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Exploring users' motivations to participate in viral communication on social media

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ABSTRACT

Despite the popularity of viral marketing, its influencing factors have not been thoroughly investigated, especially in the context of social media. Successful viral communication depends on the sender's ability to turn receivers into active marketers, which requires the sender to consider both the perspective of the user/recipient and the message content. As the best means of engaging with social-media users and leading them to make a communication viral remains debated, this study seeks to determine the factors that influence users' willingness to share viral content. In this investigation, partial least squares structural equation modeling was employed to analyze data gathered from an online survey of Facebook users, focusing on a case study of a Facebook event. The results showed that meaningful content affects users' attitudes regarding sharing communications, and revealed significant differences between user groups regarding the effect the emotional tone and arousal level of content has on sharing behaviors.

1. Introduction

Social media has become a regular part of daily life for millions of people worldwide: users post tweets and become fans; explore mobile apps; like, search, create, and share content; and make transactions. These social and emotional interactions evolve over time, becoming both real and virtual extensions of users and their relationships.

Rafailidis, Nanopoulos, and Constantinou (2014) reported that social media has changed the way people communicate, make decisions, socialize, interact, entertain themselves, and shop, and that individual and group behaviors have mutated: consumers are not only increasingly influenced by peer effects and collective intelligence, but have also become empowered in the marketplace. As consumers, social-media users can continually expand their knowledge base through their online access to massive amounts of information; can feel empowered through becoming user-content generators and knowing that products and services that suit their needs are easily accessible; are growing increasingly sophisticated regarding avoiding advertisements; and are placing greater value on their peers' opinions. Above all, they are becoming more demanding, expecting companies to offer them comprehensive, emotionally satisfying experiences (Rafailidis et al., 2014).

In the earliest stages of Web 2.0, social media was considered an essential channel for online advertising, communication, and engagement (Kaplan & Haenlein, 2011). Consequently, social media became the primary focus of many organizations' promotional activities, with these organizations constantly updating their social-media efforts to remain relevant to customers and foster engagement (Tiago & Veríssimo, 2014). Users' responses to online communication tend to be relatively straightforward, occur in real time, and echo their emotional states; they report this feedback through functions such as the "thumbs-up/like" button on Facebook, the "favorite" button on Twitter, and similar features on other social-media sites. In this social-media-communication scenario, users' reposting of content is prioritized, as this promotes viral communication; several studies have reported that successful viral-marketing communication depends on users' willingness to share viral messages (Padula & Costa, 2013; Schivinski, Christodoulides, & Dabrowski, 2016).

Viral social-media communication has become a phenomenon of increasing importance, affecting social, economic, and political outcomes (Karnowski, Kümpel, Leonhard, & Leiner, 2017). However, many brand managers have limited understanding of the factors that motivate users to interact socially and promote viral communication.

This study seeks to understand the conditions under which social-media users adopt sharing behaviors concerning content promoted by

Abbreviations: CB-SEM, covariance-based structural equation modeling; CM, convenience motivation; EM, entertainment motivation; eWoM, electronic word of mouth; IM, information motivation; IU, internet usage; MUT, media user typology; PLS-SEM, partial least squares structural equation modeling; SEM, structural equation modeling; SK, search skill; VDM, viral digital marketing; WoM, word of mouth

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companies. To examine this, the first major viral event promoted on Facebook was used as a unit of analysis. Additionally, Facebook users were questioned regarding their Facebook persona, social-media usage, opinion-leadership/information-seeking tendencies, levels of disclosed/withheld information on Facebook, and emotional and cognitive needs.

The results identified three types of social network users, and reinforced the theory that some users are not suited to instigating the diffusion of messages. Moreover, they highlight the important influence content's meaningfulness and emotional arousal has on users' decisions to share it, and the need to pay close attention to users' overall attitudes toward viral campaigns, as some campaigns can negatively influence their willingness to share the content. The data illustrate that sharing behavior can differ among users, and is motivated largely by content characteristics; that participation is based on social motives; and that low sharing behavior is motivated by attitude toward a specific event. These results show that not all social network users are equally keen to share content, and that the event itself is a determinant regarding willingness to participate or share viral content. As the current understanding of user viral marketing attitude and behavior is quite narrow, this knowledge can be helpful for social-media marketers and brand managers.

2. Research scope

Viral digital marketing (VDM) has various definitions. Academics have referred to it as "word-of-mouth" (WoM), "buzz marketing," "stealth marketing" (Kaplan & Haenlein, 2011), "word-of-mouth marketing" (Baker, Donthu, & Kumar, 2016; Kozinets, De Valck, Wojnicki, & Wilner, 2010), "word-of-web," and even "customer-to-customer" and "peer-to-peer communication" (Bampo, Ewing, Mather, Stewart, & Wallace, 2008).

Research on VDM is relatively new. To identify pertinent research focuses and stages, this study applied a process similar to that of Sultan, Wong, and Sigala (2018), using the phrases mentioned above as search keywords. Crosschecking "viral marketing" with "digital," "word-of-mouth," "word-of-mouth marketing," and other keywords in one of the largest research databases (Scopus) yielded 443 references for 1999–2018 (see Fig. 1).

As visualization can produce a better interpretation and understanding of main research areas, a bibliometric network was constructed using VOSviewer software, based on the references retrieved from Scopus (see Fig. 2).

Fig. 2 shows two major clusters: the left-hand side, with 76 items, is dominated by consumer behaviors concerning communication, advertisement, and marketing campaigns, while the right-hand side, with 66 items, features the marketing concept, which is the main node, and integrates a wide set of probabilistic models concerning the reach or structure of the dissemination methods used to establish content's virality within the network. Consumer motivation to participate in VDM is relatively minor within the left cluster; cross-tabulating VDM with consumer motivation to engage in electronic-word-of-mouth (eWoM) marketing yields only nine references. Many articles concerning marketing and networks suggest that viral marketing uses pre-existing networks to spread marketing content through WoM.

The two main streams of research on VDM communication focus on two distinct phenomena: the spontaneous dissemination of messages through eWoM, and the production and dissemination of content under a brand-management strategy. Almeida, Costa, Coelho, and Scalco (2016) categorized studies of these phenomena into four groups:

1) analyses of eWOM communication over various social-media sites. In such analyses, the interactions between brands and social-network users are assessed, using reach, frequency, and perceived adoption risk as variables.
2) analyses of eWOM communication through surveys that explore sharing behaviors and intentions, frequency of visiting digital platforms, number of comments shared, searches for peers' opinions, and the probability of sharing.
3) analyses of the effect of individual-incentive strategies and reviews made through eWoM, measuring the volume of purchases based on recommendations, number of recommendations and online reviews, and reasons for recommendation success.
4) analyses of message-propagation dynamics through analytical models and theoretical structures based on social networks, using as variables the reach, propagation, and number of recommendations.

The differences between the four groups highlight the difficulty of defining the terms "eWoM communication" and "viral-marketing communication" (Camarero & Jose, 2011; Jose-Cabezudo & Camarero-Izquierdo, 2012), thereby delineating the difficulties of studying this phenomenon.

