Seeding Viral Content

The Role of Message and Network Factors

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Online viral campaigns require a seeding strategy that involves choosing the first-generation consumers to spread a viral message to. Building on social-capital theory and social-network analysis, this research examines key aspects of the seeding strategy by tracking the diffusion of 101 new videos published on YouTube. The results show that the need for a "big-seed" strategy (i.e., using many seed consumers) depends on message quality. Furthermore, one should choose consumers who have strong ties with the advertiser and who also have strong influence on others, rather than simply wider reach. Among seed consumers, they should share a moderate amount of interest overlap instead of being too homogeneous or heterogeneous as a group.

INTRODUCTION

"Viral marketing" refers to the act of propagating marketing messages through the help and cooperation from individual consumers. It departs from traditional advertising in its reliance on consumer word of mouth (WOM) instead of mass media as the message conveyance vehicle.

Compared with traditional advertising, viral marketing enjoys the benefits of lower cost, higher credibility, faster diffusion, and better targeting of consumers (Bampo et al., 2008; Dobele, Toleman, and Beverland, 2005). Furthermore, the emergence of online communities and social media in recent years have vastly extended individual consumers' influence beyond their immediate circle of close friends to more casual acquaintances and sometimes even strangers (Duan, Gu, and Whinston, 2008). This significantly increased the scale of viral marketing, putting it into a more central position in company strategy (Ferguson, 2008).

Despite its increasing use, both marketing practitioners and researchers have pointed out the elusiveness of viral marketing success and a general lack of understanding of what drives the success of viral marketing efforts (Ferguson, 2008; Kalyanam, McIntyre, and Masonis, 2007). Some see viral marketing as more of an art than a science (De Bruyn and Lilien, 2008). This view comes from the realization that viral marketing outcomes are affected by many factors that firms have limited control over. Although these factors introduce a great deal of uncertainty into the viral-marketing process, it does not mean that firms cannot make informed decisions to maximize the possibility of success (Kalyanam et al., 2007).

One such area that marketers may control is how to start the viral diffusion process—what usually is referred to as the "seeding strategy." A seeding strategy involves determining how many initial consumers ("seeds") are needed to disseminate a viral message to and what types of consumers to choose as seeds. As these seed consumers are responsible for the initial dissemination of the viral message to other fellow consumers, selecting the right targets as seeds can have a significant impact on later rounds of the viral diffusion process (Bampo et al., 2008; Watts and Peretti, 2007).

Academic research on online viral marketing offers limited guidance on choosing a proper seeding strategy. Although existing studies have examined the impact of individual and content characteristics that affect the pass-along of viral information, few have explicitly addressed the proper choice of seed consumers.

Addressing this gap in the literature, the current research draws from the social-capital theory and social-network analysis to identify four key elements of the seeding strategy:

- the number of seeds to use,
- the strength of tie between seed individuals and the message originator,
- the level of influence of individual seeds, and
- the interest homogeneity among seed individuals.

Using viral videos from YouTube as the backdrop, it empirically tests the relationship between these seeding decisions and viral-diffusion outcome. Because information for making these decisions easily can be obtained from observable online social-network activities and internal customer data, the findings from this research can offer very practical guidance to optimally seeding a viral-marketing campaign.

WHAT AFFECTS ONLINE VIRAL MARKETING SUCCESS?

In the last 5 to 10 years, interest in online viral marketing has increased among marketing and advertising scholars. Studies in this area typically have focused on either intermediate actions/processes such as probability of opening and passing along viral information (e.g., Ho and Dempsey, 2010; Phelps et al., 2004), or end outcomes such as the eventual reach of a viral campaign and the adoption of the promoted product (e.g., Bampo et al., 2008; Katona, Zubcsek, and Sarvary, 2011).

In answering the question of what affects viral marketing success, three types of factors have been suggested:

- message characteristics,
- individual sender or receiver characteristics, and
- social network characteristics.

Message characteristics relate to the content and creative design of a viral message, which are under the control of the advertiser (Ho and Dempsey, 2010; Kalyanam et al., 2007). An effective viral message should break through clutter and consumer indifference to encourage further pass-along of the message. Researchers have found, for instance, that humor and sex appeal are popular tactics used in viral messages (Golan and Zaidner, 2008) and that the social visibility of a viral message encourages its diffusion (Susarla et al., 2012; Salganik, Dodds, and Watts, 2006).

Besides message characteristics, individual consumers also play a critical role in the viral marketing process. This category of influence has received the most extensive examination in the literature. Findings in this area show that consumers' personality traits (e.g., Chiu, Hsieh, Kao, and Lee, 2007; Sun, Youn, Wu, and Kuntaraporn, 2006); demographics (e.g., Trusov, Bodapati and Bucklin, 2010); usage characteristics (e.g., Niederhoffer, Mooth, Wiesenfeld, and Gordon, 2007; Sun et al., 2006); and motivation for sharing content (e.g., Eccleston and Griseri, 2008; Phelps et al., 2004) all can affect the success of viral messages.

For example, researchers have found female and younger consumers tend to exert more influence on their targets and to be more susceptible to viral influences than male and older consumers (Katona et al., 2011; Trusov et al., 2010). Studies also have associated both extroversion and innovativeness with a higher tendency to pass along content (Chiu et al., 2007; Sun et al., 2006). From a motivational standpoint, research has consistently found altruism to drive message sharing (e.g., Ho and Dempsey, 2010; Phelps et al., 2004).

