

A Social Networks Approach to Viral Advertising: The Role of Primary, Contextual, and Low Influencers

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Abstract

The diffusion of social networking platforms ushered in a new age of peer-to-peer distributed online advertising content, widely referred to as viral advertising. The current study proposes a social networks approach to the study of viral advertising and identifying influencers. Expanding beyond the conventional retweets metrics to include Twitter mentions as connection in the network, this study identifies three groups of influencers, based on their connectivity in their networks: Hubs, or highly retweeted users, are Primary Influencers; Bridges, or highly mentioned users who associate connect users who would otherwise be disconnected, are Contextual Influencers, and Isolates are the Low Influence users. Each of these users' roles in viral advertising is discussed and illustrated through the Heineken's Worlds Apart campaign as a case study. Providing a unique examination of viral advertising from a network paradigm, our study advances scholarship on social media influencers and their contribution to content virality on digital platforms.

Keywords

viral advertising, social networks, Twitter, viral marketing, social media influencers

Introduction: The Disruption of Traditional Advertising

For decades, the advertising industry was based on an asymmetrical communication model, where marketers would engage audiences via paid media channels. The advent of social media platforms completely transformed the general media landscape, along with the advertising model, as audiences shifted from the role of content receivers to content creators, distributors, and commentators (Keller, 2009; Scott, 2015). Simply put, the empowerment of audiences from mere viewers to active content distributors effectively flipped the advertising model on its head. Where paid media (in this case, advertising) was once supported by earned and owned media, the modern advertising model uses owned, shared, and earned media as the key media planning strategy, supported by paid media (Pearson, 2016). Recognizing the increased potential for free content distribution, marketers realized that creating highly engaging advertising content could expand potential reach, a cheaper and more credible tactic than traditional paid advertising (Cho, Huh, & Faber, 2014; Golan & Zaidner, 2008). This fundamental disruption of the advertising and marketing world led to growing interest in content creation, co-creation, and distribution.

Generally defined, advertising refers to the “paid non-personal communication from an identified sponsor using mass media to persuade or influence an audience” (Wells, Moriarty, & Burnett, 2000, p. 6). Consistent with most, but not all, of these requirements, Porter and Golan (2006) defined viral advertising as “unpaid peer-to-peer communication of provocative content originating from an identified sponsor using the Internet to persuade or influence an audience to pass along the content to others” (p. 33).

The expanding literature on viral advertising recognizes the ways in which peer-to-peer distribution of advertising content are redefining the industry. When examined holistically, the literature has several limitations. First, existing viral advertising research is limited primarily to advertising spread within one step of the original source (e.g., predicting the number of message shares), while information on social

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media often spreads beyond a single step from the original source. Second, in focusing on the characteristics of shared content or sharing users, researchers make the assumption that all shares are equal in terms of their impact. However, sharing-impact varies among users, based on their connectivity. Third, the metaphor of virality, the idea that content is spread gradually among individuals and their immediate contacts, may not fully capture what is often a complex multi-actor process of content distribution. Cascades of content distribution were found to be centered on a small number of distributors, creating a hierarchical, rather than egalitarian, pattern of content distribution (Baños, Borge-Holthoefer, & Moreno, 2013).

This study proposes a social networks approach to address these limitations, using Heineken's Worlds Apart campaign as a case study. Data are collected for all Twitter users posting links to the original advertisement on YouTube, and the subsequent retweets and mention relationships. While a growing body of scholarship examines the potential impact of social media influencers in online marketing campaigns, they often treat all influencers as one and the same (Evans, Phua, Lim, & Jun, 2017; Phua & Kim, 2018).

We argue that different types of influencers impact social networks in different degrees and ways. Informed by a body of scholarship in social networks, we propose that there are three types of influencers: primary, contextual, and low influencers. Primary influencers are hubs, users who attract large and disproportionate retweets from other users in the network. Contextual influencers play a role of bridges in the network by providing context regarding the overall discussion and thus help to understand the distribution of content beyond the quantity of retweets. Low influencers are users who shared a link to online content; however, these users were neither retweeted nor mentioned by anyone else in the network. While low influencers have limited individual contributions to content distribution, their aggregate influence is substantial.

Social Media Influencers

An emergent body of scholarship in the field of marketing, advertising, and public relations examines the intermediary function of influencers between brands and consumers, organizations, and stakeholders in social media engagement (De Veirman, Cauberghe, & Hudders, 2017; Freberg, Graham, McGaughey, & Freberg, 2011; Phua, Jin, & Kim, 2016). At the most basic level, influencer is identified by their number of followers and their ability to impact social media conversation regarding brands or topics (Watts & Dodds, 2007). While the term social media influencer is ubiquitously applied, there are few formal definitions of what an influencer actually is. Brown and Hayes (2008) defined influencers broadly as individuals who hold influence over potential buyers of a brand or product to aid in the marketing activities of the brand. Others narrow the definition of an influencer to

reflect on the latest marketing trend in which social media celebrities are paid by advertisers to promote products (Abidin, 2016; Evans et al., 2017; Senft, 2008).

Moving beyond definitions, scholars attempt to theorize why it is that some social media users grow more influential than others via relationship building. To explain the influence of influencers, media scholars often depend on the parasocial relationship explanation (Daniel, Crawford, & Westerman, 2018; Lou & Yuan, 2018; Rasmussen, 2018). Moving beyond a temporary parasocial interaction (as originally conceptualized by Horton & Wohl, 1956), parasocial relationships between audience members and mediated characters are formed over a period of time and provide audience members with a sense of engagement with on-screen characters (Klimmt, Hartmann, & Schramm, 2006; Tukachinsky, 2010). In the context of social media, such parasocial relationships provide influencers with unique social capital that leads to audience trust (Tsai & Men, 2017; Tsotsou, 2015).

