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Brand content diffusion on Social Networking Sites: Exploring the triadic relationship between the brand, the individual, and the community

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The background features a large, abstract geometric shape. It is primarily black, with a white, angular cutout on the right side. The cutout has a curved bottom edge and a sharp top edge. The overall composition is minimalist and high-contrast.

CHAPTER 1

The influence of the message

Chapter 1: The influence of the message

This chapter has been accepted for publication as:

Araujo, T., Neijens, P.C., & Vliegenthart, R. (2015). What Motivates Consumers to Re-Tweet Brand Content? The Impact of Information, Emotion, and Traceability On Pass-Along Behavior. *Journal of Advertising Research*.

The version presented here has been adapted to follow the overall standards and terminology included in the other chapters of the dissertation.

ABSTRACT

This study investigated how informational, emotional and traceability cues influence pass-along behavior of brand messages on Twitter. Analyzing 19,343 messages from 65 top global brands, the results indicate that informational cues are predictors of higher levels of retweeting, particularly when these informational cues are about product information and links to the brand website, to Social Networking Sites (SNSs), and to photos or videos. While emotional cues do not influence retweeting on their own, they reinforce the effects of informational and traceability cues when combined in the same message. The results indicate that consumers are especially interested in informational messages on Twitter, and are more likely to pass such messages along. Furthermore, the findings of this study suggest that type of communication (one-to-one versus one-to-many) and type of information (generic information versus brand information) influence pass-along behavior on SNSs. The paper also discusses the theoretical implications, as well as practical implications for marketing managers.

The influence of the message

Consumers increasingly use Social Networking Sites (SNSs) to engage in brand-related activity. This activity includes consuming and creating content about brands (Muntinga et al., 2011), as well as spreading messages about or from the brand (Jansen et al., 2009). Brands stimulate this type of activity, often inviting customers to share information with their friends (Araujo & Neijens, 2012). For brands, one of the key advantages of this phenomenon is being able to stimulate positive word-of-mouth and extend the reach of the brand message (comScore, 2011) while benefiting from the higher credibility that messages from consumers or validated by them have, compared to advertising (Goldsmith & Horowitz, 2006).

Consumers do not use all SNSs the same way. Brands are more central to consumers' activities on Twitter than on other SNSs (Smith, Fischer, & Yongjian, 2012), with up to 80% of the Twitter users involved in a recent study habitually mentioning brands in their tweets (Nagy & Midha, 2014). One of the characteristics of Twitter that may explain this behavior is the concept of retweeting. Retweeting emerged as a key mechanism for information diffusion (Boyd et al., 2010; Suh et al., 2010), and happens when a user decides to republish a message created by either an individual or a company. By republishing the message, the user passes it along to her/his own followers on Twitter. It is still unclear what influences pass-along

behavior, in particular what influences consumers to pass on brand content on Twitter.

Although marketers cannot control how brand information is disseminated by word-of-mouth (De Bruyn & Lilien, 2008), earlier research on Electronic Referral Marketing (ERM) and viral advertising suggests that the manner in which messages are designed can influence consumers' disposition to pass them along. The emotional tone or the presence of emotional cues in the message can stimulate pass-along behavior by creating an emotional connection between the consumer and the message (Dobele et al., 2007; Eckler & Bolls, 2011). The informational value of a message can also stimulate pass-along behavior, as consumers are more likely to pass along information they find useful (Chiu et al., 2007). Emerging research on the diffusion of general information (i.e. not brand specific) on Twitter also indicates that elements such as hashtags that make the message more findable or traceable are related to higher levels of retweeting (Suh et al., 2010). However, we still do not fully understand how these message characteristics influence pass-along behavior, specifically for brand messages on Twitter. This is a particularly pressing gap, since message characteristics are arguably one of the few elements that marketers can control to stimulate pass-along behavior.