Viral marketing is considered "a form of peer-to-peer communication in which individuals are encouraged to pass on promotional messages within their social networks" (Bampo et al., 2008). Meanwhile,

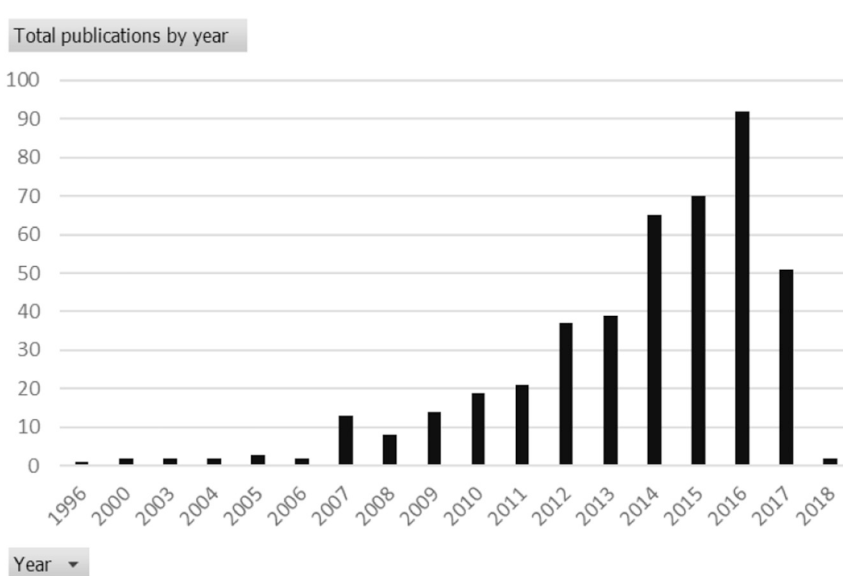

Fig. 1. Number of publications from 1999 to January 2018.

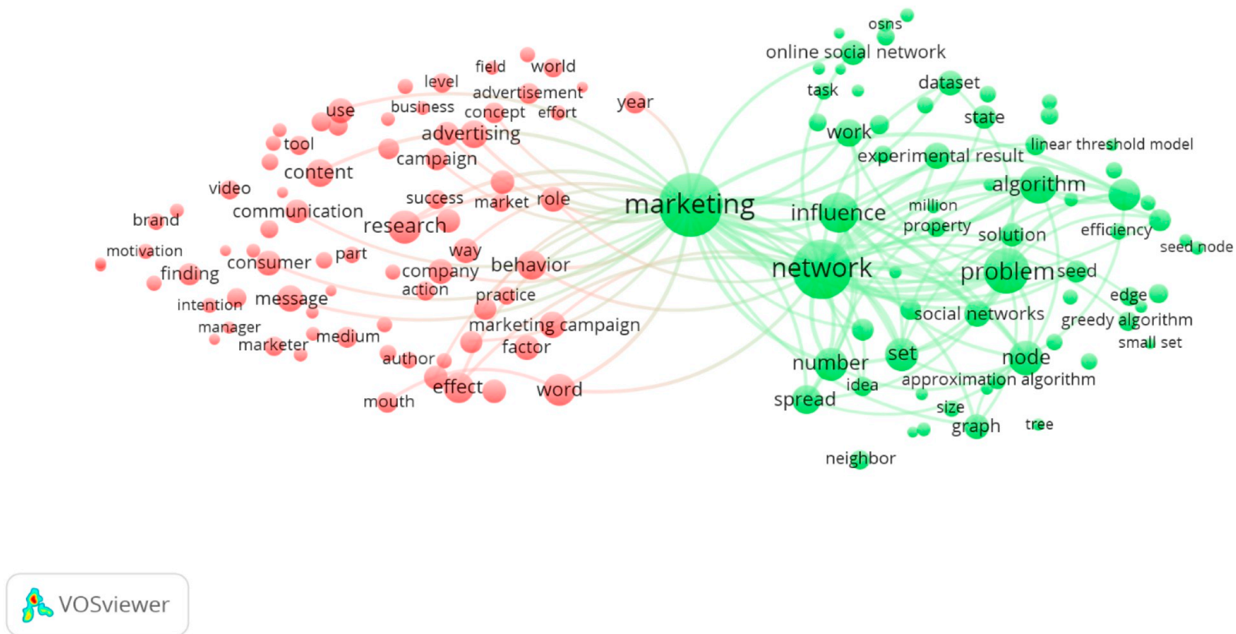

Fig. 2. Visualization of the key concepts network.

eWoM concerns any positive or negative comments made and shared by users regarding a product, service, or company that then become available to their peers via digital platforms (Chiu et al., 2014; Hsieh, Hsieh, & Tang, 2012). This study adopts the definition used by Gunawan and Huarng (2015), that "viral marketing is the consumers' act of eWoM" on social-network platforms.

Bampo et al. (2008) highlighted the need to more closely examine users' motivations to participate in viral communications, as the viral-marketing process is both random and unmanageable. But who are these consumers? Recent research on social-media consumers' behaviors has found that (i) not all consumers are equally active online (Correa, Hinsley, & De Zuniga, 2010; de Vries, Peluso, Romani, Leeflang, & Marcati, 2017), and (ii) content is generated by a small number of users with specific motivations regarding the concept, product, or project (Crowston & Fagnot, 2018; Naab & Sehl, 2017; Park, Kee, & Valenzuela, 2009).

Although the exchange-of-information phenomenon may not be new, the Internet has revolutionized the pace at which this occurs (Kozinets et al., 2010), as well as the origin of the messages; Kaplan and Haenlein (2011) proposed that message diffusion can be initiated either by companies or consumers. Berger and Milkman (2010) stated that positive content is normally shared more often, as it reflects positively on the sender and indicates potential rewards, and it is also likely to make recipients feel good. Nevertheless, useful content also holds social-exchange value, and people may share it to generate reciprocity (Berger & Milkman, 2009). Berger and Milkman (2009) also noted that these findings remain unaltered even when the authors of the content have control over how surprising, interesting, or practically useful it is, or even over external drivers of attention, such as how prominently the content is featured. These researchers also found practical use to be a common trait of viral content, as useful information can be shared for altruistic reasons or for self-enhancement (Berger & Milkman, 2012). This is consistent with the abovementioned reasons people engage in eWoM activities.

Consumers are empowered, deciding where to focus their and their peers' attention (Kozinets et al., 2010). Borges, Gonçalves, Veiga, Gosling, and Fernandes (2012) noted that viral communication capitalizes on the level of influence individuals wield among their peers, using this to enhance the impact of the message. According to these researchers, this represents a relatively softer method of conveying a message, since this occurs between individuals who share bonds of trust, meaning the messages are more likely to be seen. Adopting a perspective of use and gratification, some researchers have suggested that status seeking and social-exchange value can influence one's attitude toward viral communication (Park et al., 2009; Wu, Tan, Kleinberg, & Macy, 2011). This theory has led the authors of the present study to formulate the following hypotheses: social pressures are positively associated with users' attitude toward viral movements (H1) and the tone of emotional content (H2).