Though individual characteristics focus on a single consumer, network characteristics describe the connection *between* consumers. The central thesis from this stream of research is that the structure of the social network through which a viral message spreads can affect the eventual reach and influence of the message (Bampo et al., 2008; De Bruyn and Lilien, 2008). Furthermore, a consumer's role in diffusion depends on his or her position in the social network as defined by the consumer's relationship with others in the network, such as network centrality and tie strength (Goldenberg, Han Lehmann, and Hong, 2009; Kiss and Bichler, 2008; Susarla et al., 2012).

Research in this area has often produced conflicting results. For instance, on the effect of network structure, some researchers have shown that a scale-free network, where only a few members have many connections, facilitates social contagion (Barabási, 2002; Smith, Coyle, Lightfoot, and Scott, 2007). Others have found no difference, however, between a scale-free network and a random network, where most network members have a similar number of network connections (Kiss and Bichler, 2008). Yet, a third study concluded that cascades were less likely to happen in a network where individual influence is highly unbalanced than in a random network (Watts and Dodds, 2007).

Gaps in the Literature

Although academic researchers have started to construct a roadmap of factors contributing to the success of online viral marketing, research in this area still has been very limited (Chiu et al., 2007; De Bruyn and Lilien, 2008) and has produced fragmented and sometimes conflicting results.

More specifically, there are two important gaps in the literature that need to be addressed:

- Most existing studies have relied on computer simulations or consumer

surveys. Although simulation allows controlled experimentation with network properties that are difficult to implement in a field setting, results from such studies are constrained by parameter and model assumptions that often prove unrealistic in the real-world (Bampo et al., 2008). As a result, the conclusion that a viral campaign can be more successful under a certain simulated condition may not mean it will happen in reality.

Studies based on consumer surveys partly make up for this by offering a closer view of consumers' attitudes and intentions. They suffer, however, from noise and bias often present in self-reported and retrospective data (De Bruyn and Lilien, 2008). Furthermore, previous survey studies often used a rather homogeneous sample such as college students to draw their conclusions and they were disproportionately focused on successful communications (De Bruyn and Lilien, 2008). This limited the generalizability of the findings from these studies. Recognizing such limitations, other studies have issued a call for more research based on actual behavior of heterogeneous consumers in a natural setting (Bampo et al., 2008).

- Existing research often has failed to recognize the strategic nature of online viral marketing. Although online viral marketing often has been viewed more as an art than a science (De Bruyn and Lilien, 2008), a study of an online service provider showed that companies can tweak the inputs into a viral campaign to increase the chance of success (Kalyanam et al., 2007).

To aid companies in such efforts, more research is needed to examine the decisions that advertisers can make in designing a viral-marketing campaign.

Specifically, researchers have called for more analysis of a viral campaign's seeding strategy (Bampo et al., 2008; Yang, Yao, Ma, and Chen, 2010), which defines the choice of consumers that companies should initially spread the viral message to.

As these seeds will initiate viral propagation among fellow consumers, they can play a critical role in the eventual success of a viral campaign (Bampo et al., 2008; Watts and Peretti, 2007). More research is needed to help identify ideal seed targets for viral-marketing campaigns.

RESEARCH HYPOTHESES
Overview
Addressing the gaps in the literature, the current research focused explicitly on the optimal seeding of viral-marketing campaigns. The author drew upon the social-capital theory and its paralleling social resources theory (Lin, 1999; Portes, 1998) to identify important factors to consider when designing a seeding strategy.

These theories state that one can derive significant tangible and intangible benefits from one's social network and from the resources embedded in the network. In other words, one's social connections are a form of capital that can be utilized to attain one's goals (Coleman, 1990).

Although the relevance of social capital to brands is less obvious and less pervasive in the traditional advertising environment, the one-to-one interaction between businesses and consumers through social media has elevated the social plain for brands and has transformed brands into active participants in online social networks.

From this view, a brand (or its company) can be considered an actor embedded in an extended network of consumers and other entities in the marketplace. Its relationship with these consumers and other entities

then comprise the social capital that it can draw upon for fulfilling its goals such as spreading a viral message or increasing brand awareness.

An important benefit of social capital is the facilitation of information flow (Lin, 2001; Van den Bulte and Wuyts, 2007), which, in essence, is what an advertiser aims for when it launches a viral campaign. To successfully propagate a viral message to a wide network of consumers, an advertiser needs to purposefully construct and mobilize its social capital for optimal outcomes (Portes, 1998).

This process involves careful selection of the initial target consumers (i.e., seeds) to maximize access to and mobilization of resources within the advertiser's social network. In this respect, the social capital theory suggests three dimensions that should be considered (Lin, 2001):

- the extensity of ties, which is captured by the size of the network (Bourdieu, 1986);
- relationship strength between the focal actor and its network connections (e.g., Granovetter, 1973; Lin, Ensel, and Vaughn, 1981);
- the resources embedded within the network as held by its members (Lin, 1999). The last dimension can be further broken down into the level and the diversity of resources possessed by network entities (Lin, 2001; Van den Bulte and Wuyts, 2007).

Based on these dimensions, the current research identified four critical aspects of a seeding strategy:

- seed network size,
- tie strength,
- seed influence, which signals resource level, and
- seed homogeneity, which serves as an indicator of seed resource diversity.

More specifically, when designing the seeding strategy of a viral campaign, an advertiser needs to answer four questions:

- How many seeds should be used?
- Should these seed consumers have strong or weak ties with the firm/ brand?
- Is it superior to use seed consumers who are social hubs with a large number of connections with other consumers?
- Should seed consumers be chosen from a heterogeneous or homogeneous population?