The present study will:

- Review reasons for online pass-along behavior identified by ERM and viral advertising literature, as well as emerging research on information diffusion via Twitter, identifying message characteristics that may help stimulate pass-along behavior.
- Extend ERM and viral advertising literature by testing whether earlier findings are applicable to Twitter content.

In particular, this study will test the influence of emotional, traceability and informational cues on pass-along behavior of brand content on Twitter.

- Advance emerging literature on diffusion of information via Twitter by specifically investigating brand messages and their diffusion processes. The influence of message characteristics on pass-along behavior will be studied using a sample composed exclusively of messages created by brands, instead of general messages.
- Present recommendations for marketers on how to extend the reach of brand messages on Twitter.

THEORETICAL FRAMEWORK AND HYPOTHESES DEVELOPMENT

The present study draws on this earlier research – in particular ERM and viral advertising studies – to identify some of the key message characteristics related to brand content that may induce consumers to pass along information. We also include additional insights from emerging literature on Twitter information diffusion into specific characteristics of Twitter that may influence pass-along behavior.

THE ROLE OF EMOTION

Research on ERM has found that messages triggering emotions tend to be passed along the most by consumers (Dobele et al., 2007; Phelps et al., 2004); these triggers are frequently used in viral advertising, especially in online videos (Golan & Zaidner, 2008; Porter & Golan, 2006). These studies propose that only content that is

somehow extraordinary (Porter & Golan, 2006) and that links emotion to the message (Dobele et al., 2007) will capture the attention of consumers enough to be subsequently passed along. Likewise, the presence of emotions or different types of emotional tone in email messages (Eckler & Bolls, 2011) significantly influences pass-along behavior, especially when these messages are more hedonic in nature (Chiu et al., 2007).

In line with earlier research, our study determines whether emotional cues influence pass-along behavior of Twitter messages. This is primarily necessary for two reasons:

- Twitter messages are mainly composed of short texts. Viral advertising studies have, however, mostly focused on online videos. It is unclear whether emotional cues exert the same influence when the type of content is changed.
- ERM and viral advertising studies have mostly focused on pass-along behavior via email, which allows consumers to target who they want to see a given message. When a consumer decides to pass-along brand messages by retweeting, he or she passes the message to all his or her followers on Twitter – usually in a public manner.

We therefore propose the following hypothesis:

H1: Messages with emotional cues will be retweeted more often than messages that do not contain emotional cues.

THE ROLE OF INFORMATION

ERM research has indicated that people are more likely to pass along email based on their ability to evaluate the message as valuable or helpful (Huang et al., 2009) and when the message contains useful content (Chiu et al., 2007). Research on Twitter also indicates that users actively consider whether the content will be useful to their audience when retweeting (Boyd et al., 2010).

The question then becomes, what would be considered useful content in the context of brand messages? Previous studies have indicated that providing information about the product or brand is one of the reasons ERM and viral advertising are used (Golan & Zaidner, 2008; Porter & Golan, 2006). Earlier studies (Kwon & Sung, 2011) identified informational cues in the majority of the global-top brand messages on Twitter, distinguishing between brand names, product-related cues, and company-related cues in the message content. We define information as an announcement made by the brand, either about the brand itself (or the company that owns the brand), or about products from the brand, and propose the following hypotheses:

H2: Messages with brand information cues will be retweeted more often than messages that do not contain brand information cues.

H3: Messages with product information cues will be retweeted more often than messages that do not contain product information cues.

Links may be considered “redirecting informational cues” (Kwon & Sung, 2011, p. 12), as they provide additional information. Research on the diffusion of general information on Twitter has found that the presence of links is a predictor of increased levels of

pass-along behavior (Petrovic et al., 2011; Suh et al., 2010). Moreover, Twitter messages linking to different types of websites have been associated with varying levels of retweets (Suh et al., 2010). Since we do not know which types of links lead to higher numbers of retweets, we propose the following set of four sub-hypotheses regarding types of links related to brand activity on Twitter:

H4a: Messages that contain links to the brand website will be retweeted more often than messages that do not contain links to the brand website.

