- **Title:** "A Typology of Viral Ad Sharers Using Sentiment Analysis"

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Abstract

Viral advertising is the most popular manifestation of viral marketing phenomena. The purpose of this study is to demonstrate sentiment analysis as a promising tool to quantify consumer responses towards branded viral video advertisements and thereupon, propose a sentiment-based typology of viral ad sharers. Results of this experimental study (1) suggest that sentiment-based measures of consumer responses offer better prediction of consumers' ad sharing intentions compared to the traditional and widely used thought-listing method; and (2) help identify four distinct segments of viral ad sharers (based on the relative strength of ad- and brand-related sentiments), namely: "Active", "Brand-fanatic", "Content-hungry", and "Dormant", labelled as ABCD typology of viral ad sharers. This study highlights that for creating successful viral campaigns, marketers should consider the distinctive characteristics of these four segments of viral ad sharers (based on their processing of ad content and brand information) to identify the right seeds to initiate a viral campaign.

Keywords Viral advertising; Cognitive responses; Thought-listing method; Sentiment analysis; Typology

A Typology of Viral Ad Sharers Using Sentiment Analysis

Abstract

Viral advertising is the most popular manifestation of the viral marketing phenomena. The purpose of this study is to demonstrate sentiment analysis as a promising tool to quantify consumer responses towards branded viral video advertisements and thereupon, propose a sentiment-based typology of viral ad sharers. Results of this experimental study (1) suggest that sentiment-based measures of consumer responses offer better prediction of consumers' ad sharing intentions compared to the traditional and widely used thought-listing method; and (2) help identify four distinct segments of viral ad sharers (based on the relative strength of ad- and brand-related sentiments), namely: "Active", "Brand-fanatic", "Content-hungry", and "Dormant", labelled as ABCD typology of viral ad sharers. This study highlights that for creating successful viral campaigns, marketers should consider the distinctive characteristics of these four segments of viral ad sharers (based on their processing of ad content and brand information) to identify the right seeds to initiate a viral campaign.

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1. Introduction

In this age of the Internet, social media has become one of the most powerful branding tools for organizations to effectively communicate with their targeted customers and enhance the impact of promotional activities on the customers' perceptions and awareness levels (Alalwan, et al., 2017; Nisar et al., 2018; Alalwan, 2018). From the consumers' perspective, social media and social networks have become a part of their daily lives (Shareef et al., 2018; Shareef et al., 2017; Shiau et al., 2017; Shiau et al., 2018) and these have changed the way in which individuals acquire information and communicate with each other (Dwivedi et al., 2015; Kamboj et al., 2018; Kapoor et al., 2018; Aswani et al., 2018). In the last decade, significant interest in social media marketing has been seen in terms of advertising from both researchers and practitioners (Alalwan et al., 2017; Shareef et al., 2017; Shareef et al., 2018; Kamboj et al., 2018; Alalwan, 2018). This is also evident considering that the global video advertising market size has grown to about US$28 billion (as of 2018) and this is further expected to grow at an annual rate of 14.6% (Statista, 2017). Kantar Millward Brown's report titled 'Digital and Media Predictions' (2018) highlights that online video advertisements are the most significant form of content marketing because of their expressiveness and their ability to elicit active involvement of the viewers. Particularly, online viral branding campaigns (viral advertising) are an emerging trend, wherein advertisers create attractive and entertaining advertising messages and seed them in video platforms encouraging consumers to share these messages with their online social networks (Berger and Iyengar, 2013). World-renowned brands, such as Burger King, Evian, Old Spice and Unilever's Dove have successfully employed viral advertising (Kaplan and Haenlein, 2011; Beverland, Dobele, and Farrelly, 2015), a new and promising marketing communications' tool to engage millions of consumers instantly (Petrescu, Gironda, and Korgaonkar, 2016).

Consumers' processing of viral ads follows the popular 'Emotion-Cognition Model' (Zajonc and Markus, 1982), wherein viral ads are found to elicit emotions and trigger the cognitive appraisal that motivates consumers to pass-on the ad to their friends and connections (Berger and Milkman, 2012; Huang et al., 2013). At present, marketers don't have direct access and/or appropriate tools to measure emotions of every consumer viewing their ad; however, the appraisal of such emotions does get captured in the cognitive responses that are easily available on social media platforms in the form of user generated content (such as textual responses/comments on the ads). In the context of viral ads, Huang et al. (2013) showed that such cognitive responses, generated in response to a viral ad, trigger formation of subsequent attitude and sharing intention (SI). Although there are several studies that have used the traditional 'thought-listing method' (TLM) to analyse cognitive responses (Wright, 1973; Cacioppo and Petty, 1981) across different topics like consumer evaluation of online banner advertising (Yun Yoo and Kim, 2005), Facebook advertising (Shareef et al., 2018), as well as sharing of viral advertisements (Huang et al., 2013); to the best of our knowledge, there has been no study that has analyzed these cognitive responses to segment consumers for seeding viral ads. Moreover, this thought-listing method has serious limitations concerning empirical indicators of measurements (Lutz and Swasy, 1977; Huang and Hutchinson, 2008). This method captures consumers' evaluations of objects in the valence-congruent direction (Olson, Toy, and Dover, 1982), but fails to appraise the effect of the intensity of responses on consumers' attitudes and behaviours. Nevertheless, areas of psycho-linguistics and Natural Language Processing (NLP) have introduced tools like sentiment analysis that can effectively determine the valence as well the strength of consumers' opinions. Hence, we advocate the use of sentiment analysis for a holistic measurement of these cognitive responses and use these sentiment-based measures of cognitive responses to further segment consumers/sharers to help marketers identify the "actionable segment" of consumers or 'seeds', who show a higher likelihood of sharing viral ads vis-à-vis other consumers. This may help marketers effectively design and distribute advertising content using the viral phenomenon. With this background, an experimental study is designed to address the following two research objectives:

1. To examine whether sentiment analysis is a better tool compared to the traditional thougth-listing method (TLM) in explaining the Social Networking Site (SNS) users' viral ad sharing intentions?
2. To develop a typology of viral ad sharers using sentiment-based measures of cognitive responses.