Indeed, the central role of trust in parasocial relationships may provide a plausible explanation for the influencer phenomenon and the rise of influencer marketing (Audrezet, De Kerviler, & Moulard, 2018). Trust has been identified as a key predictor of several advertising consequences including recall, attitude, and likelihood to share (Cho et al., 2014; Lou & Yuan, 2018; Okazaki, Katsukura, & Nishiyama, 2007). Abidin (2016), building on the concept of parasocial relations, identified four ways that influencers appropriated and mobilized intimacies: commercial, interactive, reciprocal, and disclosive. Influencers are identified not only based on their sheer number of such parasocial relationships, such as subscribers or followers on social media, but primarily based on their ability to impact social media conversation and subsequent behavior regarding brands or topics (Watts & Dodds, 2007).

We propose to complement existing conceptualization of influencers by shifting the focus from influencers' engagement or the nature of individual connections with them, to their ability to reach large, unique, and relevant audiences and to shape the conversation about brands and topics. It is the distribution of content that allows influencers to influence, and therefore provides a key theoretical framework for identifying social media influencers. We next discuss viral advertising as a theoretical framework for content reach, followed by its limitations. We then take a social networks approach to theorize social media influencers, bridging both bodies of literature.

Viral Advertising

As explained by Golan and Zaidner (2008), there are several key differences between viral and traditional advertising. First, viral advertising earns audience eyeballs, as opposed to paying for them. This is a major departure from the traditional advertising exchange, where brands purchase media

space and interrupt an audience's media consumption with advertisements. Second, viral advertisements provide such increased value to audiences that they transform audiences from passive content receivers to active social distributors who play a key role in advertisement distribution. Third, although there are limited studies speaking to this point, it is worth noting that information sharing has been shown to increase a user's followers on Twitter, which is a long-term benefit for marketers (Hemsley, 2016).

What Makes Advertising Go Viral?

Why do some advertisements receive wide-scale viewership via audience distribution, while others do not? Scholars offer different approaches to this question, one focusing on content characteristics (Brown, Bhadury, & Pope, 2010; Golan & Zaidner, 2008; Petrescu, 2014) and another examining virality attribute factors such as brand relationships (Hayes & King, 2014; Ketelaar et al., 2016; Shan & King, 2015).

Porter and Golan (2006) specifically identify provocative content as contributing to advertising virality. Other studies identify appeals to sexuality, as well as shock, violence, and other inflammatory content as key elements of message virality (Brown et al., 2010; Golan & Zaidner, 2008; Petrescu, 2014). Eckler and Bolls (2011) argue that the emotional tone of advertisement is directly related to audience intention to forward ads to others. Yet advertising content, tone, and emotion cannot fully account for ad virality. Scholars point to a variety of other variables significantly related to advertising virality including brand relationship (Hayes & King, 2014; Ketelaar et al., 2016; Shan & King, 2015), attitude toward the ad (Hsieh, Hsieh, & Tang, 2012; Huang, Su, Zhou, & Liu, 2013), and credibility of the sender/referrer (Cho et al., 2014; Phelps, Lewis, Mobilio, Perry, & Raman, 2004).

Hayes, King, and Ramirez (2016) advanced research on viral advertising by illustrating the importance of interpersonal relationship strength in referral acceptance. Their study suggested that individuals are motivated to share advertising content based on reputational enhancement and reciprocal altruism. Alhabash and McAlister (2015) conceptualized virality based on three key components: viral reach, affective evaluation, and message deliberation. The authors linked virality and online audience behaviors in what they refer to as viral behavioral intentions (VBI). This linkage is supported by later research indicating that the virality of digital advertising is often related to several VBIs motivated by a variety of audience-based characteristics (Alhabash, Baek, Cunningham, & Hagerstrom, 2015; Alhabash et al., 2013).

Limitations of Viral Advertising Research

In essence, viral advertising represents a "peer-to-peer communication" strategy that depends on distribution of content (Petrescu & Korgaonkar, 2011; Porter & Golan, 2006). Despite the fact that most peer-to-peer social media shares

include multiple distribution phases (e.g., from user A to user B to user C), existing viral advertising research is mostly limited to one-step advertisement spread (e.g., predicting number of message shares). Studies suggest that while content may be shared by many users, most viral content is spread beyond this single step (Bakshy, Hofman, Mason, & Watts, 2011). The body of literature concerning viral advertising does not examine advertising spread beyond a user's immediate set of connections.

Second, the literature conceptualizes virality based on such sharing metrics as shares or retweets. In doing so, scholars fail to account for the possibility that the overall impact of such user actions may not result in equal content distribution outcomes. In fact, studies on virality of content and cascades of information flow highlight that "popularity is largely driven by the size of the largest broadcast" (Goel, Anderson, Hofman, & Watts, 2015, p. 180). In other words, it is not only the number of consumer-to-consumer interactions but the connectivity of these consumers with others that determines the impact of viral advertising. One user's retweet may count more than another user.

A third limitation is the more subtle assumption of virality as metaphor. The idea that content is spread gradually from one source to that source's immediate small group of connections, to their neighbors, and so on is a powerful metaphor that resonates well with many scholars (Miles, 2014; Porter & Golan, 2006). However, research shows no foundation for such an egalitarian assumption. Connections are distributed in a skewed manner across individuals, a phenomenon referred to in ways that vary by discipline:

in economics it goes by the name "fat tails," in physics it is referred to as "critical fluctuations," in computer science and biology it is "the edge of chaos," and in demographics and linguistics it is called "Zipf's law." (Newman, 2000)

At the end of the day, most pieces of shared content are not re-shared by others, and thus are spread by very few. Similarly, from an advertisement and social media perspective, Nielsen (2006) presented the "1-9-90 rule," suggesting that content is created by 1% of users and distributed by 9% to the remaining 90% of content receivers. Baños et al. (2013) showed that only a small minority of content distributors will account for content virality. In addition, Pei, Muchnik, Andrade, Zheng, and Makse (2014) suggested that "due to the lack of data and severe privacy restrictions that limit access to behavioral data required to directly infer performance of each user, it is important to develop and validate social network topological measures capable to identify superspreaders" (p. 8).