Researchers have recently begun examining the content characteristics that drive diffusion and persistence (Naab & Sehl, 2017). This latter focus is interesting, since the popularity of viral-marketing campaigns commonly persists for approximately two weeks, fueled by users' excitement (Kaplan & Haenlein, 2011).

Wu et al. (2011) explored the link between content and the temporal dynamics of information, and concluded that persistent information generally contains more words related to positive emotion, leisure, and lifestyle. Further, Tiago, Tiago, Faria, and Couto (2016) analyzed six global celebrities' social-media activity (specifically, Facebook and Twitter) and found that the most engaging users include four dimensions in their content: storytelling, amusement, triggers, and reaction, with storytelling being most effective for creating engagement.

To identify content characteristics related to diffusion, examining the phenomenon of *memetic videos* seems pertinent. Shifman (2012) defines these as popular video clips that drive high levels of user engagement through the use of creative derivatives, and whose creation and shareability benefits from the popularization of the Internet and Web-2.0-based technologies.

Moreover, Shifman (2012) noted that features of widely diffused memetic videos are not necessarily identical to those that have been found to improve the dissemination of other content types. For instance, although these memetic videos commonly include humor, which evokes positive, strong emotions normally related to greater levels of diffusion, Shifman (2012) noted that differences exist between content that users share and content with which users hope to interact through imitation.

More recently, a new content phenomenon has emerged on social media: fake news (Allcott & Gentzkow, 2017). This first manifested in 2010, but was highlighted during the 2016 US presidential election.

Shao, Ciampaglia, Varol, Flammini, and Menczer (2017) found that fake news tends to involve "false or misleading content—hoaxes, rumors, conspiracy theories, fabricated reports, click-bait headlines, and even satire." Under these categories, the common point of emotion-based content can be found.

Relatively ignored content normally contains more words related to negative emotions and actions and complicated cognitive processes (Wu et al., 2011). In contrast, a typical news cycle lasts 24 h, and content that exceeds this period is consequently more likely to receive consistent waves of attention (Wu et al., 2011), as seen during the US election (Allcott & Gentzkow, 2017).

Taking a psychological approach, Stephen and Berger (2009) suggested that emotions shape viral dynamics; specifically, that content that evokes emotion has higher viral potential than content that does not (Berger & Milkman, 2010). Further, positive content has been found to hold higher viral potential than does negative content (Tubenchlak, Faveri, Zanini, & Goldszmidt, 2015; Zhang, Zhang, & Law, 2014); however, negative content has survival value, as it can inform people of elements to avoid (Berger & Milkman, 2010). Considering the content characteristics of social-media communication, we hypothesize that users feel emotions when content is meaningful (H3), resulting in positive attitudes toward sharing (H4).

Berger and Milkman (2010) also found that the link that connects emotion to social transmission transcends valence, stating that physiological arousal motivates diffusion. Berger (2011) reported that content that evokes high-arousal emotions, whether positive, such as awe, or negative, such as anger and anxiety, is more likely to become viral; contrasting with content that evokes rather low-arousal, or deactivating emotions, such as sadness. This shows a strong activation-based contrast, as high-arousal states are characterized by mobilization and activity, while low-arousal states are generally related to relaxation and inaction (Berger, 2011; Berger & Milkman, 2010, 2012). Since sharing information requires individuals to take action, activation has been found to affect whether messages are shared, and even two emotions of the same valence could induce different levels of activation (Berger & Milkman, 2012). Therefore, when content is meaningful and evokes emotions, it is arguable that users are more likely to feel arousal emotions (H5), resulting in a positive attitude toward sharing (H6).

Brandtzæg (2010), based on an examination of media-user typologies, suggested that Internet users can be sorted into "non-users," "sporadics," "debaters," "entertainment users," "socializers," "lurkers," "instrumental users," and "advanced users." Other researchers have highlighted several individual characteristics that influence users' online behavior, such as information literacy, digital skills, and even social interactions (Chiu, Hsieh, Kao, & Lee, 2007; Yu, Lin, & Liao, 2017).

Berger and Milkman (2009) also noted that, in related studies, individuals reported being more eager to share advertisements that evoked amusement, and customer service experiences that evoked anger. Thus, besides users' personas, content becoming viral also depends on individual decisions regarding what to share and participate in. Viral dynamics can, therefore, be considered a consequence of both message activation and sharing (Bampo et al., 2008) that is influenced by users' personas (Crowston & Fagnot, 2018). Therefore, we hypothesized that users with more established digital social personas are likely to participate (H7) and share viral content (H8).

3. Material and methods

Existing eWoM and viral-marketing-communication research have mainly focused on comment type, credibility, and comparing the communication of positive and negative content (Bao, Wang, Wang, Wu, & Lau, 2016; Boo & Kim, 2013; Shao et al., 2017). Further, several researchers have examined the motivations, attitudes, and behaviors influencing the sharing of messages on social media (Correa et al., 2010; Crowston & Fagnot, 2018; Hsieh et al., 2012; Kozinets et al., 2010). In this context, for the purpose of this study, viral dynamics are considered to represent the process of acknowledging, creating, and sharing viral events/movements.

As previous research of social-media-based viral communication is sparse, the present authors have chosen to explore this concept using a discovery-oriented, theories-in-use approach; this work is, thus, exploratory in nature. As the object of inquiry is a viral social-media campaign, a case study approach was considered most appropriate (Yin, 2011).

The event chosen for this case study, Facebook's "a look back" feature, was released on 4 February 2014 to celebrate Facebook's 10-year anniversary. This feature enabled each user to review and celebrate their history on the social network through compiling their most emotional and notable moments. These moments were reportedly selected by an algorithm that took into account aspects such as likes, comments, and shares. Consequently, depending on the amount of information concerning their profiles, users would receive a 62 s personalized video set to music, a collection of photos, or a thank-you card. Interestingly, this feature promoted the anniversary of the social network through user-generated content. The videos were private to their owners, but could be shared on their timelines at will.

3.1. Sample and data collection

Data were gathered through an online survey of Facebook users. Considering time and resource constraints, the snowball-sampling technique, a non-probability sampling technique (Malhotra & Birks, 2007), was applied. The survey was opened on April 28, with 1.394 emails sent via mass mailing. By June 3, 674 people had accessed the link and viewed all of the survey sections; of these 674 individuals, 638 answered some or most of the questions (a 95% response rate). The final sample comprised 292 respondents, as some participants provided unclear or incoherent answers regarding their Facebook usage or attitudes toward the case study, and were subsequently excluded.

Of the 292 participants, approximately 62% were female and 36% were male. Ages were reported via an open-ended question format and later recoded into age intervals, similar to the method of Duggan and Brenner (2013). However, the first interval was adjusted as a result of the existence of 16-year-old respondents. The majority of the participants were 16–29 years (68.5%), followed by 30–49 (27.1%). The sample predominantly featured female young adults and adults. Most participants reported being from Southern Europe (89.73%), followed by Northern America (3.77%), Western Europe (2.05%), Northern Europe (1.71%), Eastern Europe (1.37%), Western Asia (0.34%), and Southern Asia (0.34%).