By addressing these questions and empirically testing the effects of these decisions on actual diffusion outcomes, the current research aims to provide a systematic guide to choosing the best seed consumers for initializing a viral-marketing campaign.

Number of Seeds

When picking the seed individuals to spread a viral message, a natural first consideration is how many seeds to use.

From a social-capital standpoint, the more network connections that are mobilized in a given situation, the more resources will be available for the focal actor to utilize in achieving its objectives (Burt, 1997; Lin, 1999). This supports the use of a large number of seeds. From a mathematical perspective—other things being equal—the larger the number of seeds, the more opportunity there is for a message to reach other consumers and the more likely the message will create an impact. This is the basic idea behind mass-media advertising and explains the popularity of advertising during major events such as the Super Bowl.

The downside to using many seeds, however, is the high cost associated with the strategy. This partly defeats the cost-effective nature of viral marketing.

Consequently, there is a tradeoff between using many seed individuals and maintaining a low viral campaign cost.

To determine the right balance, some insight can be gleaned from epidemiology research. A key concept in that literature is the basic reproductive ratio, defined as the expected number of secondary infections an infected individual will cause (Heffernan, Smith, and Wahl, 2005). When this ratio is smaller than one, the network will show subcritical growth (Bampo et al., 2008), and the disease will wane out without saturating the population. When the ratio is greater than one, by contrast, a truly viral process is established, and exponential growth will be experienced through generations of the disease propagation process.

The larger the ratio, the more likely an epidemic will occur and affect the entire population (Heffernan et al., 2005). The relevance of this basic reproductive ratio to the seeding decision lies in its impact on how important the size of the initial seed group is. When the ratio exceeds one and exponential growth ensues, having many initial seeds is not critical.

The main consideration in this context is to have enough seeds to ensure that the propagation does not stop early (Bampo et al., 2008). When the ratio is smaller than one, however, the size of the seed group becomes much more important and can determine the final reach of a disease or campaign. In such situations, there is research that advocates a "big-seed" approach, where a large number of seeds are used (Watts and Peretti, 2007).

Applying the preceding to a viral marketing message, the importance of the initial seed group size may be contingent on the likelihood of seed consumers to pass along the viral message to other consumers. Although various message and individual characteristics can affect this likelihood, the current research

focuses on one factor: quality of the viral message.

In this case, "quality" broadly is defined as consumers' general evaluation of the message. A high-quality message may be one that is creative, entertaining, informative, *or* socially valuable; a low-quality message, conversely, may be one that fails to pique interest among consumers. In the former situation, the pass-along rate (hence basic reproductive ratio) is likely to be high, and the number of seed consumers becomes less important; in the latter situation, the number of seed consumers may determine the final outcome of a viral campaign.

This leads to the first two hypotheses:

H1: The number of seeds will have a positive effect on the diffusion of a viral message.

H2: The relationship in H1 will be stronger when the viral message quality is low than when the message quality is high.

Strength of Tie with Seeds

Besides choosing the right number of seeds to start a viral campaign, it is also important to consider the strength of connection a viral content creator has with seed consumers. For instance, in the case of viral brand messages, companies may want to consider tie strength as measured by brand loyalty or brand usage. According to the social-capital theory, strong ties provide ecological reasons for network members to lend resources to others, not necessarily for direct gain from the borrower but for reputation and other benefits that one can derive from the entire network (Burt, 1997; Lin, 2001). As a result, network members who are connected to the focal actor through a strong tie will be more motivated to cooperate with the actor than those connected via a weak tie.

More specifically, in the context of an online viral-marketing campaign, a few advantages can result from having a strong tie with seed consumers:

- In today's already-cluttered online environment, information shared through a strong tie is more likely to be noticed. Either due to higher interest or due to social pressure, consumers are more likely to open messages sent from an entity that they feel close to (De Bruyn and Lilien, 2008).
- For similar reasons, stronger ties can also increase the possibility that the message will be passed along to others (Chiu et al., 2007), which is crucial to starting later stages of the viral process.
- When persuasion is the goal, information shared through a strong tie tends to be more persuasive and, therefore, can have a larger influence on the recipient (Bansal and Voyer, 2000; Sun et al., 2006). These advantages suggest the superiority of choosing seed consumers who have a strong tie with the firm.

It should be noted, however, that the social-capital literature also has suggested a critical role played by weak ties (Granovetter, 1973). The argument is that weak ties connect network clusters that would otherwise be isolated from one another and, as a result, can increase the reach of a viral message (Godes and Mayzlin, 2004). A field experiment compared the effectiveness of spreading WOM through a restaurant's loyalty-program members (i.e., regular customers) versus non-customers recruited from a third-party panel by BzzAgent (Godes and Mayzlin, 2009). The authors concluded that WOM initiated by non-customers (i.e., weak company-consumer tie) created more incremental impact than that initiated by customers (i.e., strong company-consumer tie).

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Although such results seem to suggest that one should select consumers with weak ties to the company as viral campaign seeds, a few issues undermine the strategic appropriateness of this decision.

First, as the authors pointed out, the results do not reflect the impact of overall WOM but rather the incremental influence of WOM by the sample consumers beyond existing WOM (Godes and Mayzlin, 2009). As loyal customers likely already spread words about the restaurant, their true impact is likely to have been underestimated.

Second, non-customers have not experienced the company that is being promoted. As a result, their testimonials may be considered less credible and trustworthy than those conveyed by consumers who have a strong tie with the company.