This study contributes to the existing literature by demonstrating the usefulness of sentiment analysis to overcome the measurement problems associated with the traditional thought-listing method used for analysing consumers' cognitive responses generated in response to viral advertisements. There are few important studies that have explored content virality in different social media platforms [like Facebook (Aswani, et al., 2017a), Twitter (Aswani et al., 2017b) and online news articles (Aswani et al., 2017c)] to identify what type of content goes viral or becomes popular. By taking the context of viral video advertisements, this study contributes to such literature by identifying types of 'consumers' that can actually trigger/stimulate content virality. Further, there exists number of typologies to segment Internet or social media users (e.g. types of Facebook Fans as defined by Wallece et al., 2014) that help marketers strategise their marketing efforts and target the appropriate set of consumers. However, there remains a lack of such segmentation to classify viral ad sharers. Using the psychographic segmentation approach, this study proposes a typology of viral ad sharers that will help marketers identify appropriate 'seeds' to begin their branding campaigns and make them viral.

This paper is structured as follows: First, we review the literature on seeding strategies in viral advertising, Cognitive Response Theory (CRT) and sentiment analysis. Next, in the Methodology section, we demonstrate the effectiveness of sentiment analysis over the traditional thought-listing method in measuring consumer cognitions. Subsequently, using ad- and brand-related sentiments, we conceptualize and illustrate a typology of viral ad sharers. Finally, we conclude with theoretical and managerial implications, limitations of this study, and future areas for research.

2. Literature Review

2.1 Viral Advertising and Seeding Strategies

Viral potential of advertising messages is a key benefit of using Internet marketing (Eckler and Bolls, 2011; Porter and Golan, 2006). Academicians (Nelson-Field, Riebe, and Newstead, 2013) and practitioners (Valos, Ewing, and Powell, 2010) suggest a need to understand why only a few viral campaigns (less than 5%) succeed. Extant viral advertising research mainly focuses on products, content or the recipient of these ads. For example, studies on products (Schulze, Schöler, and Skiera, 2014) or brand characteristics (Lovett, Peres, and Shachar, 2013) identify key features of product categories or brands that drive word-of-mouth (WOM) and motivate people to talk about them. Pertaining to content, existing studies show that consumers share messages that offer high entertainment and enjoyment levels (Phelps et al., 2004), high utilitarian or hedonic value (Chiu et al., 2007), or high levels of emotional experience (Dobele et al., 2007; Berger and Milkman, 2012). Studies on recipients/audience of these messages seek to identify people (seeds) with a higher propensity to share, based on their personality traits (Chiu et al., 2007), motivation (Ho and Dempsey, 2010), or positions in a social network (Hinz et al., 2011).

Very few studies have looked at seeding strategies, that is, the careful selection of the initial target consumers and placement of a viral message (Kiss and Bichler, 2008; Zhang, Li, and Wang, 2013). For a successful seeding strategy, Hinz et al. (2011) identified four decisive factors: content (e.g., Berger and Schwartz, 2011), network structure (e.g., Kiss and Bichler, 2008), behavioural incentives (e.g., Libai, Muller, and Peres, 2013) and the seeding strategy itself (e.g. Liu-Thompkins, 2012). Research investigating optimal seeding strategies has largely focused on the issue relating to the profiles of the 'seeded' individuals, often labeled as 'hard-to-find' influencers, who have a disproportional effect on the 'others' (Trusov, Bodapati, and Bucklin, 2010). These influencers can be identified based on either their social network features (Kiss and Bichler, 2008; Zhang, Li, and Wang, 2013) or certain psychological variables like personality traits (Chiu et al., 2007). However, individuals differ in their information processing abilities (Petty and Cacioppo, 1986), which can be measured by analysing their cognitive responses. In their study, Huang et al. (2013) found that ad- and brand-related cognitions (Cad, Cbr) drive sharing intentions (SI) for viral ads. However, no attempt has been made to analyse these consumer cognitions in the form of unstructured (latent) texts as a means to identify and segment influencers (initial sharers) of viral ads. Researchers studying cognitive responses have largely benefited from the 'Cognitive Response Theory' for conceptualizing and measuring these responses. This theory has been discussed in the following section.

2.2 Cognitive Response Theory (CRT)

Cognitive responses are simply the thoughts that consumers construct in response to persuasive advertising (Petty, Ostrom, and Brock, 2014). According to the Cognitive Response Theory, spontaneous thoughts (cognitive responses) elicited by an exposure to a message act as direct mediators of attitude formation or change (Greenwald, 1968; Petty, Ostrom and Brock, 2014). According to Wright (1973), cognitive responses can be further classified into: counterarguments (CA), support arguments (SA), source derogation (SD) and source bolstering (SB). Among these, CA and SD are believed to result in less favourable attitudes, whereas SA and SB result in positive attitudes.

Measurement of Cognitive Responses:

The traditional method of measuring cognitive responses to an advertisement is the thought-listing method (e.g., Cacioppo and Petty, 1981; Wright, 1973; Huang and Hutchinson, 2008), in which the respondents are asked to write down all their thoughts either during/immediately after exposure to a message. Then, the cognitive responses are categorized according to the various criteria by the subject/experimenter to see whether or not the responses meet the prescribed definition for a class of cognitive responses [for example, CA, SA] (Wright, 1973, 1974). The third step is to compute the cognitive response scores that represent either a simple addition of the number of CA, SD, or SA, or more elaborately, use a model in which each cognitive response type is weighed by subjective indications of importance to predict attitude or intention. Typically, these cognitive responses are coded for valence and summed or averaged to form a measure of the net affective response. This measure is a reliable predictor of attitudes (e.g., Petty and Cacioppo, 1979; Wright, 1973). To the best of our knowledge, the thought-listing method has always been used to compute a valence-weighted aggregate index of cognitive responses, and no measures of specific thoughts have been used to predict attitudes. Moreover, TLM-based indicators of cognitions have potential measurement problems. This is because they are proposed on an intuitive, ad hoc basis to categorize cognitive responses at a broad, fairly abstract level, typically in terms of the evaluative direction of the thoughts vis-à-vis that of the message (Lutz and Swasy, 1977), capturing the dimension of *'direction'*, but failing to measure the *'strength or intensity'* of cognitive thoughts (Greenwald, 1968). Furthermore, TLM indicators are subjective in nature, making them unsuitable to study the subtle nuances in the message on attitudes and intentions. Thus, for an objective assessment of cognitive responses (Lutz and Swasy, 1977), an improvised method is needed to quantify these cognitive responses in terms of both, their *valence/direction* and *strength/intensity of the valence*. This is where sentiment analysis, a method from psycho-linguistics is more appropriate to overcome the issues associated with the traditional thought-listing method. In the next section, we discuss sentiment analysis in detail.