Characterizing their social-media usage, 71.92% reported using Facebook daily. Regarding the main purpose of their social-media use, respondents reported using Facebook and Instagram mainly to socialize or communicate (55.14% and 18.15%, respectively), and Twitter, Tumblr, Pinterest, Vine, and YouTube to share content or obtain information (10.62%, 11.64%, 17.12%, 3.77%, and 54.11%, respectively); some also used YouTube to follow pages and topics (24.66%). Finally, LinkedIn and Google Plus were used mainly for academic or professional purposes (50% and 11.30%, respectively).

Regarding the users' level of disclosure on Facebook, almost all respondents had posted their names on Facebook, and over 60% of both male and female respondents had posted a personal photo and information regarding their work and education. Additionally, over 50% disclosed their birth dates, but fewer than 50% disclosed the year of their birth. Also, fewer than 50% of both male and female respondents disclosed their relationship statuses or identified family members. Almost 30% did not see the "a look back" campaign and had no intention to share it.

3.2. Measurement of variables

Variables related to Internet usage were used for clustering

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Table 1
Scales used in the study.

Applied measures	Scale description and origin
Internet usage	Internet Usage (Time): Developed by Mathwick and Rigdon (2004), four seven-point Likert-type statements are used to measure the time a person spends on the Internet relative to other users.
	Internet Search Skill: Three seven-point Likert-type statements are used to measure a person's belief regarding his/her knowledge and ability to find information on the Internet. This scale was developed by Mathwick and Rigdon (2004) and comprises a subset of items from a scale by Novak et al. (2000).
	Internet Usage (Convenience Motivation): Developed by Ko, Cho, and Roberts (2005), this scale has three seven-point Likert-type statements and measures reasons for using the Internet, focusing on the ease with which it can be used.
	Internet Usage (Entertainment Motivation): Developed by Ko et al. (2005), this scale comprises four seven-point Likert-type statements that measure the degree to which a person uses the Internet because of the enjoyment they receive from it.
	Internet Usage (Information Motivation): Developed by Ko et al. (2005), three seven-point Likert-type statements are used to measure reasons for using the Internet, focusing on its usefulness for learning information.
	Internet Usage (Social Motivation): Developed by Ko et al. (2005), this scale has three seven-point Likert-type statements that measure the extent to which a person uses the Internet because of its ability to facilitate communication with others.
Social pressure	Susceptibility to Peer Influence: Created by Bearden, Netemeyer, and Teel (1989), this scale comprises 12 items reflecting two correlated dimensions of susceptibility to interpersonal influence, which is assumed to vary across individuals and to be related to other individuals' traits and characteristics.
	Opinion Leadership and Information Seeking (Reynolds & Darden, 1971)/Interpersonal Influence: Consumer susceptibility to interpersonal influence (Bearden et al., 1989)
	Need for Emotion: Developed by Raman, Chattopadhyay, and Hoyer (1995), this 12-item Likert-type scale measures the tendency to enjoy emotional stimuli, seek emotional situations, and show a preference for using emotion to interact with others.
	Need for Cognition: Developed by Cacioppo, Petty, and Kao (1984), this scale comprises 18 Likert-type items that measure tendency to engage in and enjoy effortful information processing.
Emotion tone	Affective Response to the Ad (Approval): Initially developed by Bhat, Leigh, and Wardlow (1998), this scale comprises nine semantic differential phrases measuring reaction to an ad, with an emphasis on the positive and/or pleasurable types of feelings experienced.
Arousal	Level of Arousal: This scale, sourced from Mehrabian and Russell (1974), comprises six semantic differentials that are intended to measure arousal-related emotional reaction to a stimulus in the environment.
Meaningfulness	Meaningfulness General: This scale comprises seven-point bi-polar adjectives intended to measure the extent to which a person perceives a stimulus to be relevant and important. Although all of the items have been used previously, Mano and Oliver (1993) appear to have been the first to use them as a summated scale.

Source: Adapted from Gordon and Bruner (2009) and Bearden, Netemeyer, and Haws (2011).

purposes, while demographic variables (age, gender, country, academic level, field of study/professional field, and occupation) and attitudinal variables (Facebook persona, social-media usage, opinion leadership/information-seeking tendencies, level of disclosed/withheld information on Facebook, and need for emotion and cognition) were used for the external characterization of the obtained clusters. Regarding Facebook persona, respondents were presented with a set of statements concerning their interest in shares, likes, and comments regarding the content they shared on their profiles. Another section aimed to obtain attitudinal variables concerning the "a look back" feature, and applied measures to assess approval, arousal, and meaningfulness. To increase its validity, the study developed a questionnaire using scales applied in previous research (Table 1).

There are two main approaches to structural equation modeling (SEM): partial least squares structural equation modeling (PLS-SEM), and covariance-based structural equation modeling (CB-SEM). As most communicational models and theories are too complex for full testing with traditional statistical techniques, partial least squares (PLS) was used for the data analysis of our research model, which is consistent with prior research concerning online user behaviors (Kamis, Koufaris, & Stern, 2008). PLS-SEM is a second-generation multivariate data analysis method used in marketing research that has several advantages over CB-SEM regarding the testing of theoretical-component-based models (Ringle, Sarstedt, & Straub, 2012).

Exploratory factor analysis was undertaken to better understand the relationships between the various constructs, and some low-loading items were consequently removed. The average variance extracted (AVE), a criterion used to measure convergent validity, should be over 0.50 (Ringle, Wende, & Becker, 2015), and applying this filter reveals that the results found through our model are indeed valid; further, all of the Cronbach's alphas for the constructs exceeded the recommended 0.70 value, indicating that the scales had good reliability (Table 2). (See Table 3.)

4. Results

To understand digital-user behavior patterns, segmentation procedures were conducted, using cluster analysis to group users based on their Internet usage. After a first visual clustering using the hierarchical clustering technique, the K-means clustering method, by minimizing the distance between each data point and the center of the cluster, was applied to divide the dataset into a small number of clusters. In addition, to assess the different characteristics of each segment, a one-way analysis of variance (ANOVA) was conducted to assess the statistical significance of the differences between groups, using post-hoc or multiple comparisons tests.

4.1. Cluster analysis

To apply the cluster analysis, we considered as dependent variables Internet-related measures, identified by the following indicators: Internet usage (time) (IU), search skill (SK), convenience motivation (CM), entertainment motivation (EM), and information motivation (IM). By applying the aforementioned methodology, three groups were identified, and the ANOVA results revealed that all of the classification variables adopted were significant.

The first cluster included Internet users with high average scores for many of the presented measures, and this cluster had the highest average regarding individuals' self-identification as heavy users. This group was, therefore, labelled "Heavy Users," which may be considered similar to the advanced users group identified by Brandtzæg (2010), who described these individuals as "*users that use a wide range of media frequently, using the most advanced facilities compared to the rest of the user population*" (p. 11).

