4	#LIKEAGIRL: extreme Barcelona-categoría de chicas	Katty Bmx	19	3.750
4	#LIKEAGIRL: ¿Qué es Like a Girl ?	Katty Bmx	19	3.750
4	#LIKEAGIRL: Cómo hacer 180 -TUTORIAL-	Katty Bmx	19	3.750
4	#LIKEAGIRL: sesión en BikeParadise	Katty Bmx	19	3.750
4	Always #LikeAGirl | Olympian Alex Morgan - Keep Playing #LikeAGirl	Always	12	3.602
4	Whisper - Keep Supporting #LikeAGirl	Always	11	1.973
5	Always #LikeAGirl – Keep Going	Always	19	13.896
5	#LIKEAGIRL: se saca un truco en 7 intentos	Katty Bmx	18	0
5	#LIKEAGIRL: Gente con talento -Luis el Pollo-	Katty Bmx	18	0
5	#LIKEAGIRL: gente con talento-ERICK PONCE-	Katty Bmx	18	0
5	#LIKEAGIRL: como hacer TAILWHIP-tutorial-	Katty Bmx	18	0

5. Discussion

The current study examined how the Always brand activism campaign spread on YouTube by conducting a network analysis of YouTube video networks generated by the #LikeAGirl campaign during a four-year period spanning across five campaign periods. From a longitudinal analysis of views, comments, likes, and dislikes across five campaign periods, this study found that the first campaign ‘Always #LikeAGirl’ period resulted in the greatest number of views, comments, likes, and user-generated videos inspired by the campaign. However, the initial impact of the campaign did not seem to last long. The total number of videos, views, comments, and likes generated during the second campaign period dropped considerably from the first. The third campaign period generated the lowest proportion of likes to overall rating. The fourth campaign period seemed to regain positive ratings with a greater number of views and a large number of user-generated videos. However, with diminished number of comments and lower ratings, the impact of the fourth campaign was not comparable to the initial impact of the first campaign. Videos generated within the fifth period received the lowest number of views, comments, and likes and negative ratings outweighed the positive. Although the follow-up campaign periods were not as successful as the initial campaign, the substantial amount of views, comments, likes, and user-generated content showed that the consecutive campaigns still had impact. The evidence of cognitive (views, comments), affective (likes, dislikes, comments), and behavioral participation (user-generated videos, comments) in the hierarchy of effects [27] were observed in all five periods of the campaign, attesting to the campaign's reach and influence.

The initial adoption and peak in 'contagion' followed by a tapering off of further adoption is consistent with information diffusion patterns observed in various social media models [43]. Even with a refreshed and varied multi-stage campaign, if operating under one 'bursty topic' such as the Always #LikeAGirl (i.e., a social movement for girl empowerment), it could be expected that adoption patterns would adhere to the patterns of the diffusion of innovation theory [31]. If companies want to take on a long-term cause they believe that aligns with the company's values, in order to maintain engagement, under the bigger umbrella of the cause, they would need new innovative ideas that could provide new solutions to particular needs [34]. Which is why the fourth period ad 'Keep Playing' could have achieved a spike in engagement and user-generated content. Under the broader theme of girl empowerment, it focused on encouraging girls to keep playing sports, tackling the issue of sports gender inequality [44] and emphasizing the importance of sports and physical activity for female physical and mental wellness [45]. The fourth campaign recognized a particular need in society and gave it a new focus, reviving the strength of the overall campaign and seeing another wave of adoption.

Network analysis results showed that a series of #LikeAGirl ad campaigns played a central role in the network of #LikeAGirl related YouTube videos. Always #LikeAGirl main ads representing the first three periods were located at the center of the network for each period and had high degree and betweenness centrality scores. This means that these ads were more influential in the network because they were extensively connected to other videos and played the role of a bridge. In other words, Always #LikeAGirl ads were at the center of online viewers' attention and actions. At Period 4, an interesting pattern was found. The network graph included two major clusters: one consisted of user-generated videos connected densely to each other and the other was a connection of mainly Always videos. At Period 4, more than 30 videos were uploaded by Always to revitalize campaign diffusion and this attempt was deemed successful. It resulted in a greater number of user-generated videos, which created a more densely connected cluster than the one consisting of Always videos. The finding indicates that these user-generated videos were more actively reviewed and co-commented by a group of engaged viewers. 'Always #LikeAGirl – Keep Playing' ad still played an important role by connecting these two clusters. At Period 5, user-generated videos formed a cluster and 'Always #LikeAGirl – Keep Going' was located outside of the main cluster. As we predicted based on the two-step theory of information flow [39], the pattern of centrality shifted from Always ads to user-generated content. This finding also echoes with Xu et al. [46], which found that mass media videos played a central role with high degree and betweenness centrality scores but user-generated videos became more central to cultural diffusion over time.

Interestingly, some user-generated videos ('Like A GIRL!? #LikeAGirl,' 'RE #LikeaGirl,' 'The #LikeAGirl Lie') containing negative reactions ranked high in terms of centrality measures (degree and betweenness centrality). Xu et al. [46] also found that videos containing opinion-laden cultural critiques brought a large number of co-commenting actions, which aligns with the finding of this study. Social media listening is considered essential for companies and organizations, especially those that run social media viral marketing campaigns [47]. Brands should actively conduct social media listening to such opinion-laden critique videos and the comments they generate as they could provide invaluable information on what is working and what is not working about the campaign.

Several limitations give way for future research. First, the link between the nodes in the network was captured through co-commenting on pairs of videos. Other links could not be considered when choosing to study videos as the nodes in the network. Future research could designate users or commenters as the nodes to observe other link relationships. Second, the current study limited the video search to the keyword #LikeAGirl. Other searches with different keywords or a set of keywords could generate a greater network of videos, including more user-generated content. Third, future studies could conduct additional analysis on the content of the comments on the videos. The third and fifth period ads had significantly negative ratings thus a study of the kinds of specific sentiments that came out of the comments could provide future insight for campaign planners interested in longitudinal follow up campaigns. Fourth, YouTube was Always' primary launching pad for this campaign but they also used Twitter and Facebook to spread the word. It would be interesting to observe how the campaign was diffused on these other social media and to compare between platforms. Fifth, examining the success and information flow of other viral marketing campaigns could accumulate greater knowledge of the phenomenon and uncover a greater pattern for success or failure regarding such campaigns.

6. Conclusion

Previous marketing campaign studies relied on survey or interview methods to examine its effects but the current study showed that social network analysis could play a vital role in capturing consumer responses and studying how viral campaigns are disseminated.

We examined how #LikeAGirl campaign related videos were spread on YouTube by looking at quantifiable data (i.e., views, comments, likes, dislikes, user-generated videos) and structural network patterns. The Always #LikeAGirl campaign showed great impact by both standards. This campaign serves as a great case study for a longitudinal brand activism campaign maintaining a consistent theme but still garnering user attention and interaction online throughout its campaign periods. Just as in the case of Always, companies launching longitudinal viral campaigns could first promote a primary topic by creating online content that motivates active participation. Then, they could promote follow-up secondary topics supporting the main primary campaign idea, which could help revitalize consumer conversations and online action. For greater diffusion and contagion on social media space, brands need to conduct thorough research to understand and capture important issues in society ('bursty topics') for both the primary and secondary topics.

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