To address these key gaps in the literature of viral advertising and subsequently our ability to theorize influential users in terms of their content diffusion, we take a social networks approach, which focuses on patterns of connectivity among users. We propose that social media influencers are

ultimately determined by their position in an issue or brand-specific conversation network, allowing their posted content to be distributed in a strategic manner. As such, these influencers play key roles in the virality of any advertising campaign on social media. A social networks approach, as illustrated by Himelboim, Golan, Moon, and Suto (2014) provides for a macro-understanding of social media relationships, content flow, and the role of social media influencers within the network.

The Social Networks Approach

The social networks conceptual framework shifts the focus from individual traits to patterns of social relationships (Wasserman & Faust, 1994). Applying a social networks approach to social media activity allows researchers to capture content virality and identify key social media influencers that affect the conversation about a brand and reach key groups of consumers. A social network is formed when connections (“links”) are created among social actors (“nodes”), such as individuals and organizations. The collections of these connections aggregate into emergent patterns or network structures. On Twitter, social networks are composed of users and the connections they form with other users when they retweet, mention, and reply to (Hansen, Shneiderman, & Smith, 2011).

The network approach can bridge the viral advertising and social media influencer’s bodies of literature. As discussed earlier, social media platforms allow individuals to maintain parasocial relationships with influencers (Abidin, 2016). In the case of Twitter, such engagement is manifested in the form of mentions, likes, and retweets. In social networks research, these relationships are conceptualized as links in a network.

The social networks approach allows us to capture the distribution of a specific piece of content (i.e., an advertisement) and identify users in key positions in the network that are responsible for the distribution of ads, as social media influencers. It should be noted that even in studies on information diffusion in related disciplines, it is quite rare to track the virality of a single piece of content, rather than the overall diffusion of messages in a broader conversation.

Viral advertising research often focuses on the most visible type of content that is spread, shared, or retweeted on Twitter. Social media influencers are often examined by their number of connections in a social media platform (De Veirman et al., 2017). However, a link to a video advertisement, or any other source of paid advertising content, may be posted by more than a single user who contributes to its diffusion. In other words, while the advertisement itself may have a single point of origin (e.g., a YouTube video page), this advertisement may have multiple users who may account for multiple points of origin for distribution on Twitter. While a particular video may have gained many views and shares on its platform of origin (“gone viral”), not all shares on

Twitter contributed equally to its virality. We therefore initialize our understanding of content distribution patterns by asking,

RQ1: What is the distribution structure of a viral advertisement on Twitter?

A single network can have different types of links, or ties, that connect its users. On Twitter, users can be connected, among others, by relationships of retweets and mentions. A network of advertising virality captures users who posted content with a hyperlink to a given ad. Such Twitter users share a link to a given advertisement via a tweet, expanding its reach one step away from the source (YouTube). Some studies have examined the overall network structure to explain virality. Pei et al. (2014) used social network analysis on LiveJournal, Twitter, Facebook, and APS journals and found that users who spread the most content were located in the K-Core (a metrics of subgroup cohesiveness in the network). At the node-level, a few users are expected to contribute further to the virality by having their tweets shared, or retweeted, by many additional users. Such users capture virality beyond a single step away from the source. Users with many connections in the network are known as social hubs (Goldenberg, Libai, & Muller, 2001) or simply *Hubs*. Using computer simulations, Hinz, Skiera, Barrot, and Becker (2011) found that seeding messages to hubs outperformed a random seeding strategy and seeding to low-degree users, in terms of number of referrals. Kaplan and Haenlein (2011) also illustrated the role that hubs play in integrative social media and viral marketing campaigns.

Recognizing that the emergent literature on social media influencers is somewhat undermined by the various uses of the term influence to reflect different functions of influence, we recommend the categorization of influencers into three different types, based on the type of relationships, links in the network, that makes them central in a network.

Social networks literature repeatedly shows that given the opportunity to interact freely, connections among users will be distributed unequally, as a few will enjoy large and disproportionate number of relationships initiated with them, while most will have very few ties. On Twitter, content posted by a few users will enjoy major distribution via retweeting, while the rest will gain little shares, if any. Indeed, Araujo, Neijens, and Vliegenthart (2017), define influentials as “users with above average ability to stimulate retweets to their own messages” (p. 503), consistent with conceptualization of influencers based on impact on content distribution (Cha, Haddadi, Benevenuto, & Gummadi, 2010; Kwak, Lee, Park, & Moon, 2010). Hubs as conceptualized in social networks literature, therefore, are one type of social media influencers as conceptualized in social media scholarship, as each one makes a major contribution to content distribution. One type of influencer, from a social networks conceptualization, is therefore the *Primary Influencer*, as it

is one of few members responsible for the distribution of content in the network. We therefore present the following research question:

RQ2: Which users serve as Primary Influencers in a viral advertising network?

On Twitter, retweets are attributed to the original tweet; therefore, operationalizing links in this network only as retweets fails to capture information flow beyond one step away from a user who shared a link to an ad. In other words, since users are unlikely to share the same link more than once, the network of retweets will create distinct subsets of users, each retweeting a single tweet. These subsets are completely, or almost completely, disconnected from one another. As discussed earlier, a key limitation of viral advertising literature is that studies are limited to the extent they measure diffusion from a single source. In order to maximize insights from the social networks approach to viral advertising, other types of ties should be considered.