The second cluster also included individuals with high averages for various measures; however, many were lower than those from the Heavy Users cluster. Nevertheless, in this second cluster, the measures that scored highest related to Internet usage due to convenience, information, and social motivation. Thus, this group was labelled the "Social-Driven" cluster. When compared to the media-user typology (MUT) proposed by Brandtzæg (2010), this group may be considered to be similar to the socializers type, which the authors described as a "*quite new and increasing user type because of the advent of social media applications*" (p. 11).

Table 2
Descriptive statistics (n = 292).

	Construct and items	
	Emotional state achieved with viral communication - rhoA: 1.000	
EMS1	Stimulated	Mean: 3.26 SD: 1.19
EMS2	Involved	Mean: 3.34 SD: 1.19
EMS3	Happy	Mean: 3.49 SD: 1.07
EMS4	Envious	Mean: 1.66 SD: 0.94
EMS5	Curious	Mean: 2.93 SD: 1.24
EMS6	Loving	Mean: 3.03 SD: 1.24
	Arousal - Cronbach's alpha: 0.938 AVE: 0.834	
AR1	Aroused	Mean: 3.23 SD: 1.31
AR2	Concerns me	Mean: 3.32 SD: 1.27
AR3	Relevant	Mean: 3.18 SD: 1.27
	Socializing – Cronbach's alpha: 0.710 AVE: 0.459*	
SI1	It is important that others like the content I share	Mean: 2.47 SD: 0.77
SI2	I like to know what messages make good impressions on others	Mean: 2.43 SD: 0.79
SI3	I often consult other people to choose the best content available from a given author or channel	Mean: 2.04 SD: 0.84
SI4	I feel that I am generally regarded by my friends and neighbors as a	Mean: 2.25 SD: 0.83
SI5	good source of advice about the latest popular posts/topics	Mean: 1.96 SD: 0.83
	I often seek the advice of my friends regarding the types of content I share	
	Meaningfulness - Cronbach's alpha: 0.969 AVE: 0.863	
MF1	Valuable	Mean: 3.23 SD: 1.23
MF2	Meaningful	Mean: 3.45 SD: 1.20
	Attitude - Cronbach's alpha: 1.000 AVE: 1.000	
ATT1	Attitude toward "A look back"	Mean: 3.85 SD: 1.75
	Viral dynamic: Participate - Cronbach's alpha: 1.000 AVE: 1.000	
VDP1		Mean: 2.62 SD: 1.18
	Viral dynamic: Share - Cronbach's alpha: 1.000 AVE: 1.000	
VDF1		Mean: 3.03 SD: 1.05

Note. AVE: average variance extracted; SD: standard deviation.

Lastly, the third cluster included individuals with rather low averages for most of the presented measures, although they returned higher averages for measures concerning information-motivated Internet usage. For some measures, these individuals had higher average scores than members of the social-driven cluster. Consequently, this third group was labelled "Research-Driven" and, in terms of the MUT groups proposed by Brandtzæg (2010), may be considered similar to the instrumental users type, described as being "*a quite common user type related to media in general and the Internet in particular*. *Users that use media for utility and as an information tool, both at work and in private*" (p. 11).

All three clusters from this sample were predominantly characterized by young adults and adults, with Heavy Users tending to be more concentrated within the first age group (namely, 16–29). This finding is consistent with that of Assael (2005), who also found that heavy Internet users are predominantly 18–34.

Regarding social-media usage, Facebook proved to be the main social network used by all three groups (92.55%, 68.55%, and 51.35% for Heavy Users, Social-Driven individuals, and Research-Driven individuals, respectively). Regarding YouTube, however, Heavy Users used it daily, while Social-Driven and Research-Driven individuals used it frequently. Most Social-Driven individuals reported being registered on various platforms, but not being particularly active on any of them; however, they used LinkedIn more frequently than did members of the other two groups. For the Research-Driven users, apart from Facebook and YouTube no other network was particularly popular; however, some members of this group used LinkedIn once a week.

In terms of usage purposes, Facebook was mostly associated with socialization and communication, followed by obtaining and sharing information. Social-Driven users had higher scores in socialization and communication purposes for both Facebook and Google Plus.

Over 50% of Heavy Users had over 500 connections, while

Table 3
Cluster analysis results.

Internet-related measures		Heavy user (n = 94)	Social-driven (n = 124)	Research-driven (n = 74)
IUa	I spend several hours a week on the Internet	3.97	3.67	3.07
IUb	Compared to most people, I think I spend a lot of time on the Internet	3.32	2.77	2.03
IUc	Aside from the time I spend using e-mail, I consider myself to be a "heavy user" of the Internet	3.44	2.83	1.86
IUd	In a typical week, I visit dozens of sites	3.40	2.93	2.12
SKa	I am extremely skilled at using the Internet	3.57	3.05	2.36
SKb	I consider myself knowledgeable about good searching techniques on the Internet	3.53	3.09	2.77
SKc	I know how to find what I am looking for on the Internet	3.67	3.28	3.08
CMa	It's convenient to use	3.87	3.38	3.22
CMb	I can get what I want with less effort	3.63	3.15	2.85
CMc	I can use it anytime, anywhere	3.38	2.96	2.64
EMa	I use it to pass time	3.62	2.79	2.65
EMb	I just like to surf the Internet	3.45	2.59	2.55
EMc	It's enjoyable	3.44	2.89	2.69
EMd	It's entertaining	3.66	2.99	2.82
IMa	I use it to learn new things	3.83	3.20	3.36
IMb	I use it because it's good for research	3.85	3.45	3.53
IMc	I use it to learn useful things	3.81	3.25	3.32