H4b: Brand messages that contain links to the photos or videos will be retweeted more often than messages that do not contain links to photos or videos.

H4c: Brand messages that contain links to SNSs will be retweeted more often than messages that do not contain links to SNSs.

H4d: Brand messages that contain links to news media will be retweeted more often than messages that do not contain links to news media.

THE ROLE OF TRACEABILITY

Research on Twitter indicates that elements related to how messages are displayed – and how easily they can be found –also affect pass-along behavior. One element that increases the traceability of Twitter messages is the usage of hashtags (#) to indicate the topic of the message (Boyd et al., 2010). Twitter converts these tags into links, which makes it easier to find other messages on the same topic, and also makes the message itself more findable (Suh et al., 2010). Hashtags have been found to be predictors of higher levels of pass-

along behavior in general (Suh et al., 2010), which leads to the following hypothesis:

H5: Brand messages that contain hashtags will be retweeted more often than messages that do not contain hashtags.

INTERACTION EFFECTS

Even though Twitter messages are brief, they can combine more than one message characteristic. Marketers can, for example, create informational messages containing product cues and links, while at the same time including emotional cues and making the message more traceable by using hashtags.

In line with our hypotheses, we expect that combining these characteristics (linearly) reinforces pass-along behavior. However, it is possible that these combinations also create interaction or synergy effects. In other words, we do not always expect that the combination of two characteristics would simply add main effects. One possible interaction effect is that a characteristic (for example, emotional cues) only has a significant effect when in combination with another characteristic (for example, product information cue).

These interaction effects have, however, seldom been investigated, as most ERM and viral advertising studies have focused either on emotional or on informational cues, and not on their combination. Considering the lack of earlier literature, we propose the following research question to explore this topic:

RQ: How does the combination of different message characteristics influence brand message pass-along behavior on Twitter?

METHODS

SAMPLE

This study uses brand messages (tweets) from the top 100 global brands (based on the 2011 Interbrand ranking) to investigate the influence of message characteristics on pass-along behavior. This set of brands covers a wide range of markets, customer segments and brand characteristics, thus increasing the generalizability of the results. The data collection followed two steps, summarized in Figure 1.

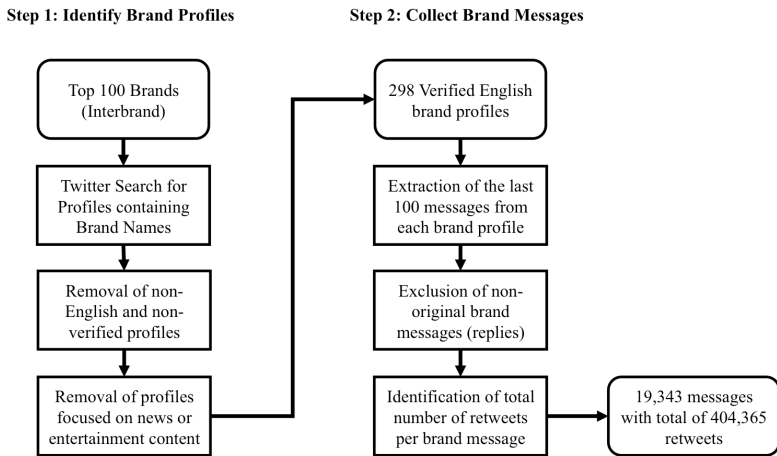


Figure 1. Data Collection Summary

The first step of the data collection was to determine which of the 100 top brands were actually present on Twitter. Brands can have multiple profiles on Twitter, so a search was conducted for the first 100 Twitter profiles that matched each brand name. These searches covered both the brand names as well as alternative names by which the brand is known. For example, for American Express, we also

searched for “Amex”. We kept only profiles in English that had a special verification of genuineness from Twitter (“Verified Profile”).