2.3 Sentiment Analysis

Sentiment analysis, also known as opinion mining, is a field of study that analyses people's opinions, sentiments, evaluations, appraisals, attitudes, and emotions towards entities such as products, services, organizations, individuals, issues, events, topics, and their attributes (Pang and Lee, 2008; Aswani et al., 2017a). Consumers are more able to evangelize their own experience with many more people via the social media (Alalwan et al., 2017). Hence businesses are increasingly capturing more information about their customers' sentiments that has led to wide applications of sentiment analysis in various business domains including marketing (Liu, 2010; Dwivedi et al., 2015). There are different types of sentiment analysis techniques, such as feature-based sentiment analysis and document-based sentiment analysis. Feature-based techniques are mostly used to extract a special feature from a piece of textual document; whereas, document-based techniques are more appropriate to extract the overall polarities of a piece of text (Eslami and Ghasemaghaei, 2018; Liu, 2010). Sentiment analysis, a social analytics tool (Misirlis snd Vlachopoulou, 2018), can be used to extract the polarity of the consumer opinions in terms of positive, negative, or neutral and also assign a score to reflect the strength of the sentiment (Kim et al., 2016). Hence, such tools seem to be helpful in measuring both, the valence as well as the 'strength' of cognitive responses. Thus, we propose that sentiment analysis is an effective alternative to the TLM in measuring and quantifying the affective strength of consumers' cognitive responses, that plays an important role in consumers' attitude formation and sharing intentions for the viral ads.

3. Methodology

We designed an experiment to empirically compare and test whether sentiment analysis is a more effective method to understand cognitive responses better than the traditional thought-listing method. At first, cognitive responses were collected and analysed for their influence on attitudes towards the ad and the brand and sharing intentions, using both the thought-listing (Model I) and the sentiment analysis (Model II) methods. This further helped in selecting the method that offered a richer understanding of consumers' cognitions (See Figure 1) and effectively segmenting viral ad sharers.

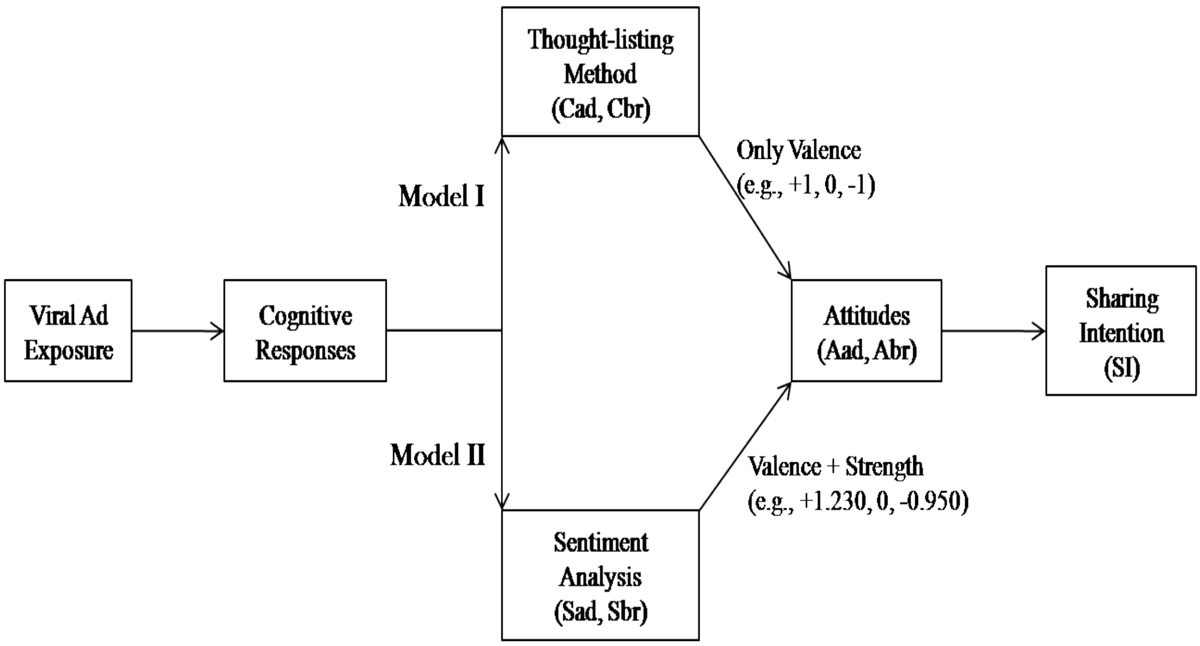

Fig. I Research Methodology – Thought-listing Method vs. Sentiment Analysis

3.1 Stimuli

Viral ads from three years prior were chosen to avoid recent exposure effects. Following the procedures of Huang et al. (2013), the first author screened the "TOP 100" viral videos from one of the top video ranking website 'Viral Video Chart™' (Powered by Unruly®) to identify ads that (1) have high ratings and a large number of views, (2) contain product and brand information and (3) contain a complete story and were not more than five minutes in duration. After initial screening, seventy viral ads were selected, which were then screened by two trained coders (students), each picking the top 20 of their favourite videos and they also categorised these ads as either 'emotional' or 'rational/informational'. On cross-comparison of these "Top 20" viral ads of both the coders, ten common videos were selected. Then these shortlisted ten videos were shown to another pool of fifty-six respondents. After viewing the ad, each participant was asked to report their sharing intention for these ads on a 7-point Likert scale (Huang et al., 2013), based on which the top two viral ads, one emotional (Google Search: Reunion; SI = 6.41) and one rational (Volvo Trucks - The Epic Split, SI = 5.50) were selected for the experiment (See Appendix A for the total counts on the actual views and shares of the shortlisted ads on different social media platforms). A pre-test confirmed that the two shortlisted viral ads were perceived differently ($M_{Volvo} = 2.85$ vs. $M_{Google} = 4.40$; $t(34) = 6.46$, $p < .01$) in terms of ad appeal (Liu and Stout, 1987) by the different set of undergraduate participants ($n = 35$; 57.1% males; average age = 21 years) who were not the part of the final experiment; wherein the Volvo ad was rated high on the *rational* and the Google ad was rated high on the *emotional* appeal.