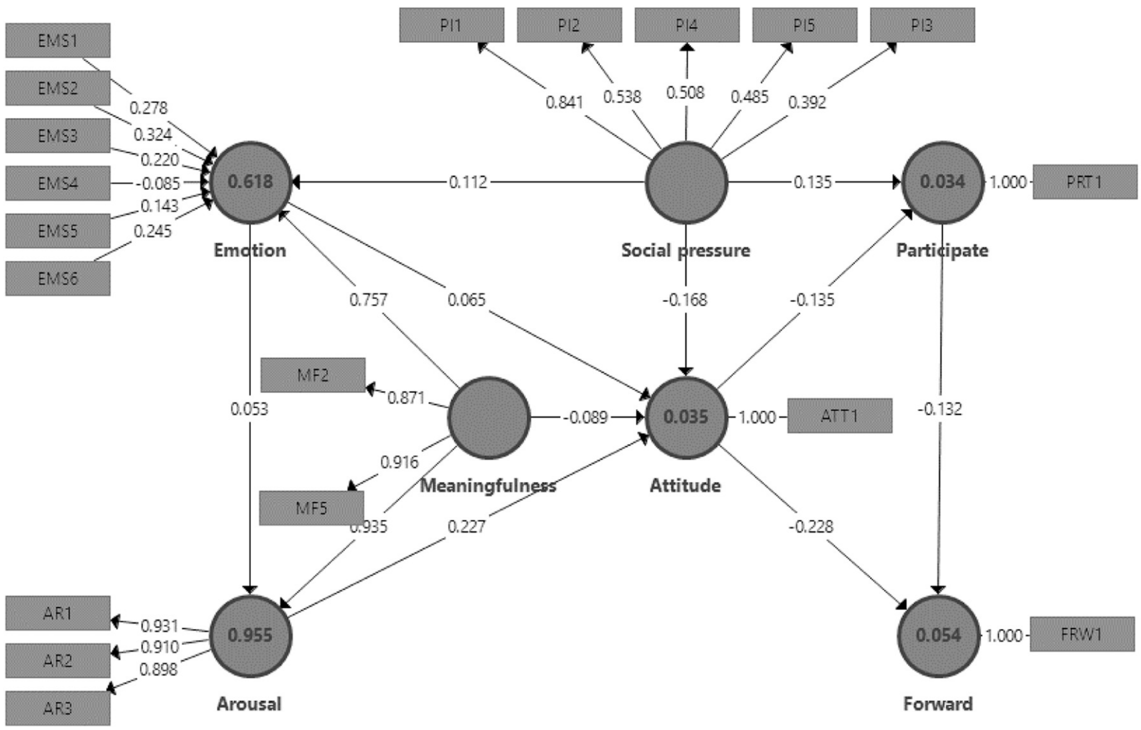

Fig. 3. Model estimation.

Research-Driven individuals had smaller network structures. Regarding the disclosed information on Facebook, all clusters reported disclosing their names, but Social-Driven individuals disclosed much more information (birth date, year of birth, languages, religious views, political views, family members, email address, and phone number).

4.2. Estimated results

As these results reveal, there are currently different segments of users exploring the Internet in various ways (Kaplan & Haenlein, 2011), and it is important to acknowledge and understand their attitudes toward viral marketing. To pursue this, SEM analysis was conducted using PLS-SEM with SmartPLS 3.0 (Ringle et al., 2015). According to Hajli (2014), the path coefficients in research models are significant at the 0.05 level. In the obtained results, the R^2 of the constructs showed that emotion and arousal accounted for almost 85% of the variance in the meaningful construct (see Fig. 3); therefore, the proposed model can be assumed to sufficiently reflect user behavior regarding sharing viral communications.

The remaining coefficient paths indicate that emotion has a small positive impact on arousal (0.053), supporting H5, and that arousal has a positive impact on attitude toward viral communication, confirming H6. Further, the positive impact of emotion tone on attitude toward viral content supports H4. Content meaningfulness positively affects both arousal and emotion tone constructs, confirming H3. On the other hand, social pressure positively influences willingness to participate in viral-communication processes, confirming H1. Social pressures (perceived peer influence on participants' social sharing behaviors and perception of participants' own influence on others' sharing behaviors) positively affected willingness to participate in viral communications, supporting H7. However, contrary to our prediction (H6a and H8), willingness to participate, as well as attitude toward viral content, did not positively affect willingness to share content.

Splitting the sample into Heavy Users, Social-Driven users, and Search-Driven users revealed that search-driven users are most likely to promote viral content (see Table 4).

The results of a multi-method multi-group analysis (using Henseler's multi-group analysis) revealed significant differences between Heavy Users and Social-Driven users regarding the effect of peers' influence on user willingness to share content ($p = 0.002$), of content arousal on attitude toward viral communication ($p = 0.012$), and of content meaningfulness on attitude ($p = 0.006$). Significant differences were also found between social-driven and research-driven users concerning the effect of content meaningfulness on attitude ($p = 0.030$). These results suggest that social pressures have a greater influence on Heavy Users, reinforcing the notion that more established digital social personas are most likely to participate in viral communication (H7).

5. Discussion and conclusions

Previous studies have investigated the sharing of viral content through the Internet by examining users' demographic characteristics, motivations, and behaviors, but few have investigated what motivates users to share viral communications on social media. Berger and Milkman (2010) defined social-media viral communications as a form of peer-to-peer communication in which individuals are encouraged to share promotional messages within their social networks; they mainly focused on how content features drive virality, especially at the emotional level. The need to understand how social-media personas affect viral marketing communication, and why some users are better suited to beginning the dissemination of messages (Kaplan & Haenlein, 2011) impelled us to conduct this research.

Adopting dimensions of Berger's model (Berger, 2011; Berger & Milkman, 2012), this study demonstrates that attitude toward a viral communication has a negative impact on user willingness to engage with and share such content, particularly less intensive social-network users. Content characteristics, such as meaningfulness, emotional tone, and arousal, are relevant to individuals' attitudes toward viral communication; further, heavy users are more likely to participate in a sharing event, motivated by social pressures. Thus, users are less likely to participate than share content, and are greatly influenced by content characteristics.

Our findings, to some extent, conflict with our hypothesis regarding the overall motivation to participate in and share viral communications.

Table 4
Results from Henseler's multi-group analysis.

	Path coefficients: original			Path coefficients: diff		
	Heavy users	Research-driven	Social-driven	Heavy users–search-driven	Heavy users–social-driven	Research-driven–social-driven
Arousal → attitude	−0.156	−0.977	−17.813	0.821	17.657*	16.836
Emotion → arousal	0.137	0.126	−0.109	0.011	0.246	0.235
Emotion → attitude	0.186	0.332	−2.127	0.146	2.313*	2.459
Meaningfulness → arousal	0.861	0.126	1.089	0.735	0.228	0.963
Participate → share	−0.051	−0.310	−0.167	0.259*	0.116	0.143
Attitude → share	−0.151	−0.129	−0.319	0.022	0.168	0.190
Attitude → participate	−0.191	−0.006	−0.221	0.185	0.030	0.215
Meaningfulness → attitude	0.089	0.919	19.745	0.830	19.656*	18.826*
Meaningfulness → emotion	0.737	0.744	0.785	0.007	0.048	0.041
Social → participate	0.206	−0.075	−0.186	0.281	0.392*	0.111
Social → attitude	0.289	−0.395	−0.061	0.684*	0.350	0.334
Social → emotion	0.018	0.129	0.112	0.111	0.094	0.017

* $\alpha > 0.10$

Consequently, there are several points of the theory that should be reconsidered.

Despite the differences between our initial hypotheses and our findings, the main hypothesis is supported: sharing behaviors differ between users with distinctive social-media personas. Under the premise that there are different types of Internet users (Brandtzæg, 2010; Correa et al., 2010), sufficient evidence was found to identify three groups with different online-action tendencies. This reinforced our hypothesis that some users are not suited to instigating the diffusion of messages (Bampo et al., 2008; Kaplan & Haenlein, 2011). This also supports the suggestion of Almeida et al. (2016): that there is a need to adopt carefully designed customer-segmentation strategies if one wishes to engage with consumers. When the three social-media-user types were compared regarding the elements that influence their willingness to share viral content, no significant differences were found except for the impact of the content's meaningfulness on the users' sharing behaviors and attitudes toward the viral content. In this case, significant differences were found between heavy users and social-driven users, with heavy users indicating that content meaningfulness can increase their willingness to participate in and share communications. The differences found between social-driven and search-driven users, meanwhile, related to the impact of content meaningfulness on attitude and, through this, their willingness to participate.