The practice of mentioning users on Twitter, using the @ symbol, serves two main purposes. First, it associates a post with another user (e.g., an individual, an organization, a brand), serving as metadata for that tweet. Second, it serves as a secondary route of content distribution. When a tweet mentions a given user, that tweet will appear on the recipient's Notifications tabs and Home timeline view if the author of the tweet follows the sender. Conceptualizing mentions on Twitter as links in a social network captures the context of the virality of advertisements by connecting users beyond immediate retweeting of a single source. In other words, this practice bridges the otherwise disconnected subsets of retweeting users. In social network literature, bridging is a concept that can advance the understanding of advertisement virality and the key users who play a key role in it.

Bridges and Structural Holes

Burt's (1992, 2001) theory of structural holes examines social actors (e.g., individuals and organizations) in unique positions in a social network, where they connect other actors that otherwise would be less connected, if connected at all. In Burt's (2005) words, "A bridge is a (strong or weak) relationship for which there is no effective indirect connection through third parties. In other words, a bridge is a relationship that spans a structural hole" (p. 24). A lack of relationships among social actors, or groups of actors, in a network gives those positioned in structural holes strategic benefits, such as control, access to novel information, and resource brokerage (Burt, 1992, 2001). Actors that fill structural holes are viewed as attractive relationship partners precisely because of their structural position and related advantages (Burt, 1992, 2001).

The nature of Twitter retweets, however, rarely allows bridges to form as retweets that are associated with an

original tweet (unless modified retweets are used). In other words, the spread of retweets remains within a single step away from the author who posted that message. Therefore, this additional type of structural characteristic is not enough to characterize a new type of influential user in viral advertising. Conceptualizing a second type of parasocial relationship on the network—mentions (the inclusion of a reference to another Twitter user in a post)—as links in a network allows bridges to form as they provide an additional connection among users. While mentions do not represent primary stages in content distribution, they do provide meaningful points of context that allow researchers to better understand the overall virality of an advertisement.

Since content distribution or virality on Twitter does not take place in a vacuum but rather is often responsive to the broader online conversation, the distribution of any specific tweet may be impacted by contextual factors. For example, the distribution of a tweet about a pharmaceutical company may be impacted by related actors linked to the industry in news coverage. On Twitter, users often provide context to their posted content, among others, by mentioning related users via their handles (@). While such users do not take an active role in the conversation, they are nominated, so to speak, as influencers in the network, as they provide additional explanation for content virality. In other words, they allow researchers and practitioners to understand that the vast distribution of an ad on Twitter is driven by a larger context.

We therefore define a second type of social networks-driven influencer type as *Contextual Influencer*—highly mentioned users who bridge otherwise separated groups of retweeting users.

RQ3: Which users serve as Contextual Influencers in viral advertising networks?

Beyond a few users in key positions—Hubs or Bridges—many users' content sharing is more limited. Each user contributes little to advertisement virality, as they reach only their immediate Twitter followers. However, as such users are often the majority of distribution agents, they ultimately make a major contribution to ad virality. We call users who are isolated in the network (defined as incurring no retweets for their shared video tweets) *Low Influence* users.

RQ4: What percentage do Low Influencers make of all users in the network?

Proof of Concept: Heineken's "Worlds Apart" Viral Advertisement

To illustrate the conceptual framework proposed in the current study, we selected a popular Heineken advertisement on YouTube, titled "Heineken|Worlds Apart|#OpenYourWorld." Heineken described the ad as, "Heineken presents 'Worlds Apart' An Experiment. Can two strangers with opposing

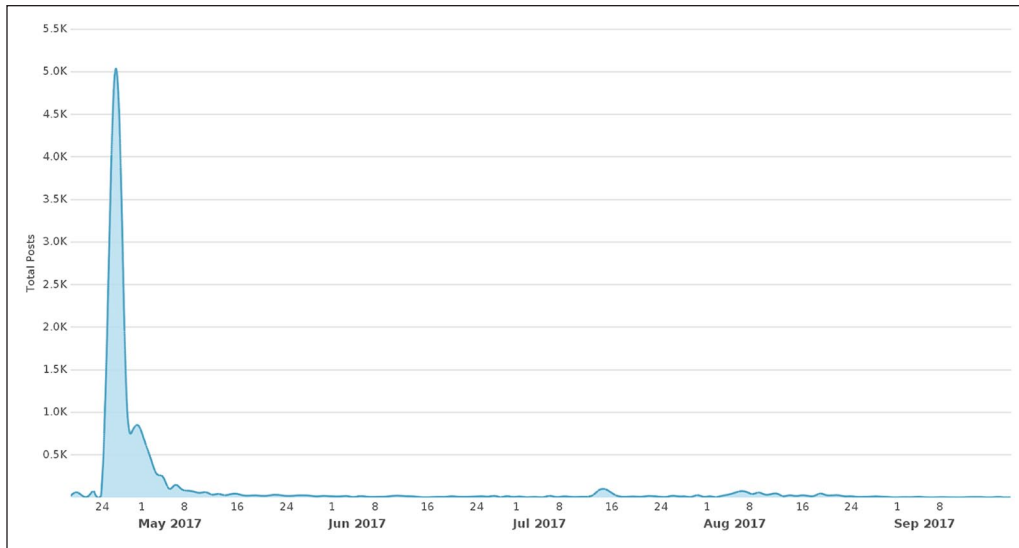


Figure 1. Twitter activity of posts including a hyperlink to the Heineken viral advertisement.

views prove that there's more that unites than divides us?" In this ad, Heineken harnesses a social issue, political and social polarization, and the importance of a constructive conversation across opinions and ideologies. This campaign received accolades from the advertising industry and popular press, as it was compared to a Pepsi campaign that drew on similar social themes but failed to resonate with social media audiences (Al-Sa'afin, 2017). The video was posted on April 24, 2017, and attracted almost 15 million views by September 30, 2017. This advertisement became viral via a range of platforms, including Twitter. The advertisement was selected for this study for its high degree of virality (AdAge.com, 2017).