Third, as consumers with no (or weak) ties to a company have low motivation to spread words about the business, the company may need to provide extra financial incentive to encourage these consumers' participation in the viral process. In the case of the foregoing study, BzzAgent compensated the non-customer sample for participation in the panel. This can make the use of weak ties a more costly strategy.

For these reasons, the current research argues that, for the purpose of initially seeding viral content, it still is more effective to select consumers who have stronger ties to the content generator than consumers with weak ties.

This leads to the third hypothesis:

H3: Seeding individuals who have strong ties with the message creator will lead to more successful diffusion than individuals who have weak ties with the message creator.

Seed Influence

As seed consumers start to pass along a viral message to fellow consumers, the extent of influence each seed has can play an important role in further spreading of the message.

This level of influence represents the social capital a seed consumer possesses that an advertiser can indirectly leverage in its viral campaign (Van den Bulte and Wuyts, 2007). A frequently used proxy for influence is the number of connections an individual has (Wasserman and Faust, 1994), which has been shown to follow a power-law distribution in online networks (Barabási, 2002). In a power-law distributed network, a small number of nodes have disproportionately large numbers of connections, whereas the rest have only a small number of connections. The former forms the hubs of the network.

Given the large disparity between hubs and non-hubs, a key question is which type of these consumers is better suited for seeding viral content. The answer to this question is not exactly straightforward. The well known two-step flow model of communication emphasizes the role of influential individuals in propagating information to a wider audience (Katz and Lazarsfeld, 1955). This view was echoed in previous research on the viral diffusion of innovation (e.g., Goldenberg et al., 2009; Rogers, 1962). The basic argument is that the more individuals that a seed is

connected to, the more people the seed can reach and potentially influence, creating what Van den Bulte and Joshi (2007) call a "multiplier effect."

This well-established argument has been challenged by recent studies, however. Specifically, one study contended that, instead of relying on influentials, it was more important to have a large mass of easily influenced individuals for viral diffusion to succeed (Watts and Dodds, 2007). The simulation in that research showed that the cascade window—a region in which large-scale diffusion was likely to occur—resided at a rather low (or moderate) average number of connections.

Several researchers have provided a theoretical explanation for why hubs are not necessarily better. Due to the cost of maintaining a large network, individuals with many connections on average have weaker connections, which results in less impact on others that are connected to them (Katona et al., 2011; Smith et al., 2007).

This weaker relationship can be especially detrimental in spreading viral marketing messages, due to the large number of messages circulating online. As one focus-group discussion revealed, individuals receiving a pass-along message often felt irritated or angry for their wasted time (Phelps et al., 2004). Therefore, when someone with a large number of connections tries to pass along a viral message to his or her weak connections, the message will be less likely to be relevant to the recipient and more likely to be ignored.

For these reasons, the author expects a negative relationship between the number of connections a seed consumer has and the outcome of viral diffusion.

This leads to the next hypothesis:

H4:   The number of connections seed consumers have will have a negative effect on the diffusion of a viral message.

Seed Homogeneity

Network "homogeneity" is the degree to which members of a network are similar to one another. Just as birds of a feather flock together, researchers have found a tendency for humans to connect with others who are similar to them, a phenomenon called homophily (McPherson, Smith-Lovin, and Cook, 2001). In an online community, homophily is likely to occur as well. Users with similar backgrounds and tastes are likely to seek out and consume similar content and, as a result, are more likely to know and connect with each other.

Network homogeneity can be assessed in multiple domains. Partly due to operational simplicity, most research has relied on demographic and socioeconomic variables to define similarity (e.g., De Bruyn and Lilien, 2008; Kalmijn, 1998; Louch, 2000). In an online community, however, some of these demographic variables either become less relevant (e.g., geographic distance) or are often unknown (e.g., age and profession) to other individuals participating in the community. Instead, users tend to be guided by their mutual interest in certain topics such as sports, politics, or humor.

Past research further has suggested that such deeper-level similarities are more important in a group setting than surface-level similarities characterized by factors such as race and gender (Phillips, Northcraft, and Neale, 2006). For this reason, the current research focuses on homogeneity as defined by the level of shared interest among seed consumers. This resembles the concept of perceptual affinity, which refers to individual similarity in personal values, experiences, and tastes (De Bruyn and Lilien, 2008).

However, instead of using perceived affinity as reported by survey data in that study, the current study derives homogeneity from interests manifested in actual content consumption behavior by seed consumers. This helps avoid potential recall error or bias that may be present in one-sided reports of perceptual affinity.

Regarding the consequence of network homogeneity, past research has produced inconsistent findings. Some studies have argued that similarities among individuals may facilitate information flow, as shared values and experiences among these individuals encourage more frequent and easier interaction with each other (McPherson et al., 2001; Watts, 2003). In support of this theory, within the marketing literature, the homogeneity of a social system has been found to expedite diffusion and increase eventual market size (Gatignon, Eliashberg, and Robertson, 1989).

More recent studies, however, have questioned this conclusion. Data from an online travel agency's viral campaign demonstrated that diffusion speed was negatively affected by homogeneity (Lee, Lee, and Lee, 2009). In a cross-cultural setting, income homogeneity in a country was shown to lead to a lower diffusion rate (Van den Bulte and Stremersch, 2004). In line with these findings, another study found that demographically similar ties decreased the effectiveness of viral messages in terms of awareness, interest, and adoption (De Bruyn and Lilien, 2008).

This latter group of findings can be explained by the social-capital theory, where having diverse embedded resources in a network is considered to increase social capital and improve the chance of finding the right resources needed to achieving one's goals (Burt, 2005; Lin, 1999).