These findings have both theoretical and managerial implications for viral communication via Facebook. Theoretically, this exploratory study empirically validates Berger's model (Berger, 2011; Berger & Milkman, 2012) as, in the "a look back" event, some of the six dimensions of the model were identified as drivers of virality.

Managerially, these outcomes challenge the common communicational approach and provide marketers and brand managers with a metric that concerns ease-of-use and affords valuable insights into consumer behavior on social media. As an initial effort to provide practitioners with information pertaining to users' behavior regarding viral communication, it highlights the need to carefully segment users and to target those who are keener to share content.

As seen in the literature, many assumptions, models, and frameworks have been used to assess users' online behaviors, but few have addressed their willingness to share content. This research was structured around the work of Berger in an attempt to provide empirical evidence to support the idea that emotion, arousal, and meaningful content can influence social-media users' behavior regarding viral communications. Although the results of this study are interesting, they do not show that these elements can, by themselves, fully promote virality. Moreover, for all of the dimensions analyzed, only minor differences were found between different social-media users' profiles. Nevertheless, the results highlight the need to consider content meaningfulness when designing a viral-communication strategy.

The results also show that attitudes toward Facebook's viral campaigns significantly influence viral communication through this social medium. However, the predictor dimensions have differing levels of influence on sharing behaviors. It seems reasonable to postulate that successful viral-communication campaigns on Facebook should focus more on the predominant dimensions identified to be most closely related to sharing content during peak diffusion; in particular, the main reported reason for sharing content was that peers were sharing it.

Although this study is rich in descriptive and analytical data, some gaps in the research allow for valuable input from future research in this field. For example, the data were derived from user statistics on Facebook, but other social networks were neglected. Moreover, this study focused on an event specific to Facebook, which may not fully represent viral-communication campaigns that span multiple social-media networks. Another limitation is the prevalence of southern European women in the sample, who may have substantially different behaviors to other users; thus, it will be necessary to enlarge the sample in future research. Finally, since this work focuses on self-disclosure, attitude, and emotion-related variables, additional studies should investigate the engagement levels produced by such communication.

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References

Allcott, H., & Gentzkow, M. (2017). Social media and fake news in the 2016 election. *Journal of Economics Perspectives, 31*(2), 211–236. https://doi.org/10.1257/jep.31.2.211.

Almeida, M. I. S.d., Costa, M., Coelho, R. L. F., & Scalco, P. R. (2016). "Engage and attract me, then I'll share you": An analysis of the impact of post category on viral marketing in a social networking site. *Revista brasileira de gestão de negócios, 18*(62), 545–569. https://doi.org/10.7819/rbgn.v18i62.2620.

Assael, H. (2005). A demographic and psychographic profile of heavy internet users and users by type of internet usage. *Journal of Advertising Research, 45*(1), 93–123. https://doi.org/10.1017/S0021849905050014.

Baker, A. M., Donthu, N., & Kumar, V. (2016). Investigating how word-of-mouth conversations about brands influence purchase and retransmission intentions. *Journal of Marketing Research, 53*(2), 225–239. https://doi.org/10.1509/jmr.14.0099.

Bampo, M., Ewing, M. T., Mather, D. R., Stewart, D., & Wallace, M. (2008). The effects of the social structure of digital networks on viral marketing performance. *Information Systems Research, 19*(3), 273–290. https://doi.org/10.1287/isre.1070.0152.

Bao, Y., Wang, X., Wang, Z., Wu, C., & Lau, F. C. M. (2016). *20–21 June 2016. Online influence maximization in non-stationary social networks. Paper presented at the 2016 IEEE/ACM 24th international symposium on quality of service (IWQoS)*.

Bearden, W., Netemeyer, R., & Haws, K. (2011). Values and goals. In W. Bearden, & R. Netemeyer (Eds.). *Handbook of marketing scales: Multi-item measures for marketing and consumer behavior research* (pp. 151–236). California: Sage.

Berger, J. (2011). Arousal increases social transmission of information. *Psychological Science, 22*(7), 891–893. https://doi.org/10.1177/0956797611413294.

Berger, J., & Milkman, K. (2009). *Virality: The science of sharing and the sharing of science.* Marketing Research Camp.

Berger, J., & Milkman, K. (2010). *Social transmission, emotion, and the virality of online content.* (Wharton Research Paper, 106).

Berger, J., & Milkman, K. (2012). What makes online content viral? *Journal of Marketing Research, 49*(2), 192–205. https://doi.org/10.1509/jmr.10.0353.

Boo, S., & Kim, J. (2013). Comparison of negative eWOM intention: An exploratory study. *Journal of Quality Assurance in Hospitality & Tourism, 14*(1), 24–48. https://doi.org/10.1080/1528008X.2013.749381.

Borges, F. R. F., Gonçalves, C. A., Veiga, R. T., Gosling, M., & Fernandes, I. B. (2012). Elaboração e Experimento de um Método de Marketing Viral e Database Marketing Baseado em Algoritmos Genéticos. *Revista Gestão & Tecnologia, 12*(1), 151–175.

Brandtzæg, P. B. (2010). Towards a unified Media-User Typology (MUT): A meta-analysis and review of the research literature on media-user typologies. *Computers in Human Behavior, 26*(5), 940–956.

Camarero, C., & Jose, R. (2011). Social and attitudinal determinants of viral marketing dynamics. *Computers in Human Behavior, 27*(6), 2292–2300. https://doi.org/10.1016/j.chb.2011.07.008.

Chiu, H.-C., Hsieh, Y.-C., Kao, Y.-H., & Lee, M. (2007). The determinants of email receivers' disseminating behaviors on the internet. *Journal of Advertising Research, 47*(4), 524–534. https://doi.org/10.2501/S0021849907070547.

Chiu, H. C., Pant, A., Hsieh, Y. C., Lee, M., Hsioa, Y. T., & Roan, J. (2014). Snowball to avalanche understanding the different predictors of the intention to propagate online marketing messages. *European Journal of Marketing, 48*(7–8), 1255–1273. https://doi.org/10.1108/ejm-05-2012-0329.

Correa, T., Hinsley, A. W., & De Zuniga, H. G. (2010). Who interacts on the web?: The intersection of users' personality and social media use. *Computers in Human Behavior, 26*(2), 247–253. https://doi.org/10.1016/j.chb.2009.09.003.

Crowston, K., & Fagnot, I. (2018). Stages of motivation for contributing user-generated content: A theory and empirical test. *International Journal of Human-Computer Studies, 109*, 89–101. https://doi.org/10.1016/j.ijhcs.2017.08.005.

de Vries, L., Peluso, A. M., Romani, S., Leeflang, P. S., & Marcati, A. (2017). Explaining consumer brand-related activities on social media: An investigation of the different roles of self-expression and socializing motivations. *Computers in Human Behavior, 75*, 272–282. https://doi.org/10.1016/j.chb.2017.05.016.