Next, brand profiles that focused on general news or entertainment were removed; since their emphasis was not on brand content, they were not relevant to the pass-along behavior that this study is investigating. Examples of profiles that were eliminated include MTV, with its primary focus on entertainment news, but also brands dedicated to republishing news from other sources, such as Google News or Yahoo! Finance. Out of 100 top brands, 65 had one or more profiles on Twitter that matched our criteria, resulting in a total of 298 profiles for analysis.

The second step of the data collection was to extract the last 100 Twitter messages from each brand profile. This was done for each of the 298 profiles included in the sample, and resulted in 27,846 individual messages (not all brand profiles had 100 messages or more). The study then collected the retweets from each of the 27,846 brand messages.

Of these messages, 31% were replies from the brand to other users. In some cases, the majority of messages consisted of replies (i.e., not original brand content). This was the case for Barclays and Pizza Hut (98% of the messages were replies), HTC (89%), Kellogg’s (88%), and Gap (85%). Other brands, including 3M, Accenture, Burberry, Louis Vuitton and Nintendo, did not have any replies to other users among their 100 latest messages.

Replies were removed from the analysis for several reasons. First, from a theoretical standpoint, it can be argued that replies are a discussion between one user and the brand. This implies, by definition, that even if brands write a public reply, this would be less interesting to the general public than original brand messages. Second,

reinforcing the first point, the sample showed a significantly higher level of retweets for original brand messages ($M = 20.9$ retweets per message, $SD = 96.01$) than for replies to users ($M = 0.45$ retweets per message, $SD = 3.22$). Third, certain message characteristics are strongly and significantly correlated to the type of message (original message or reply), in particular the presence of links ($Pbi = 0.60$, $p < 0.001$) and hashtags ($Pbi = 0.31$, $p < 0.001$). The 8,503 replies from brands to other users were removed from the sample, and only the 19,343 original brand messages were kept – i.e., the messages that brands actually create for all consumers to read.

UNIT OF ANALYSIS, DEPENDENT AND INDEPENDENT VARIABLES

The unit of analysis of this study was the individual brand message (tweet), and the dependent variable was the number of retweets each brand message received. Each of the 19,343 brand messages (tweets) was coded to determine which of the characteristics mentioned in the hypotheses was present. This coding was done using automated content analysis with the Natural Language Processing toolkit from Python (Bird, Klein, & Loper, 2009). The independent variables were operationalized as follows:

Emotional Cues: Emotional cues in the context of brand content were operationalized by messages with humorous, informal, or entertaining language. Because emotional cues always depend on the context, we employed two strategies to maximize the accuracy of the automated content analysis. First, we used the WordNet-Affect 1.0 domain (Strapparava & Valitutti, 2004) to identify texts containing

nouns, adjectives or verbs that are associated with emotion in the English language. Second, we also identified messages that contained emoticons, or punctuation (such as exclamation marks) associated with emotions, in line with earlier research on blog texts (Aman & Szpakowicz, 2007).

Informational Cues: We followed Kwon and Sung's (2011) investigation of the content that brands post on Twitter, and adopted two types of informational content cues: Brand and Product Cues.

- **Brand Cues:** Brand Cues combined two categories from Kwon and Sung's (2011) study, namely whether the brand or the company that owns the brand was mentioned in the message. The automated content analysis procedure searched for the name or acronym of the brand in the text of the message. If the brand name was found (e.g., "Ford"), the procedure checked whether a product cue (see below) was also present in the same sentence (e.g., "Ford Focus").
- **Product Cues:** This variable indicated whether information about the products or services from the brand was also mentioned in the tweet. We built a custom vocabulary of product names employing two strategies. First, natural language analysis procedures were adopted to determine the most frequent combinations of words starting with brand names in all the messages (e.g., "Google Apps", "Nissan Leaf"). Second, all the sentences in the sample were compared to an annotated corpus of English texts. Words that were not part of the general English vocabulary were selected for further inspection, as product names are often non-standard (e.g., "CS6" for Adobe or "VW Beetle" for

Volkswagen). Words whose function in the phrase was not clear were also selected for further inspection, as product names are sometimes made of English words (e.g., “Windows” for Microsoft). All these words were then reviewed so that product names could be identified and included in the custom vocabulary associated to specific brands. This custom vocabulary was then used to determine which messages had at least one product cue.