Reconciling the disparate findings, the current research argues that the impact of seed homogeneity on diffusion success does not follow a linear relationship. Instead, it is an inverted U-shaped pattern, where both low and high levels of homogeneity can be detrimental to diffusion.

At very low levels of homogeneity, the network consists of an eclectic and somewhat random set of connections. For these heterophilous individuals, group identification, tie strength, and stability are low (Lee et al., 2009), and it is more difficult to effectively reinforce social norm (Algesheimer, Dholakia, and Herrmann, 2005; Horne, 2008). Network members do not have strong incentives to pass along any particular message to others within or outside the network, which impedes the flow of information and the diffusion of viral messages. Along this line, network science suggests that highly diverse networks make it difficult for information to reach its destination, even when available network connections are present (Watts, 2003).

A highly homophilous group, by contrast, consists of individuals with highly similar interests, which fosters group identification and makes individuals more susceptible to peer influence (Hovland, Janis, and Kelley, 1953). When a message traverses across the network, individuals are motivated to pass on the information, either due to personal interest in the content topic or due to group norm.

At the macro-level beyond the initial network, however, because of these individuals' tendency to attach to others highly similar to them, the message is likely to get stuck in the circle of other similar individuals. This prevents the content from reaching a larger, more diverse universe of users (Brown and Reingen, 1987).

This leads to the next hypothesis:

H5: Seed homogeneity will have an inverted U-shaped effect on viral diffusion, with moderate homogeneity leading to better diffusion than low and high homogeneity.

DATA AND MODEL
Study Context and Sample
To examine empirically the impact of seeding strategy, this research used the context of viral videos posted on YouTube. YouTube is a leading online community for sharing videos and has been the origination point for many successful viral videos in the past. YouTube videos offer a rich variety of primarily user-generated content. Consequently, it might seem that studying the diffusion of YouTube videos would have limited value to a commercial entity (i.e., an advertiser).

There are, however, a number of reasons why the opposite may be the case:

• YouTube is an important social-media channel for many businesses, capturing as many as 50 percent of Fortune Global 100 companies (Burson-Marsteller, 2010). Faced with the same universe of YouTube users, advertisers are subject to the same diffusion channel and similar scrutiny as other YouTube videos. What is especially relevant is the same reliance on consumer WOM and social contagion to spread the message.

• Social media such as YouTube have blurred the line between commercial messages and user-generated content and thereby have created a need to shift from traditional communication to a new, more consumer-focused communication paradigm (Mangold and Faulds, 2009).

In this space, advertisers have been advised to tone down the "commercial" component of their messages (Kaplan and Haenlein, 2010). Instead of a well-crafted professional message, advertisers may be better off acting as an ordinary participant in the social conversation and use subtler marketing in their messages.

As aptly described by a successful viral marketer, the process of making a viral marketing video is less about "creating advertising" than about "creating something people want to watch" (Angwin, 2009). Consequently, a successful viral marketing message is likely to resemble more closely an ordinary YouTube video than a traditional advertisement. This makes knowledge about how a video on YouTube gains popularity relevant and important to viral marketers.

• The commercial relevance of the YouTube context also is accentuated by advertisers' increasing encouragement of user-generated content related to their brands (Van den Bulte and Wuyts, 2007). For instance, video contests frequently are offered by brands on YouTube and other social-media channels, which invite consumers to make their own videos on a given brand theme and as a return earn prizes and sometimes fame.

Content from such programs as Dunkin' Donuts's "How Do You Keep America Running?" YouTube contest (Greenberg, 2008) often is used later in the sponsoring brand's advertising materials—a phenomenon that, again, demonstrates the increasingly blurred line between commercial content and user-generated content.

For these reasons, it is not surprising that YouTube frequently has been used as the backdrop for studying online viral and social-media marketing (e.g., Campbell, Pitt, Parent, and Berthon, 2011; Susarla et al., 2012).

When a video is posted on YouTube, the video poster's immediate connections (subscribers and friends) are the first notified of the new addition, either through e-mail or on the homepage when they next visit YouTube. These immediate connections, in all practicality, function as

seed consumers for the video. Although one may argue that the video poster did not consciously choose these individuals as seeds, the difference in this initial audience across videos can reveal important information about the impact of seeding variation on video diffusion *if* the video poster had intentionally chosen these seed consumers. This approach especially is useful given the practical difficulty of experimenting with multiple seeding strategies in a self-contained setting.

In the current study, an initial pool of 105 videos was sampled over 7 days to avoid systematic bias that may be associated with a particular day of the week. Each day, a random sample of 15 videos was drawn from the list of new videos uploaded to YouTube on that day using the systematic sampling approach.[1]

For each video sampled, information about the video poster's network structure, past experience, and demographics was collected. Four videos missed complete network and demographic information and, therefore, were removed from further analysis, resulting in an actual sample size of 101 videos. Each of these videos was tracked on a daily basis over the course of 60 days. Every day, the number of cumulative views and the ratings for each video were recorded.

Variable Operationalization

A video's seed network consists of individuals who are directly connected to the video poster. The size of this network, therefore, defines the total number of seeds (*NumSeeds*). On YouTube, there are two ways to connect to an individual:

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[1] *More specifically, the new videos that were added to YouTube on each day were ordered by their uploading time, and one video from the list was randomly picked as the starting point. From that starting point, every nth video was sampled from the list. The exact interval (i.e., n) used for each day was determined by dividing the number of videos posted on that day by the daily sample size of 15.*

- as a subscriber (one-way connection to the video poster), and
- as a friend (two-way connection).