3.2 Participants and Procedure

Predominant social network site (SNS) users are young adults under the age of 25 years (Correa, Hinsley, and De Zuniga, 2010) and they are the most active video sharers (Santos et al., 2007). Particularly, college students often are the key target segment for viral advertising campaigns (Chen and Lee, 2014; Chu, 2011; Lee and Hong, 2016). Hence, the experiment was conducted with undergraduate and postgraduate students (n = 344; 72.1% males; average age = 20 years, range = 18-25 years) enrolled at a large public university in India. Among them, 194 participants watched the 'Google' ad (https://youtu.be/gHGDN9-oFJE) and 150 watched the 'Volvo' ad (https://youtu.be/M7FIvfx5J10), before filling the questionnaire.

3.3 Measures

Brand attitude (Abr) was measured using a three-item, 7-point semantic differential scale: good/bad, attractive/unattractive, and high quality/low quality (Huang et al., 2013; Olson, Toy, and Dover, 1982). Measurement of attitude toward the viral advertisement (Aad) included a four-item, 7-point semantic differential scale: like/dislike, favourable/unfavourable, interesting/boring, and extraordinary/ordinary (Huang et al., 2013). Sharing Intention (SI) was measured using a three-item, 7-point scale that captures the extent to which a respondent feels s/he will share the advertisement (1 being the least and 7 being the highest): pass-along probability, probability of telling others, and probability of talking about the video (Huang et al., 2013). All variables reported acceptable reliability values (Cronbach's $\alpha > .70$) for both the ads.

Consumers' ad- and brand-related cognitions were analysed using the TLM as well as with a sentiment analysis tool, Semantria®.

Thought-listing Method (Model I): We adopted the open-ended Thought-listing Method (Cacioppo and Petty, 1981) to measure ad- and brand-cognition responses (Huang et al., 2013). The thought-listing instructions were as follows "please write down all the thoughts, ideas, and images that occurred to you about the ad and brand while viewing the video". An independent coder collected all the responses and sorted them into brand- or video-related thoughts, global evaluation thoughts, and irrelevant thoughts. Global evaluation and irrelevant thoughts were not considered for further analysis. Then, two trained independent coders coded the responses into positive (+1), neutral (0), or negative opinions (-1). Out of the total 688 opinions coded, the inter-coder reliability coefficient, Krippendorff's alpha was 88% in case of ad-related cognitions (Cad) and 92% for brand-related cognitions (Cbr). A third coder was consulted to resolve the discrepancies.

Sentiment Analysis (Model II):

There are different types of sentiment analysis techniques, such as feature-based sentiment analysis and document-based sentiment analysis (Eslami and Ghasemaghaei, 2018; Liu, 2010). In this study, as we were interested in the consumer evaluation of the video ad content and the brand shown in the viral ads, we used the document-based sentiment analysis method; wherein each specific thread of the ad- and brand-related thoughts were considered as a unit of analysis by focusing on words and phrases used by the respondents (Aston, Liddle, and Hu, 2014). Sentiment analysis was conducted using the Semantria® application (freely available on www.lexalytics.com/semantria/excel), which uses a cloud-based corpus of words tagged with sentiments to analyze the dataset and then tag each sentence with a numerical sentiment score (Kim et al., 2016). This score ranges from -1.5 to +1.5 and the polarity is categorised as (i) negative (ii) neutral or (iii) positive.

Besides demographic variables (gender and age), usage of Social Network Sites (SNS) was measured by asking the respondents the question that how many hours do they spend online in a typical day for various activities: (i) SNS platforms like Facebook and Twitter, (ii) for study or work and (iii) total time spent on online activities. The categories of choices were:

(1) 0 hrs; (2) 1–3 hrs; (3) 4–6 hrs; (4) 6–8 hrs, (5) 9–10 hrs and (6) 11 hrs and more (Zhong, Hardin, and Sun, 2011).

4. Results

4.1 TLM versus Sentiment Analysis

An ANOVA test revealed no significant interaction between ad appeal and ad-related sentiments {$F(1, 343) = 1.212$, $p > .10$, $\omega^2 = .004$)}. Hence, both the ads were entered simultaneously for the hierarchical regression to assess the effect of cognitions/sentiments (ad- and brand-related) and attitudes (Aad, Abr) on sharing intentions (SI). TLM-based indicators of cognitive responses were entered in Model I and sentiment-based indicators representing quantified cognitions were entered in Model II. The results are presented in Table I below.

Table I: Results of the Hierarchical Regression Analysis

		Model I Thought-listing Method (Cad, Cbr)			**Model II** Sentiment Analysis (Sad, Sbr)		
Predictor		Change in R^2	F Change	β	Change in R^2	F Change	β
Step 1	Cognitions	.027	4.682	.128*	.090	16.794	.285**
Step 2	Attitude (Aad, Abr)	.124	24.658	.308*	.109	23.031	.279**
Final Model		Adj. R^2 = .140; F = 14.99*			Adj. R^2 = .189; F = 20.99**		

Notes:
Aad - Attitude towards ad content, Abr - Attitude towards embedded brand; Cad - Ad-related cognitions, Cbr - Brand-related cognitions; Sad - Ad-related sentiment score, Sbr - Brand-related sentiment score; Significance at: *p < .05; **p < .01, n = 344

The results show that TLM-based indicators of cognitions (Cad, Cbr) are explaining only 2.7% ($\beta = .128$, $p < .05$) variance in Step 1, whereas the sentiment scores (Sad, Sbr) explained 9% ($\beta = .285$, $p < .01$) of SI. In Step 2, attitudes (Aad and Abr) were entered and found to be significant predictors of SI ($p < .01$) under both the TLM- and the sentiment-based approaches. These results illustrate that the sentiment-based measures are more effective (Model II; Adj. $R^2 = .189$) in predicting sharing intentions, when compared to the traditional TLM-based indicators (Model I; Adj. $R^2 = .140$).