Presence of links: Each message was automatically analyzed to determine if there was a link in the text. When a link was found, the study employed an automated procedure to follow the link to its target destination, and then extract the main domain of the page (e.g., “youtube.com”, “disney.com”). The main domain was then categorized using a custom dictionary to determine whether the website belonged to the brand, to a SNS (e.g., Facebook), to a video or photo sharing site (e.g. YouTube, Flickr, Vimeo), or to news media (e.g., Huffington Post, NYT). Certain sites were categorized differently depending on which brand referred to it (e.g., Flickr was considered a brand website for Yahoo, which owns it, but a photo or video sharing site for Disney). The variable was first operationalized generically, namely whether the message had any links at all, and then specifically by type of link (brand website, SNS, photo or video, news media).

Traceability cues: This variable was operationalized as the occurrence of at least one hashtag (#) in the message. Automated content analysis was used to identify the hashtags.

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Four control variables were introduced:

- **Brand equity:** Interbrand's (2011) brand valuation was used as a measure of brand equity. The brand valuation included aspects such as customer loyalty, financial performance, and role of the brand on the purchase-decision process.
- The **number of followers** of each brand profile was introduced as a control variable for two reasons:
First, there was a large variance in terms of number of followers in the final sample depending on the specific brand profile ($M = 151,488$; $SD = 406,860$).
Second, the number of followers indicates the number of Twitter users who tend to see the brand message first, and therefore impacts the absolute number of potential retweets, as has been pointed out in earlier studies on general content (Petrovic et al., 2011; Suh et al., 2010).
- The **day of the week** was included in the analysis to alleviate concerns about possible differences in Twitter audience size during the week. Sunday was used as the reference category.
- **Message age:** The amount of time between the original post and the subsequent message posted by the brand, measured in minutes. The log version of the variable was used, in line with earlier findings indicating diminished returns after a certain period of time (van Liere, 2010). The average age for messages of the same brand was used for the latest message, since this would not have a subsequent message.

The descriptive statistics are presented in Table 1.

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Table 1
Dependent and Independent Variables (N = 19,343)

Variables	M	SD	Range
Number of Retweets	20.90	96.01	0 – 5,986
Emotional Cues	27.69%	0.45	0 – 1
Brand Information Cues	21.30%	0.41	0 – 1
Product Information Cues	24.89%	0.43	0 – 1
Links to:			
Brand Website	35.39%		
SNS	9.22%		
News Media	5.25%		
Photo or Video	8.47%		
Hashtag Presence	48.15%		
Followers	155,633.6	432,901.6	172 – 4,461,628
Brand Equity	27,693.52	20,062.5	3,512-71,861
Day of the Week:			
Monday	14.42%		
Tuesday	19.35%		
Wednesday	19.47%		
Thursday	19.06%		
Friday	16.95%		
Saturday	6.13%		
Sunday	4.59%		
Message Age	35.24	52.91	0 – 1,295

BRAND CONTENT DIFFUSION ON SNSs

All 19,343 messages were categorized using the automated procedures. To determine the reliability of the automated procedures, four independent coders and the first author manually coded a random subsample of 400 messages. Each independent coder reviewed 100 messages, and the first author reviewed all the 400 messages in the subsample. Reliability was calculated following procedures adopted by Aman and Szpakowicz (2007). First, intercoder reliability was calculated using the kappa statistic to determine the reliability of the coding (Fleiss, Levin, & Paik, 2003). After the manual categorization, the level of accuracy of the automated content analysis was measured by comparing its outcome with the messages for which there was intercoder agreement. The automated analysis had agreement levels of 72% for emotional cues, 84% for brand information cues, and 75% for product information cues (Cohen's Kappa were: 0.35, 0.40 and 0.47); this agreement can be considered acceptable, especially when taking into account the exploratory nature of the study and the diversity of brands included in the sample. The other variables – links to additional content, message age, and hashtag presence – were not subject to manual coding as they could be extracted directly from the message without interpretation or processing.