Because establishing a friend connection requires explicit approval of the video poster, it is reasonable to assume that this type of connection represents a stronger relationship tie with the video poster than that of a subscriber connection. Consequently, the proportion of seed consumers who are connected to a video poster as friends is used in the current study to indicate the average tie strength between the seeds and the video poster (*TieStrength*).

Seed influence is operationalized as the number of individuals who are in turn connected to each seed consumer. An average of this measure across all seed consumers of a video indicates average seed influence for the video (*SeedConnection*). For video quality, YouTube allows users to rate each video on a five-point scale. This research used the average rating at the end of the observation period as a proxy of quality for each video (*Quality*).

For network homogeneity (*Homogeneity*), this research focused on interest homophily, which—in the YouTube context—could be gauged through shared subscriptions. Consumers who share common interests with one another are likely to have many overlapping subscriptions with one another. To derive a measure of interest homophily, the current research drew upon the idea of an affiliate network from social-network analysis (Wasserman and Faust, 1994):

Let Sub_{jg} be a binary variable indicating individual *j*'s subscription status to channel *g*. We can define the level of dyadic interest homophily between individuals *j* and *k* as:

$$Homophily_{jk} = \sum_{g=1}^{G} Sub_{jg} Sub_{kg} \qquad (1)$$

where *G* represents the full set of subscriptions by all seed consumers.

Based on this dyadic interest homophily, one can then calculate the homogeneity of a seed network as in equation (2) (Wasserman and Faust, 1994). It represents the extent of subscription overlap among video *i*'s seed consumers as a portion of all possible overlaps across the entire subscription set.

$$Homogeneity_i = \frac{\sum_{j=1}^{NumSeeds_i} \sum_{k \neq j}^{NumSeeds_i} Homophily_{jk}}{G*(G-1)}$$

$$(2)$$

A few control variables also are included in the analysis to account for the impact of other demographic, historical, and content factors. For historical influences, this research controls for a video poster's past experience with two variables:

- the volume of past contribution as signaled by the number of videos posted in the past (*Vol*), and
- the popularity of past contributions as measured by the average number of views across past videos (*AvgView*).

These two variables control for the possibility that a video poster's reputation and/or consistent success with past materials may affect the diffusion outcome of the new video. The current study also included a video's lagged rating (*LagRating*) to control for the influence of existing ratings on diffusion.

In addition, because a video can be discovered from sources other than the seed consumers (e.g., through site searches), the author controlled for this influence by considering other sources that had led to significant traffic to the video. This information is listed on YouTube as "significant discovery events" and includes the date on which the first referral from each significant source occurred. The current

study counted the number of such events during the 60-day period (*OtherSrcs*) and included it in the model.

For demographic influences, this study considered a video poster's age (*PosterAge*) and gender (*PosterFemale*), and the corresponding seed network's average age (*SeedAge*) and proportion of females (*SeedFemale*), thus allowing gender and age differences in viral diffusion. Another factor the study controlled for was the category that a viral video was posted under. As some topics inherently were more appealing than others (e.g., entertainment content may inherently appeal to more people than science-related content), a video's category could have affected its diffusion potential.

The Model

As the number of views for viral videos very likely contains multiple views from the same individual (and these views may not have a systematic pattern), the current study used the proportional rates/means model developed in the biometrics field (Lawless and Nadeau, 1995; Lin, Wei, Yang, and Ying, 2000)—a frequently used model for studying event recurrence. Using a multiplicative formulation similar to proportional hazard models, it offers an efficient and parsimonious way to capture the effects of covariates and provide a mechanism for inferring event recurrence (Lin et al., 2000):

Specifically, let $View_i(t)$ be the cumulative view of video i up to time t, and let $dView_i(t)$ be the increment in views over a small time interval $[t, t + dt]$. The rate function is defined as the expectation of $dView_i(t)$ given the observable history of the video and a set of covariates that may affect recurrence. Similar to the proportional hazard formulation, the proportional rates model presents the recurrence rate in a

multiplicative form as:

$$dR_i(t) = \exp(\beta' X_i(t))*dR_0(t) \qquad (3)$$

where $R_0(t)$ is an unspecified continuous function and $X_i(t)$ is a vector of time-independent or time-varying covariates discussed in the last section.

This research estimated the model using the approach recommended by Lin et al. (2000), allowing arbitrary and complex dependence structures among recurrences, thereby permitting future views of a video to depend on past events in many ways.

RESULTS

Ninety-one of the sample videos were used to estimate the model and the rest were used as a holdout sample. Compared with an unconditional model that did not have any explanatory variables, the

proposed model showed a significantly better fit ($\chi^2 = 537.63$, $p < 0.001$).

To check the robustness of the model, the author compared the predicted versus actual cumulative views of the holdout sample during each time period. These predicted views correlated highly with the observed views, ranging from 0.76 to 0.97 for the holdout videos, indicating a good fit of the model. The mean correlation coefficient was 0.91.

HYPOTHESES TESTING

As the covariates were entered into the model as exponentials (Table 1), the percent change in diffusion rate due to one unit change in a covariate was indicated by $100 \times [\exp(\beta) - 1]$.

On the effect of seed network size (H1), as expected, the total number of seeds for a video had a positive effect on the video's diffusion ($\beta = 0.0017$, $p < 0.001$).