To provide a rigorous test of the differential predictiveness of the two methods, we performed a set of regression analyses as suggested by Sirgy et al. (1997). The first set entered the traditional measures (Cad, Cbr) into the regression equation ($R^2 = .027$), followed by the new measures (Sad and Sbr) ($R^2 = .101$). If the hypothesis (that the new measure is more predictive than the traditional measure) is true, then we should expect the R^2 change due to the addition of the new measures to be significant. In this case, the R^2 change was significant (R^2 change = .074; $p < .001$). Conversely, if we enter the new measures (Sad and Sbr) first ($R^2 = .090$), followed by the traditional measure i.e. Cad and Cbr ($R^2 = .101$), we should expect R^2 change to be non-significant. This was evident here (R^2 change = .011, $p > .10$). As the range of scores for the sentiment analysis was greater (-1.5 to +1.5) than that for the thought-listing method (-1 to +1), we repeated the analysis by using the same range of scores for sentiments analysis as well as TLM and found that the results were the same. Hence, this provides additional support for the effectiveness of sentiment analysis method over the traditional TLM, when measuring cognitive responses. Therefore, the sentiment-based cognitive measures were selected for conducting the cluster analysis for testing whether any segments of viral ad sharers can be identified based on their sentiments expressed on the ads.

4.2 Cluster Analysis

The ANOVA results revealed that both ad-related sentiments (Sad) {M_{LowSad} = 5.15, $M_{HighSad}$ = 5.97; F (1, 343) = 32.02, p < .01} and brand-related sentiments (Sbr) {M_{LowSbr} = 5.16, $M_{HighSbr}$ = 5.96; F (1, 343) = 30.98, p < .01} are found to be significant predictors of consumers' sharing intentions. Hence, sentiment scores (Sad and Sbr) were divided into "high" versus "low" categories by a median split and then a two-step cluster analysis was conducted (Sarstedt and Mooi, 2014; Punj and Stewart, 1983) using these categorical variables, which helped identify the most interpretable four-cluster solution in terms of practical relevance. This two-step method allows in discriminating natural groups from a set of variables stabilizing the nearness criterion, with a hierarchical agglomerative clustering whose centres are far apart (Sarstedt and Mooi, 2014; Aldenderfer and Blashfield, 1984). Average Silhouette Coefficient (a measure of how tightly grouped all the data in the cluster are) measures the goodness-of-fit and can range between −1 and +1 (Rousseeuw, 1998; Sarstedt and Mooi, 2014). For the present study, the goodness-of-fit was appropriate, with good Average Silhouette Coefficient equal to 0.70.

5. Findings

5.1 Composition of Clusters

Four clusters emerged, with sample sizes of 104 (30.2%), 103 (29.9%), 78 (22.7%) and 59 (17.2%) respondents, respectively. With respect to sharing intentions (SI), the ANOVA test showed significant mean differences between these four clusters {F (3,343) = 18.24, p < .001}. Based on the relative importance that these ad sharers bestow on the ad- and brand-related sentiments, these clusters were labeled as 'Active sharers', 'Brand-fanatic sharers', 'Content-hungry sharers' and 'Dormant sharers' (See Figure II). We name this typology using the acronyms of these four clusters, calling it the 'ABCD' typology of viral ad sharers.

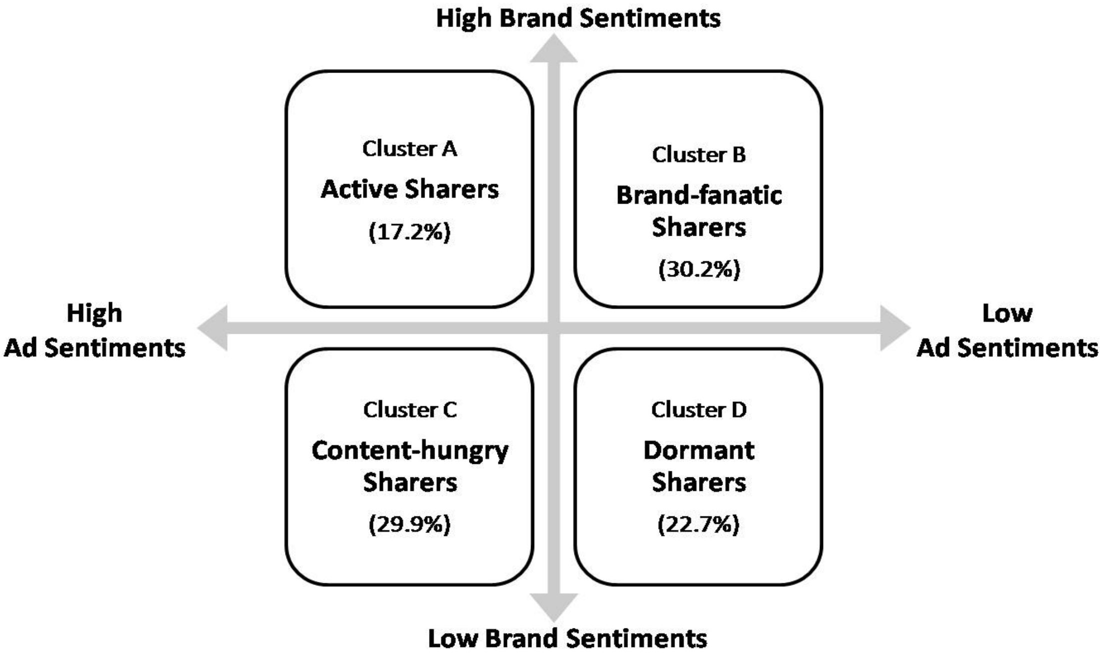

Fig. II Sentiment-based ABCD Typology of Viral Ad Sharers

For these clusters, qualitative word maps were created using a word cloud generator (www.wordclouds.com) based on participants' ad- and brand-related cognitive responses, with the size of the word reflecting the relative frequency of occurrence (See Table II). Each of these types is discussed below:

5.2 Cluster Profiles

Active Sharers (Cluster A): This is the smallest cluster (17.2%) of SNS users, who are most likely to share viral ads (SI = 6.55). Active sharers experience the same level of intensity of affect for the ad as well as the brand, which is reflected in their ad- and brand-related thoughts. Those who saw the Google ad, describe it with words like 'Good', 'touching', 'friendship', 'amazing', 'attractive' and 'impressive'; and they also think the brand Google to be the 'best' and is the 'top' brand associated with their Internet 'search' and the brand is 'innovative' and a 'useful' means of 'communication'. Similarly, those who saw the 'Volvo' viral ad, described the ad execution with words such as 'good', 'amazing', 'stability', 'music', ‘cinematography’, ‘incredible’ and ‘unbelievable’ for the ‘brilliant’ and ‘creative’ ‘stunt’. According to them, the brand ‘Volvo’ stands for ‘good’, ‘attractive’, ‘famous’ and ‘safety’, with its ‘international’ presence focused on ‘innovating’ constantly in areas of ‘technology’ and ‘precision engineering’ products, ‘worldwide’. Such thoughts reveal the strong sentiments that the ‘active sharers’ have for these brands and they love forwarding emotionally-charged viral ads to their friends online. This cluster represents the *‘ideal seeds’* given the fact that they provide high probability of fastening the diffusion of viral ads on social media platforms.

Table II: Qualitative Word Maps for Identified Clusters of Viral Ad Sharers

Clusters	**Viral ad: Google Search-Reunion**		**Viral ad: Volvo-Epic Split**	
	Ad-related Sentiments	*Brand-related Sentiments*	*Ad-related Sentiments*	*Brand-related Sentiments*
Active Sharers				
Brand-fanatic Sharers				
Content-hungry Sharers				
Dormant Sharers				

Brand-fanatic Sharers (Cluster B): This is the largest cluster (30.2%) of SNS users who are more traditional, displaying more affective gravity to the embedded brand vis-à-vis the ad content. For *Brand-fanatics*, a viral ad is perhaps perceived as being more effective or social if it is associated with portraying the functional benefits of the brand and uses linked with the embedded brand. The word cloud reveals the use of more affective words to describe the two brands (like 'important', 'amazing', 'helpful', 'connecting' and 'best' for Google; 'luxurious', 'reliable', 'safe' and 'trustworthy' for Volvo) vis-à-vis the ads. Brand-fanatics think more about their connection with the *embedded brand* within the viral ad, when it comes to deciding whether to forward a particular ad or not. Their sharing intention (SI = 5.38) is lower than that of the 'Active sharers'.

Content-hungry Sharers (Cluster C): This segment comprises of SNS users (29.9%) who experience stronger sentiments towards the ad 'content', regardless of the embedded brand. They exhibit strong positive sentiments for the ad content and might discount any brand-related information if the ad content is sufficient to charge them emotionally. Word clouds of these 'content-hungry' ad sharers highlight more affective words for the advertising message elements (e.g. 'friends', 'childhood', 'partition' and 'relationship' for describing the Google ad and 'creative', 'interesting', 'surprising' and 'suspense' to describe the Volvo ad) rather than the brand. Content-hungry sharers love the emotional and provocative elements of viral ads, and are more likely to share such ads with their social network connections. They score slightly higher on the variable of sharing intention (SI = 5.40), when compared to brand-fanatics.

Dormant Sharers (Cluster D): This segment, with the sample size of 22.7%, represents individuals with weaker sentiments for both, the message as well as the embedded brand within the viral ads, resulting in lowest sharing intentions (SI = 4.93). These SNS users, who are ‘passive’ processors of viral content, describing only facts and storylines from the ad (e.g. use of words like ‘Internet’, ‘people’, ‘search’ and ‘meet’ for describing ad-related thoughts in case of Google ad) without any affective feelings. Moreover, they might be suspicious about the way the ad has been designed. For example, ‘Dormant’ respondents who saw the Volvo ad described it with words like ‘fictitious’, ‘confusing’, ‘photo-shopped’ and so on. Hence, they must not be considered as a seeds to begin viral ad campaigns.

5.3 External Validity of the Clusters

Criterion-related validity of the cluster solution was assessed using demographic variables (gender and age) and SNS usage behaviour. Age does not play a role in discriminating these four clusters. We found significant differences across clusters in terms of gender distribution ($\chi^2 = 10.373$, df = 3, $p < .05$). Although the sample is biased towards male respondents, clusters differ in terms of the number of males included, with clusters A and C having more males than clusters B and D. Furthermore, results of the Kruskal-Wallis test indicate significant differences across the four clusters in terms of total time individuals spend for various online activities ($\chi^2 = 7.537$, df = 3, $p < .10$), but not with respect to the time spend on using SNS platforms (e.g. Facebook) and using internet for working or studying purposes ($p > .10$).

As one of the viral ad, i.e. Google Search’s Reunion ad, had the context of India-Pakistan, the above results may be questioned on their reliability, as the respondents are from India only. Also, the other ad, Volvo, has a popular celebrity presence, which may have influenced the sharing intentions for this ad (Southgate, Westoby, and Page, 2010). To validate the reproducibility of the proposed typology, another follow-up experiment (n=37) was conducted using another viral ad (https://youtu.be/uaWA2GbcnJU) of a lesser known brand (Thai Life Insurance) from the same pool of selected Top 10 viral ads, having no celebrity endorser. The results reproduced a highly significant {$F(3, 36) = 30.61$, $p < .001$} four-cluster solution just as in the main study, highlighting the replicability of the proposed typology.