Method

Data

We used the social media analytics and library platform Crimson Hexagon to capture all Tweets that included the URL to the YouTube video ad (https://www.youtube.com/watch?v=_yyDUOw-BIM). Crimson Hexagon is a Twitter Certified social media data analysis archive, and collects all publicly available tweets directly from the Twitter "firehouse." The data collected for this study capture all public Twitter posts that used the hyperlink to the ad in question (including shortened hyperlinks). We captured all 18,942 tweets posted by 13,009 users between April 20, 2017, when the video was posted, and September 20, 2017. We elected for a longer period of data collection time, due to the fact that viral advertising content often results in mainstream and trade media (Wallsten, 2010). Furthermore, the exploratory nature of this study required a more inclusive data collection period to account for unexpected waves of engagement (see Figure 1).

Note that the users @Youtube and @Heineken were removed from the network data analysis as these handles were automatically added to any tweet shared from YouTube, and therefore created artificial connections between all tweets, potentially misinforming the analysis.

The Network

A customized application was used to extract the retweets, mentions, and replies relationships from the list of tweets; the 5,765 retweets relationships; and the 7,212 mentions ties (including 392 replies, which serve the same function of appearing on a target user wall). The treatment of mentions and replies as a single link-type is a common practice in Twitter network analysis (Isa & Himelboim, 2018; Lee, Yoon, Smith, Park, & Park, 2017; Yep, Brown, Fagliarone, & Shulman, 2017). The MS Excel add-on network analysis application, NodeXL, was used to calculate user- and network-level analysis, as well as for visualization.

For each user in the network, two types of centrality measurements were calculated, using NodeXL. *In-degree centrality* was measured as the number of connections initiated with a given actor (Wasserman & Faust, 1994). On Twitter, in-degree centrality is based on ties or relationships that others have initiated with a user (e.g., the number of users who have retweeted or mentioned that specific user). Users with the highest values in this metric can be considered Hubs, highlighting users who have successfully gained attention to their messages. We determined the cutoff point for identifying hubs by plotting the distribution of in-degree by number of users and the drop point in the scree plot-like graph. *Betweenness centrality* measures the extent that the actor falls on the shortest path between other pairs of actors in the network (Wasserman & Faust, 1994). The more people depend on a user to make connections with other

people, the higher that user's betweenness centrality value becomes. This value is therefore associated with Bridges in a network.

Findings

The study identified a total of 13,009 users who posted a link to the original Heineken advertisement on YouTube. With almost 15 million views of this video on YouTube, this number of tweets may appear low. However, each tweet posted by a user reaches all its Twitter followers. A message's potential reach or impressions are therefore calculated as the total number of Twitter *walls*, or user accounts, on which these tweets appeared. This metric is calculated by adding up all followers of all users who posted an original tweet with the advertisement URL and the followers of all users who retweeted such posts (Sterne, 2010). For the 13,009 users, the total reach was 48,962,936 users (the sum followers of all users in the network), meaning that for almost 50 million users, this advertisement appeared on their own Twitter pages. While it does not necessarily mean that the users all saw the ad, or even the link to it, and it does not take duplicates into account, the high reach value illustrates the *potential* advertising distribution of the 13,009 tweets.

Characteristics and Viral Advertising—Time

The vast majority of advertising spread on Twitter (16,152 tweets, 85.27%) were posted within the first 2½ weeks following the date the video was posted (April 20, 2017—May 6, 2017). The remaining posts were spread over the remaining 4.5 months of data collection. Notably, within the first 5 days of the video's publication, only 248 tweets linked to it. This relatively low-engagement period was followed by highly retweeted activity of individual users such as @Cait_Kahle, a consumer public relations professional, who tweeted on April 26, "Incredible perspective from @Heineken via an advertisement #OpenYourWorld: <https://t.co/ApmYwteLwn>." This tweet gained 463 retweets. @CaseyNeistat, a photographer, posted on April 27, "y'all see that heineken commercial yet? it should win ALL ad awards—<https://t.co/gFDXwy7F31>," gaining 1,172 retweets (see Figure 1).

Characteristics of Viral Advertising—Distribution of Spread and Reach

RQ1: What is the distribution structure of a viral advertisement on Twitter?

The distribution histogram of tweets was found to be highly skewed. Of the 7,422 users who posted an *original* tweet with a link to the advertising video on YouTube, 5,875 received no engagement from others (79.19% of original

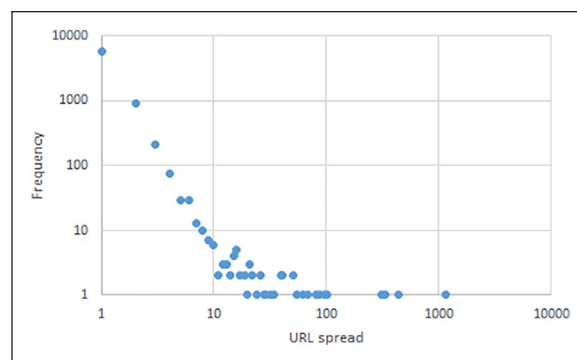


Figure 2. The histogram of URL spread by Twitter users. Both axes are in logarithmic scales.

tweets and 45.16% of total tweets). These are isolated users in the network in terms of advertising spread. For 933 users, only one retweet occurred (i.e., two users spread); 214 users were retweeted by two users, 214 by three users, 75 by four, and 29 users had five retweets each. At the other end of this skewed distribution, a few single tweets were shared many times (1,154; 435; 336; 310; and 102 retweets for each of the top five most shared users). Figure 2 illustrates the distribution.