TABLE 1
Parameter Estimates from the Model

Covariates	Unstandardized β	Standard Error	*p*
NumSeeds$_i$	0.0017	0.0001	<0.001
*NumSeeds$_i$*Quality$_i$*	−0.0006	0.0001	<0.001
TieStrength$_i$	0.176	0.083	0.034
SeedConnection$_i$	−0.00004	0.00001	<0.001
Homogeneity$_i$	0.518	0.168	0.002
Homogeneity$_i^2$	−1.182	0.324	<0.001
Vol$_i$	−0.0008	0.003	n.s.
AvgView$_i$	0.0003	0.00002	<0.001
LagRatings$_{i(t-1)}$	0.003	0.014	n.s.
OtherSrcs$_i$	0.007	0.002	<0.001
PosterAge$_i$	−0.003	0.001	0.024
SeedAge$_i$	−0.021	0.003	<0.001
PosterFemale$_i$	−0.271	0.057	<0.001
SeedFemale$_i$	−0.256	0.067	<0.001
−2LL	58178.69		
AIC	58228.69		

Each 100 extra seeds contributed to about a 17.01-percent increase in diffusion rate. This effect was qualified by a significant negative interaction between video quality and total number of seeds ($\beta = -0.0006$, $p < 0.001$).

To help interpret this interaction, the procedure recommended by Aiken and West (1991) was followed, which involved calculating the simple slope for *NumSeeds* at video quality one standard deviation ($SD = 2.28$) above and below the mean ($M = 522.5$).

When video quality was low, 100 additional seeds contributed to as much as a 30.72-percent increase in diffusion rate. When video quality was high, by contrast, each 100 extra seeds led to only a 3.32-percent increase in diffusion rate. This was consistent with the prediction in H2 that the need for a large seed network becomes less important as video quality improves.

On the effect of tie strength, it was predicted that using seed individuals who have a strong tie with the content originator will facilitate viral diffusion (H3). This was confirmed by a significant positive coefficient for *TieStrength* ($\beta = 0.176$, $p = 0.034$). As this variable captured the proportion of seed individuals connected to the video poster through a stronger friendship link, increasing the proportion by 10 percent would lead to a 1.92-percent increase in diffusion rate.

Concerning the impact of secondary connections that a seed consumer has (H4), the result confirmed a significant negative effect ($\beta = -0.00004$, $p < 0.001$). As mentioned earlier, a larger number of connections represent a wider reach but potentially weaker ties between a seed and his or her friends. This suggests that it is the quality rather than mere quantity of influence that counts. Overall, the result here is consistent with the conclusion from the Watts and Dodds (2007) simulation

that cascading is most likely with low to moderate number of connections.

H5 predicted an inverted U-shaped relationship between viral diffusion and seed homogeneity as measured by interest homophily. This was confirmed by a significant positive coefficient for the seed homogeneity variable ($\beta = 0.518$, $p = 0.002$) and a significant negative coefficient for its quadratic term ($\beta = -1.182$, $p < 0.001$).

As interest homophily improved, diffusion rate first increased and then decreased after it passed a certain threshold. Using the estimated parameters, the optimal interest homophily level could be calculated as 21.91 percent. As this variable by definition lies between 0 and 1, this means that about one-fifth of interest/subscription overlap leads to optimal diffusion for viral videos.

Effect of Control Variables

The current model controlled for three types of influences:

- historical,
- demographic, and
- content influence.

For historical influence, the number of videos a video poster previously had posted did not have a significant effect on the diffusion of the current video ($\beta = -0.0008$, $p = 0.79$). The success of past videos as measured by their average number of views, however, had a positive effect ($\beta = 0.0003$, $p < 0.001$). As expected, the number of external sources that led to significant views of a video had a significant positive effect ($\beta = 0.007$, $p < 0.001$).

The effect of lagged rating was not significant ($\beta = 0.003$, $p = 0.83$). This may have been because these were newly posted videos. Especially at the beginning of the tracking period, rating information could have been sporadic and, as a result,

may have had limited influence on viral diffusion.

For demographic factors, both the poster's age ($\beta = -0.003$, $p = 0.024$) and the average age of seed individuals ($\beta = -0.021$, $p < 0.001$) had a negative effect on diffusion rate. With regard to gender, videos posted by females experienced slower diffusion than those by males ($\beta = -0.271$, $p < 0.001$). Similarly, the proportion of females among seed individuals had a negative effect on diffusion rate ($\beta = -0.256$, $p < 0.001$). These findings were opposite to previous studies that found female consumers to be more influential in viral diffusion (Katona et al., 2011; Trusov et al., 2010), suggesting that the context of the study matters.

Overall, the results of the current study suggest more favorable influence from younger consumers and males, at least in the context of online viral videos. For content category, music was used as the benchmark category. Compared with this benchmark category, the entertainment, people-and-blogs, and gaming categories showed significantly higher diffusion rates, whereas the more specialized categories of how-to/style and pets/animals had significantly lower view growth rates. The rest of the categories were not significantly different from the music category.

DISCUSSION

Although online viral marketing presents a great opportunity for advertisers, success in this area remains elusive to most firms (Ferguson, 2008; Kalyanam et al., 2007). This is partly due to the many uncontrollable factors in the online environment.

To run an effective online viral-marketing campaign, it is important to recognize these uncertainties while at the same time realize the ability of the firm to make strategic choices that can maximize the chance of success.

Taking one step in this direction, the current research treats viral marketing as a

strategic process and addresses the important issue of seeding a viral-marketing campaign, which has seldom been considered in previous research. It enriches the online viral marketing literature by linking seeding choices to actual diffusion outcomes. In doing so, it extends existing studies that often relied on mathematical simulation or consumer self-reported data, which may (or may not) have reflected real-world consumer reaction to possible firm actions (Bampo et al., 2008).