6. Discussion and Implications

Marketing practitioners have largely benefited from various typologies proposed to identify different groups of Social Networking Site users (Brandtzaeg and Heim, 2011), online shoppers (Bressolles, Durrieu and Senecal, 2014) as well as Facebook Fans (Wallece et al., 2014). Such structured segmentation of consumers help advertisers and brand managers identify potential consumers easily and enhance the marketer's ability to target important 'seeds' precisely. However, there was a lack of such structured typological framework to segment viral ad sharers. This study adds to the existing literature by exploring a consumer typology based on cognitive responses as a psychographic variable. This type of cognitive segmentation helps to group individuals based on their cognitive content and structure by capturing cognitions of each customer while incorporating their semantic uniqueness (Carrillat et al., 2009).

This proposed sentiment-based 'ABCD' typology of viral ad sharers offers a comprehensive explanation of consumers' sharing intentions and has implications for targeting and content marketing strategies. The present study uses consumers' cognitive responses and measures them using sentiment analysis to propose four types of exclusive profiles of viral ad sharers. Each profile represents a unique combination of the varying strength of ad- and brand-related consumer sentiments and exhibit significant differences in attitudes and behaviours. For example, consumers who harbour both, strong ad- and brand-sentiments are most likely to pass-on viral ads. These hard to find 'active' consumers exist in small proportion (only 17.2% of sample in this study) and make-up the pool of seeds that drive the diffusion of viral ads over social media platforms. Both online and offline research has theorized the existence of a small segment of influential individuals and these are termed as innovators, who further influence the imitators (Bass, 1969; Hinz et al., 2011). For example, consistent with the classical Pareto principle (the law of the vital few), 20% of users are expected to carry 80% of the load to propagate the message. Therefore, it is crucial to wisely select the initial hosts for starting the epidemic viral phenomena. There is a possibility that companies may fail in trying to create a viral marketing epidemic because they spread the initial message too broadly (Kaplan and Haenlein, 2011). This study validates this finding that 'active sharers' appear to be the smallest cluster in size and must be chosen as an initial set of consumers to seed the viral campaign.

Extant literature has demonstrated the importance of 'message content' as a single largest predictor of virality (Phelps et al., 2004; Dobele et al., 2007; Berger and Milkman, 2012) along with other predictors like psychological motivations such as need to belong (e.g. Ho and Dempsey, 2010) and features of social network structure such as tie strength (e.g., Kiss and Bichler, 2008). Our proposed cluster profiles demonstrate that in addition to the message content (particularly emotional content), positive sentiments towards 'embedded brand' increases the probability of that content going viral. For example, 'active sharers' (i.e. strong sentiments for both the ad and the brand) have higher intentions to share that ad when compared to 'content-hungry' (i.e. strong sentiments for ad only) or 'brand-fanatic' sharers (i.e. strong sentiments for brand only). Existing literature has also shown that high prominence of the 'brand' in an ad may distract consumers' attention from content (Hsieh,

Hsieh, and Tang, 2012). Moreover, Huang et al. (2013) have shown that consumers' are more likely to focus their attention on the content of a viral ad rather than the brand and if the ad has more brand information, it may lead to negative experience that reduces sharing intentions. Contradictory to these studies, this study puts forth a counter-intuitive finding that strong positive sentiments for a brand plays an important role along with more positive evaluations of the message content; thereby, boosting consumers' ad forwarding intentions. This finding also supports the classical 'Reciprocal Mediation' model of advertising effectiveness proposed by MacKenzie, Lutz and Belch (1986), which hypothesizes a reciprocal relationship between a consumer's 'ad' and 'brand' information processing behaviour.

The proposed meaningful categories of viral ad sharers can be mapped to the previous user typologies in the areas of adoption and consumption of products/information. Kozinets's (1999) typology is related to the consumption of products or the provision of information about goods inside virtual communities and is seemed to be the most similar to the typology proposed in our study. For example, in the context of online community, Kozinet (1999) identifies four types of users as – Tourists, Minglers, Devotees and Insiders. Tourists are users who simply drop by the community every now and then with only superficial interest and few social ties. Minglers are users who maintain strong social ties, while being marginally interested in any consumption activity. Devotees are users who maintain a strong interest in consumption but have little social attachments. Insiders are users who have strong social ties and a strong interest in consumption activity. On mapping these segments to that of the four clusters of viral ad sharers, we recognize that dormant sharers are like tourists, who hardly have any interest in either the advertising content or have any strong connections with the brand embedded in the viral ad. Content-hungry sharers are minglers, who engage easily with the content but with marginal interest or attachment with the embedded brand; whereas, brand-fanatics are the devotees, who have strong attachment for the embedded brand in the viral ad with relatively less interest in the ad content. Finally, active sharers mimic insiders, who have equally strong connection with the brand and high interest in the ad content.

Research is particularly warranted in understanding the meaning behind commenting and sharing behaviour of SNS users (Dwivedi et al., 2015; Barger, Peltier, and Schultz, 2016), in the context of viral advertising. To address this issue, an experimental set-up allowed this study to offer a holistic view, combining instantaneous measurement of sharing intentions, along with attitudes (Aad and Abr) and cognitive responses. This provides more insights about the motives and beliefs of consumers that drive the intentions to forward viral ads. Another finding and contribution relates to the use of sentiment analysis to overcome the apparently subjective nature of the traditional thought-listing method. By using sentiment analysis, this research responded to an important call by Lutz and Swasy (1977) to develop deeper and objectively measure cognitive responses in terms of their valence as well as the strength. Altogether, this study is a pioneering attempt to segment viral ad sharers based on their cognitive responses and also, makes an important methodological contribution by introducing sentiment analysis as an alternate method to overcome the limitations associated with the traditional thought-listing method.

Implications for Managers

The findings reported in this study have significant implications for advertisers and brand managers with respect to devising seeding strategies as well as designing viral advertising campaigns. This study demonstrates that both, ad- and brand-related sentiments are strong drivers of sharing intentions. User generated content (UGC) from social media platforms can provide richer understanding (Aswani et al., 2017c; Aswani et al., 2018) about sentiments that a user carries for video content as well as the embedded brand. Brand managers can make use of other freely available sentiment analysis tools like Python NLTK (Natural Language Toolkit) and RapidMiner to analyze these comments and identify active sharers as 'seeds' for their viral branding campaigns.