RQ2: Which users serve as Hubs in a viral advertising network?

The top users, those who posted the most retweeted tweets linking to the Heineken advertisement video, were primarily individuals with no affiliation to the brand: @CaseyNeistat (Casey Neistat), a videographer (1,214 retweets); Cait_Kahle (Caitlin Kahle), a consumer public relations professional (465 retweets); @ChrisRGun (The Cuntacular Chris), a user who posts political jokes and videos (99 retweets); @jrisco (Javier Risco), a Mexican journalist (96 retweets); @MaverickGamersX (Maverick Gamers), an aggregator for video game/film/entertainment industry news and reviews (88 retweets); @willwillynash (Will Nash), a director of short films and music videos (70 retweets); @anminte, a professor at the University of Tokyo (53 retweets); @TheSeanODonnell (Sean O'Donnell), an actor and producer (49 retweets); @COPicard2017, a fan account for Jean-Luc Picard (42 retweets); and @rands, a vice president at Slack (42 retweets).

Characteristics of Viral Advertising—The network

RQ3: Which users serve as bridges in viral advertising networks?

Social network analysis maps and examines patterns of spread of tweets across Twitter users. However, the network of retweets will create a set of disconnected silos, because

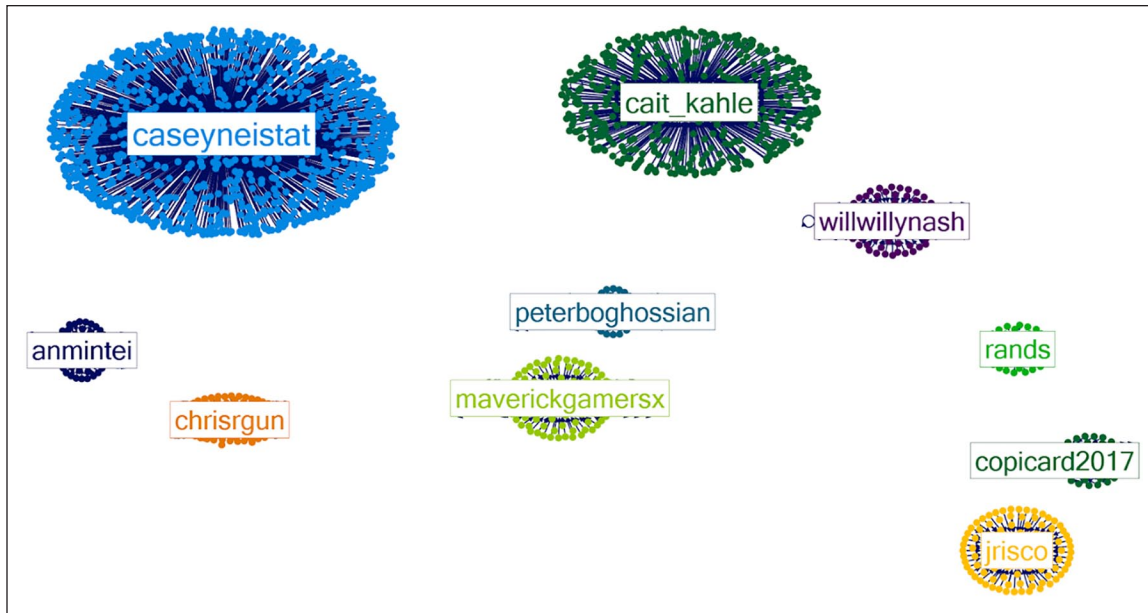


Figure 3. The retweets-based social network of Heineken's viral advertisement.

any retweet of a post will be attributed to the original tweet. Understanding the network of social ties beyond retweets reveals the cross-silo interactions. We therefore expanded the dataset to include not only retweets but also mentions and replies within the set of 13,009 users who posted content with the ad's URL.

Figure 3 illustrates the social networks created when using only retweets as links. For illustration purposes, only clusters created by the most retweeted users were included. Each highlighted user is one of the top retweeted users, surrounded by users who retweeted their post's link to Heineken's advertisement on YouTube. Clearly, such a network does not provide more information than was previously gained from identifying the top retweeted posts. The hubs were discussed in an earlier analysis. This figure highlights the limitation of examining retweets as the sole relationships in Twitter activity surrounding this viral advertisement.

Adding mention relationships into the network adds another layer of connectivity. The retweeting clusters are no longer siloed and new clusters are formed. The top betweenness user added in this network is @Pepsi (in-degree=352; betweenness centrality=1,851,055.41).

Examining the content that included @Pepsi reveals an important theme of the tweets helping to spread the Heineken ad: the controversial Pepsi advertisement criticized for cultural and racial insensitivities. In fact, 315 of the tweets mentioning @Pepsi and linking to the Heineken ad were not retweets and were not retweeted, and would have otherwise been potentially ignored, as they "failed" to attract retweets. The other cluster contained two additional bridges in the network: @Heineken_UK (in-degree=181; betweenness centrality=730,191.83) and @publicislondon, a London advertising agency (in-degree=63; betweenness=740,877.09). These two users gained no

meaningful retweets, and therefore did not reach the surface of the initial retweets analysis. However, they were highly mentioned by users who posted links to the advertisement, contributing to its virality. This finding highlights the potential significance of advertising agencies in the distribution of a viral ad on Twitter beyond their ability to inspire retweets. This analysis points to the strategic application of the agencies' Twitter networks as distribution mechanisms.

Figure 4 illustrates the connectivity power of mentions, allowing for more in-depth understanding of the viral distribution process. Specifically, we can see the siloed clusters created by highly retweeted users, and the connections created by highly mentioned users.

RQ4: What percentage do Low Influencers make of all users in the network?