Moreover, by including a diverse sample of both popular and unpopular videos, the current research responds to calls to extending existing research beyond successful communications in order to generalize existing findings (De Bruyn and Lilien, 2008).

The results of this study suggest that a positive outcome is more likely if more seeds are used to start a viral campaign, the "big-seed" strategy proposed by Watts and Peretti (2007).

This "big-seed" strategy, however, is not necessary at all times. As the general quality of the viral message improves, the need to use a large number of seeds diminishes significantly. This points to an alternative solution for firms that may not be able to afford the high cost of reaching a large number of seed individuals.

Regarding the type of seed consumers to use, the current results showed that it is best to start a viral campaign with consumers who have a strong tie with the viral message originator. As these consumers are likely to be more strongly influenced by the message originator, using these consumers as seeds increases the probability that the message will be passed along to further waves of consumers.

Moreover, the current analysis showed that it is not ideal to use seed consumers with a large number of connections. The social cost of maintaining a large network leads to weaker average connection and as a result limited influence on subsequent generations of consumers. Therefore, our results offer empirical support to the notion that, to achieve successful diffusion, it is better to have a large number of easily influenced individuals than to have a few highly connected hubs in a social network (Watts and Dodds, 2007).

Finally, the current research considered the desired level of seed homogeneity for viral marketing success. It extended previous research by focusing on the interest homophily among seed consumers and reconciled conflicting findings in this area by revealing an inverted U-shaped relationship between homophily and diffusion outcome.

When seed consumers share too few or too many common interests, diffusion outcome is not optimal. Instead, a moderately heterogeneous group of consumers can best increase the reach of a viral message to more diverse consumer populations.

Limitations and Future Research

The current study has a few limitations that should be addressed in future research:

- From a theoretical standpoint, the current research focused on the mobilization of social capital in a viral-marketing campaign. However, the social capital-theory suggests that, before being able to mobilize social capital, one first needs to deliberately construct and build social capital through economic, cultural, and social investments (Portes, 1998).

  From this perspective, in addition to an effective seeding strategy, a successful viral campaign requires long-term investments from advertisers—in addition to an effective seeding strategy—to build their social capital. For instance, active participation in social media through Twitter and Facebook can strengthen the tie between a brand and its customers, leading to increased social capital for the brand. There is currently very limited understanding of how advertisers can effectively build their social capital. This can be a fruitful area for future research.

- The current research used existing connections and network characteristics on YouTube. The advantage of this approach is that it can capture actual diffusion outcomes of a large number of viral messages, hence remedying the tendency in previous studies to rely purely on simulation or consumer self-report data. By focusing on YouTube, however, it neglects other processes that may have contributed to the diffusion of the videos. It also does not consider other viral forms such as those distributed via Twitter or blogs.

  Future research needs to replicate the current findings in other settings. It would be especially useful to conduct field experiments to compare the relative effectiveness of different seeding strategies.

- The current research examined only a narrow range of variables representing the four seeding decisions. This needs to be expanded in future research.

  For instance, from a firm's perspective, a more desirable indicator of tie strength may be how loyal the consumer is to the firm. As another example, instead of relying on public ratings to judge message quality, which is available only after a message is released, it may be better to gauge quality with consumer pretests.

  The seed influence factor also can be extended to include not only the number of individuals that a seed consumer can potentially reach but explicit measures of connection quality and how much real influence a seed consumer has on others. These extensions will

enrich the current framework to offer a more comprehensive guide to optimally seeding a viral campaign.

• The current research tracked the sample videos for only 60 days. This was based on historical evidence that many successful viral videos gained popularity in a very short period of time. The Old Spice viral campaign in 2010, for instance, garnered more than 5 million views in the first 3 days (Newman, 2010). However, in reality, it could take a while for some videos to take off, a time lag that may not be captured in the current study's 60-day time horizon. Future research should incorporate longer-term observations to test the stability of the results here.

Managerial Implications

Though online viral marketing often has been considered either a hit-or-a-miss exercise that largely depends on luck, a key conclusion from the current research is that firms can—and should—treat it as a strategic process.

This research examined the seeding strategy, an important choice that involves selecting the right consumers to initialize the viral diffusion process. The study's findings showed that the number of seeds needed is contingent on the quality of the viral message. With a high-quality message, it is not necessary to have a sizable seed network. Furthermore, it is preferable to choose seeding consumers who have strong ties with the firm and who do not have an extraordinarily large number of connections. Among seed consumers, it is best if they share a moderate amount of interest and are not too homogeneous or divergent as a group.

In applying the findings from the current study, it is worth noting that information about the factors can be easily observed through online social network activities or firm internal records. For example:

• Tie strength can be captured by an individual's customer status;
• within the context of online social networks such as Twitter, tie strength also can be gauged by the frequency of interaction the individual has with the firm;
• the reach of a consumer also can be measured by the number of followers or friends he or she has;
• when such information is unavailable to the firm, a straightforward survey can be used to separate hubs from average individuals (Gladwell, 2000);
• interest homogeneity can be measured by observing consumers' online content consumption such as Twitter followings, blog readings, or YouTube subscriptions.

Because of the easy availability of information, the seeding strategy proposed here offers a practical starting point to designing and running viral-marketing campaigns.

In conclusion, even though advertisers have considerably less control when running a viral-marketing campaign, there are decisions that they can make to maximize the possibility of success.

It is hoped that, by highlighting the strategic nature of viral marketing, the current research will stimulate more scholarly work on how advertisers can design and manage their viral-marketing campaigns more effectively. **JAR**

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