The proposed typology of viral ad sharers will also help advertising agencies in designing viral ads more strategically. In contrast to the existing literature that advocates minimal brand information to be included in an ad (Hsieh, Hsieh, and Tang, 2012; Huang et al., 2013), this study highlights the necessity to balance the ad message with brand information while producing viral ads, so as to prompt 'active sharers' at the initial stage of the campaign to boost virality. This may partly be because strong brand integration is a sign of a well-structured video (Southgate, Westoby, and Page, 2010). In their study on exploring content virality on Facebook, Aswani et al. (2017a) found that when a brand engages itself directly on the Facebook post via its name, then the probability of the content going viral increases, indicating the 'trust' aspect that the brand brings with itself to promote consumer engagement with the brand. Moreover, further including brand information supports consumers' functional needs and draws their attention and motivates them to associate the ad with a positive brand image (Lee and Hong, 2016). This finding supports the recent work of Akpinar and Berger (2017), which states that emotional ads where the brand is integrated into the narrative, boosts shares as well as the brand evaluation when compared to an emotional but non-integral ads and ads that are purely informative. For example, an advertisement for a cupcake brand in Pakistan, Peek Freans Cake Up recently garnered more than 10 million views on Facebook with over 2,30,000 reactions, 63,000 shares and 7,900 comments, shows a story of a working mother who finds a unique way to create a real connection with her son using the product

(Pattanaik, 2018). This ad integrates the brand very well in the storyline and positions itself in the consumer’s mind as being bigger than just a sweet snack by showing how it can become the catalyst for starting real conversations with the people we love. Hence, marketers must design viral ads in such a way that they generate positive sentiments in the consumer’s memory for the ad as well as brand. By doing so, they will be able to enthuse Active sharers who are motivated by both content as well as brand, thus, increasing the chances of the ad getting forwarded by these active SNS users.

Together, Brand-fanatics and Content-hungry ad sharers accounted for about 60% of sample. They are not much different when it comes to sharing intentions. However, they are conceptually different; while the former has high sentiments associated with the brand (but not the ad), the latter has high sentiments for the content of the ad (but not with the brand). Attention must be given to their communication preferences while designing viral ads. Finally, cluster D symbolizes Dormant sharers, which represents lethargic consumers having least intentions to forward viral ads. Brand managers must develop a clear seeding strategy from the get-go. If they really do not know which user segment to target, they may want to consider testing one or more of above segments before singling one out. Overall, the above findings have practical implications for marketers, particularly in terms of segmentation and targeting, as well as for designing of viral messages.

7. Limitations and Directions for Future Research

First, the videos used in the experiments were limited in variety and were known to be viral. Each of the viral videos, one emotional and one rational, was selected. An emotional viral video may have further sub-dimensions like valence (positive vs. negative) and arousal levels (high vs. low), which this research does not measure or control for. Future research may conduct field experiment or survey in order to measure the actual sharing (rather than intention to share) and test more than two viral videos featuring messages varying in terms of valence and arousal, as well as those ads that are not known to be viral. Second, gender imbalance is a limitation as 72% of the sample was males. The reason for this distribution was that in India, female constitute only 35% of the mobile internet user base and only 24% of Facebook users are women; whereas, men constitute an overwhelming 76% of the user base (We Are Social, 2016). Moreover, men spend over an hour per week on YouTube; whereas, women spend around 35 minutes per week consuming videos (Vermeren, 2015). So, the gender distribution in this study reflects the actual gender distribution of the internet users in India. However, had the number of women been the same as men, we may have seen the shift in the gender domination in some of the clusters. Finally, the viral videos used in this study involve different product categories and different levels of product involvement. Future researchers may validate these findings where these variables are controlled for.

Research on sentiment-based segmentation of SNS users could benefit from an investigation of different content consumption situations. In particular, researchers are encouraged to study segmentation of Internet users for different kinds of online communications like ads on Twitter, banner ads, movie teasers, and landing pages. Furthermore, research may investigate on how other motivating factors like personality traits of SNS users and video characteristics (length, context, creativity) might affect the valence or intensity of emotions and the feelings experienced by SNS users. This will help make better conclusions regarding the stability of the identified clusters overtime. Hence, additional research is required to validate this consumer typology in other populations, along with additional profiling variables. Brands have a sizeable number of followers across social media platforms, yet they must be aware of the types of consumer segments that are present within these followers. In conclusion, this research is a pioneering attempt to identify and analyze the different types of viral ad sharers present on social media and also provides a working framework for advertisers and brand managers to design and launch branded viral campaigns.

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Appendix A: Viral Advertisements Used in the Study

1	Google Search: Reunion 	URL: https://www.youtube.com/watch?feature=player_embedded&v=gHGDN9-oFJE Brand Name: Google Upload Date: November 13, 2013 No. of Views: 1,22,59,717 Total Shares: 9,69,419 Shares on Facebook: 9,48,793 Shares on Twitter: 20,506 Shares on Blog Posts: 120
2	Volvo Trucks - The Epic Split 	URL: https://www.youtube.com/watch?feature=player_embedded&v=M7FIvfx5J10 Brand Name: Volvo Upload Date: November 14, 2013 No. of Views: 7,86,05,590 Total Shares: 31,75,433 Shares on Facebook: 30,93,007 Shares on Twitter: 81,872 Shares on Blog Posts: 554
3	"Unsung Hero" (Official HD) : TVC Thai Life Insurance 2014 	URL: https://www.youtube.com/watch?feature=player_embedded&v=uaWA2GbcnJU Brand Name: Thai Life Insurance Upload Date: April 9, 2014 No. of Views: 2,21,90,654 Total Shares: 11,91,139 Shares on Facebook: 11,60,751 Shares on Twitter: 30,029 Shares on Blog Posts: 359

#Note: Views and Share counts as of November 2014