Of the total 13,009 users who shared a link to the Heineken advertisement, 5,875 (45.16%) were not retweeted even one time, making them isolated in the network. In other words, while each of these users did not make a major contribution to the virality of the ad, as a whole, through comprising almost half of the users, they did make a major contribution, thus supporting the idea of Low Influence users as important for viral advertising. The total potential reach of these Low Influence users, calculated as the sum of the number of their followers, is 9,091,133, 18.56% of the total potential reach (48,962,936) of all users in the network.

Discussion

The current study aims to advance social media virality and social media influencers in advertising scholarship by

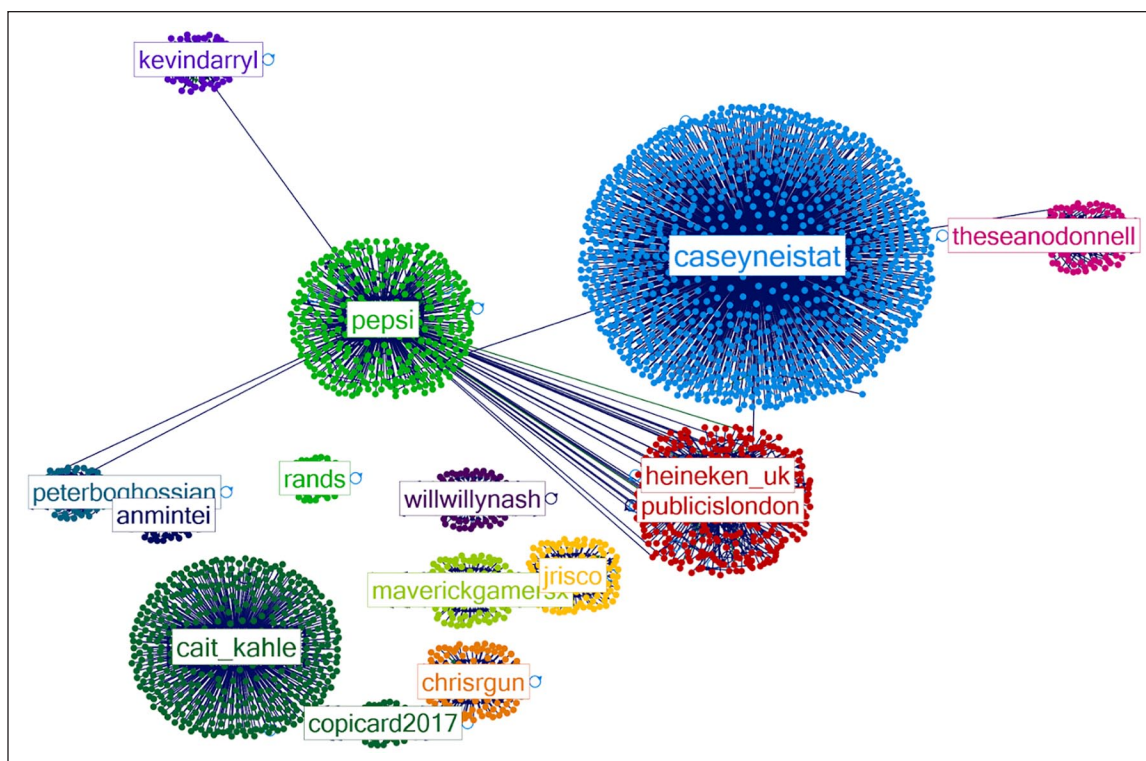


Figure 4. The retweets and mentioned-based social network of Heineken's viral advertisement.

incorporating a social networks approach. We propose and empirically identify three distinct types of social media influencers and thus highlight the multifaceted nature of distribution in viral advertising. Using the Heineken's Worlds Apart ad for proof of concept, we identified three types of key users, based on their network connectivity: Primary Influencers (retweeted hubs), Contextual Influencers (bridges), and Low Influencers (network isolates). As mentioned, viral advertising largely depends on audience participation in content distribution. Our analysis highlights the distinct role of each of the three influencers in ad distribution. The current study aims to advance the understanding of the viral advertising process by offering a more macro-view of advertisements on Twitter. This view broadens the analysis of ad distribution beyond the single peer-to-peer flow, allowing for a multi-step structure available only through network analysis. Moving away from the question of what makes an advertising viral and toward the question of who makes an advertising viral, our study points to a highly skewed nature of distribution. The results of our analysis indicate that a small number of users disproportionately contributed to the distribution of the ad on Twitter, while the vast majority of users made a more modest contribution individually, but a major contribution as a whole.

The Skewed Distribution of Primary Influence

One unique characteristic of viral advertising on Twitter is the multiple points of origin for an advertisement video.

While the ad has a single source, often YouTube or the brand website, it starts a potential cascade of sharing on Twitter via multiple tweets. This study demonstrates the differential contribution of individual Twitter accounts, either affiliated or not affiliated with a brand. Consistent with previous scholarship on viral advertising (Petrescu, 2014; Phelps et al., 2004) and information sharing on Twitter (Araujo et al., 2017), we found that a small number of users had more influence on content distribution than most. Scholarship often points to celebrities, elites, and media organizations as key influencers due to their large Twitter following (Himmelboim et al., 2014; Jin & Phua, 2014). The current study points to a more nuanced explanation.

Taking a social networks approach, the structure of interactions created by acts of sharing only (i.e., retweets) fails to explain the overall structure of information flow in the network in two main ways. First, the major clusters of retweets remain isolated. Such a siloed structure cannot explain the virality of advertising beyond a set of a few highly shared tweets. Second, the approach ignores the majority of users who made much more moderate contributions to the virality of the ad, as they received little or no retweets.