Duggan, M., & Brenner, J. (2013). *The demographics of social media users.* Washington, DC: Pew Research Center's Internet & American Life Project1–14 (Retrieved from http://boletines.prisadigital.com/PIP_SocialMediaUsers.pdf).

Gordon, C., & Bruner, I. (2009). *Marketing Scales Handbook: A Compilation of Multi-Item Measures for Consumer Behavior & Advertising Research.* GCBII Productions.

Gunawan, D. D., & Huarng, K. H. (2015). Viral effects of social network and media on consumers' purchase intention. *Journal of Business Research, 68*(11), 2237–2241. https://doi.org/10.1016/j.jbusres.2015.06.004.

Hajli, M. N. (2014). A study of the impact of social media on consumers. *International Journal of Market Research, 56*(3), 387–404. https://doi.org/10.2501/IJMR-2014-025.

Hsieh, J. K., Hsieh, Y. C., & Tang, Y. C. (2012). Exploring the disseminating behaviors of eWOM marketing: Persuasion in online video. *Electronic Commerce Research, 12*(2), 201–224. https://doi.org/10.1007/s10660-012-9091-y.

Jose-Cabezudo, R. S., & Camarero-Izquierdo, C. (2012). Determinants of opening-forwarding e-mail messages. *Journal of Advertising, 41*(2), 97–112. https://doi.org/10.2753/joa0091-3367410207.

Kamis, A., Koufaris, M., & Stern, T. (2008). Using an attribute-based decision support system for user-customized products online: An experimental investigation. *MIS Quarterly,* 159–177. https://doi.org/10.2307/25148832.

Kaplan, A. M., & Haenlein, M. (2011). Two hearts in three-quarter time: How to waltz the social media/viral marketing dance. *Business Horizons, 54*(3), 253–263. https://doi.org/10.1016/j.bushor.2011.01.006.

Karnowski, V., Kümpel, A. S., Leonhard, L., & Leiner, D. J. (2017). From incidental news exposure to news engagement. How perceptions of the news post and news usage patterns influence engagement with news articles encountered on Facebook. *Computers in Human Behavior, 76*, 42–50. https://doi.org/10.1016/j.chb.2017.06.041.

Kozinets, R. V., De Valck, K., Wojnicki, A. C., & Wilner, S. J. (2010). Networked narratives: Understanding word-of-mouth marketing in online communities. *Journal of Marketing, 74*(2), 71–89. https://doi.org/10.1509/jmkg.74.2.71.

Malhotra, N., & Birks, D. (2007). *Marketing research: an applied approach* (3rd European ed.). Pearson Education.

Naab, T. K., & Sehl, A. (2017). Studies of user-generated content: A systematic review. *Journalism, 18*(10), 1256–1273. https://doi.org/10.1177/1464884916673557.

Padula, W. V., & Costa, B. R. L. (2013). Perfil e comportamento do usuário/cliente diante de uma campanha viral. *Iniciacom, 5*(1).

Park, N., Kee, K. F., & Valenzuela, S. (2009). Being immersed in social networking environment: Facebook groups, uses and gratifications, and social outcomes. *Cyberpsychology & Behavior, 12*(6), 729–733. https://doi.org/10.1089/cpb.2009.0003.

Rafailidis, D., Nanopoulos, A., & Constantinou, E. (2014). With a little help from new friends: Boosting information cascades in social networks based on link injection. *Journal of Systems and Software, 98*, 1–8. https://doi.org/10.1016/j.jss.2014.08.023.

Ringle, C. M., Sarstedt, M., & Straub, D. W. (2012). Editor's comments: A critical look at the use of PLS-SEM in "MIS Quarterly". *MIS Q,* iii–xiv. https://doi.org/10.2307/41410402.

Ringle, C. M., Wende, S., & Becker, J.-M. (2015). *SmartPLS 3.0 (Version 3.0)*. Boenningstedt: SmartPLS GmbH. http://www.smartpls.com.

Schivinski, B., Christodoulides, G., & Dabrowski, D. (2016). Measuring consumers' engagement with brand-related social-media content: Development and validation of a scale that identifies levels of social-media engagement with brands. *Journal of Advertising Research, 56*(1), 64–80. https://doi.org/10.2501/JAR-2016-004.

Shao, C., Ciampaglia, G. L., Varol, O., Flammini, A., & Menczer, F. (2017). *The spread of fake news by social bots.* arXiv PreprintarXiv:1707.07592.

Shifman, L. (2012). An anatomy of a YouTube meme. *New Media & Society, 14*(2), 187–203. https://doi.org/10.1177/1461444811412160.

Stephen, A. T., & Berger, J. A. (2009). *Creating contagious: How social networks and item characteristics combine to spur ongoing consumption and reinforce social epidemics.* Columbia University of New York.

Sultan, P., Wong, H. Y., & Sigala, M. (2018). Segmenting the Australian organic food consumer market. *Asia Pacific Journal of Marketing and Logistics, 30*(1), 163–181. https://doi.org/10.1108/APJML-10-2016-0211.

Tiago, T., Tiago, F., Faria, S. D., & Couto, J. P. (2016). Who is the better player? Off-field battle on Facebook and Twitter. *Business Horizons, 59*(2), 175–183. https://doi.org/10.1016/j.bushor.2015.11.003.

Tiago, T., & Veríssimo, J. (2014). Digital marketing and social media: Why bother? *Business Horizons, 57*(6), 703–708. https://doi.org/10.1016/j.bushor.2014.07.002.

Tubenchlak, D. B., Faveri, D.d., Zanini, M. T., & Goldszmidt, R. (2015). Motivations for positive electronic word-of-mouth between consumers on Facebook. *Revista de Administração Contemporânea, 19*(1), 107–126. https://doi.org/10.1590/1982-7849rac20151998.

Wu, S., Tan, C., Kleinberg, J. M., & Macy, M. W. (2011). *Does bad news go away faster?* (Paper presented at the Icwsm).

Yin, R. K. (2011). *Applications of case study research.* Sage.

Yu, T.-K., Lin, M.-L., & Liao, Y.-K. (2017). Understanding factors influencing information communication technology adoption behavior: The moderators of information literacy and digital skills. *Computers in Human Behavior, 71*, 196–208. https://doi.org/10.1016/j.chb.2017.02.005.

Zhang, Z., Zhang, Z., & Law, R. (2014). Positive and negative word of mouth about restaurants: Exploring the asymmetric impact of the performance of attributes. *Asia Pacific Journal of Tourism Research, 19*(2), 162–180. https://doi.org/10.1080/10941665.2012.735680.

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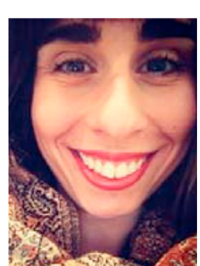

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