Bridges: The Contextual Influencers

Viral advertising does not take place in vacuum and content sharing takes place in a broader conversational context. A second type of social media influencers—Contextual Influencers—are those who conceptualize and operationalize

as users who do not necessarily take an active part in the conversation but are brought into the chatter by users who mentioned them, as they contribute to advertising virality by sharing a link to an ad. Social media influencers are often characterized by the amount of social connections they have, in terms of followers or subscribers (Abidin, 2016). Contextual influencers are defined by Twitter mentions, a unique type of parasocial relationship that captures best the idea of a sense of engagement of audience members with on-screen characters (Tukachinsky, 2010).

Building upon literature about Bridges and structural holes, highly mentioned users play a role by symbolically connecting many users who were not retweeted, based on parasocial relationships that they form in the network. In other words, introducing both a new type of ties, mentions of users as links, and an additional node-level structural network position, a bridge provides context for understanding certain mechanisms in the distribution of viral advertising that have been ignored by recent scholarship, which has focused solely on highly retweeted users.

Contextual influencers, in the mention-based clusters of low engagement users, provide the context and a possible explanation for the advertisement's virality. In the case study, a common reason for posting the video was in comparison with a failed competing campaign (Pepsi) and in the context of the advertising agency behind that campaign, Publicis London (Publicis, 2017). As one may recall, both Pepsi and Heineken launched campaigns aiming to gain advertising distribution through the production of socially provocative advertisements. While Pepsi was often criticized for its campaign, Heineken was praised. Even though Pepsi did not take an active part in distributing the Heineken ad, as it never posted a link to it, Pepsi is an influencer in the network because it influenced the virality of the Heineken ad. It is the comparison between the two campaigns that people posted about, when they distributed the Heineken ad link.

Further analysis of patterns of mentions among users in examples of viral advertising spread on Twitter can provide researchers and practitioners with an understanding of the triggers of distributing advertising content on Twitter. In other words, this proposed methodology shifts the focus from aiming to explain the reason for high levels of retweets, to explaining the reasons for high level of posts, even if these posts received no engagement. It should be noted that while @HeinekenUK appeared together in a cluster with @PublicisLondon, it had limited influence network connectivity.

Isolates: The Influence of the Low Influence Users

Expanding the breadth of the network to include mentions as network links also revealed clusters of users who contributed to the virality of the advertisement but in a more hidden manner, as they did not attract many retweets. However, these users vastly contributed to the reach of the ad on

Twitter as whole. In the Heineken case, almost four of five original tweets posted with the Heineken video were not retweeted, representing about 45% of all tweets in our dataset. At face value, the contribution from each of these users seems minimal. However, when aggregated, we find that these seemingly non-successful content distributors played an important role in the overall distribution of the advertisement. Furthermore, the video appeared on the walls of all of their followers, even if they were not retweeted, expanding their contribution to the virality even further. In the Heineken case, they accounted for almost a fifth of the total potential reach. Considering Nielsen's (2006) idea of the 1-9-90 rule, findings suggest that within the majority of seemingly non-influential users, many have limited influence on advertising distribution. But when aggregated, these users make a major impact on advertising virality.

There is no doubt that influencer analysis is an important factor in understanding viral distribution of Internet content. As made evident by previous studies, not all Twitter users are equal in their ability to promote content, with elites, corporations, and celebrities often leading the discussion. The results of our analysis point to an often-overlooked phenomenon, the influence of non-influencers, a phenomenon that occurs when individuals fail to meaningfully contribute to the structure of a network, but play an important role in shaping the network when grouped with other non-influencers, ultimately making a meaningful contribution to viral advertising.

Conclusions and Limitations

Recognizing the potential of the network approach in informing and advancing research on viral advertising, our study demonstrated the multi-level ad distribution process. Whereas most previous studies focused on what may lead to advertisement virality (Chu, 2011; Golan & Zaidner, 2008; Hayes & King, 2014), our study addresses another important question: who makes advertising viral? We identified three key types of influencers. The first are the highly retweeted users in the network, each individually makes a major contribution to the distribution of ads. The second are highly mentioned users who make a crucial yet passive contribution to content virality. These serve as Bridges, filling structural holes left in the retweets-only networks. Third are Low Influencers, who each introduced the ad to Twitter by posting an original tweet with a link. Individually their contribution to ad virality does not go beyond their group of followers; however, their aggregated influence on virality is vast, making them influential in the network.

Finally, the current study advances the methodological approach to the study of viral advertising. Network analysis is the only method that allows for a meaningful representation of the viral advertising distribution process. The definition of an advertisement as a single paid form of media requires a third approach where data are collected based on a single piece of content, namely, a hyperlink to an

advertisement. Collecting Twitter data based on a single URL results in a dataset that captures the spread of a single ad across a range of distributors, as opposed to the traditional data collection strategy based on a set of keywords capturing a conversation about a brand. We argue this strategy is not only unique to viral advertisement, but is the most appropriate strategy overall. These conceptual and methodological contributions are applicable beyond the study of viral advertising and the field of marketing, as social media influencers play a key function of content distribution on online platforms with implications for scholars and practitioners alike across discipline.

The proposed conceptual framework had the key limitation of testing only a single dataset. Future studies should apply this network approach across viral advertising campaigns and across a range of brands. Similarities and differences in the two types of influential users proposed here could lead to better understanding of the nature of viral advertising on social media. In the same vein, our analysis of the Pepsi account as a key bridge evidenced the potential contribution of non-affiliated accounts to the overall viral network. Our study did not examine other key users, and thus did not account for their potential influence. Furthermore, any study about engagement is susceptible to a bias made by fake engagement, an ongoing issue for researchers and practitioners (Pathak, 2017).

The current study is also limited by its use of a single case study on a single social media platform. Social media content is almost never distributed via a single platform alone, but rather becomes viral through the integration and distribution of content across platforms as individuals share links to content in multiple ways. We recognize this issue as a limitation of our study and call upon future studies to consider this consideration in their design.

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