ANALYSIS

The data were analyzed using a multilevel modeling approach with the brand responsible for the message being set as the contextual level, and the number of followers for each brand profile set as the random slope. This approach was selected due to its ability to isolate the individual characteristics of each message from potential effects

coming from the brands themselves, for example, that a more popular or appealing brand may elicit more retweets than other brands. While the individual characteristics of the message appear as standard regression results in such models, the variance in the dependent variable due to group characteristics (contextual level) is shown as an index, *r²_{ho}* (Rabe-Hesketh & Skrondal, 2008). This strategy also allows to control whether variations in number of followers at the contextual level would impact the effect of some variables at the individual level. In the case of the models included in this study, this index, *r²_{ho}*, indicates the variance of the dependent variable explained by the group level (brand).

To further understand how the combination of different characteristics influences the number of retweets, we also created a predictive model, where:

- All control variables (e.g., number of followers, brand equity, message age) not included in the interaction were set at their means.
- A prediction of the dependent variable was calculated for each potential combination of the independent variables included in the interaction.

RESULTS

The analysis of the 19,343 messages from 65 top global brands showed that each brand message received 20.9 retweets on average ($SD = 96.01$), with 83% of the messages receiving at least one retweet. First, we tested the relationship between the dependent variable and each type of cue – emotional, informational, traceability. A full model was then created, including all types of cues and all the

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control variables. Table 2 shows the number of retweets that each message characteristic would add to a brand message. For example, the presence of product cues adds 11.16 retweets to brand content.

The results provide substantial evidence that informational cues influence the number of retweets a brand message receives. In particular, the presence of product cues is positively associated to the number of retweets, thus providing full support for Hypothesis 3. Links to additional content on the brand website, on SNS and to photos or videos also positively influenced the number of retweets, providing support for Hypotheses 4a, 4b and 4c. Links to news media, however, did not yield significant results, thus not providing support to Hypothesis 4d. Brand cues did not yield significant results, thus not providing support for Hypothesis 2. The remaining hypotheses found little support in the results. Emotional cues did not yield significant results (Hypothesis 1), nor did hashtag presence (Hypothesis 5).

INTERACTION EFFECTS

We proceeded to explore the effect of combinations of the informational, emotional and traceability cues on the number of retweets. Brand messages often combine more than one cue. For example, the tweet from Google “People are excited about #GalaxyNexus. So are Ninjas <http://t.co/flunMFpu> Ninja Unboxing 3: play the game & unlock the power of #GalaxyNexus” has emotional cues, product cues, a link to the brand website, and hashtag presence.

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Table 2
Multilevel Models for Number of Retweets and Type of Cues (n= 19,343)

Parameter	Model 1: Emotional Cues	Model 2: Informational Cues	Model 3: Traceability Cues	Full Model
Fixed Effects				
Intercept	-5.97 (3.81)	-8.32 (3.87)	-6.90 (3.88)	-9.86 (4.01)
Emotional Cues				
Emotional Cues	1.84 (1.45)			2.11 (1.46)
Informational Cues				
Brand Cues		0.43 (1.70)		0.50 (1.70)
Product Cues		11.30 (1.63)**		11.16 (1.65)**
Links to:				
Brand Website		4.58 (1.54)*		4.83 (1.54)*
SNS		5.21 (2.38)*		5.17 (2.38)*
Photo or Video		6.29 (2.48)*		6.28 (2.48)*
News Media		-2.87 (3.00)		-2.33 (3.01)
Traceability Cues				
Hashtag Presence			2.48 (1.36)	1.31 (1.37)
Random Parameters				
Var (u _i)	28.09 (9.98)	30.07 (10.62)	29.39 (10.29)	30.98 (10.90)
Var (intercept e _{0j})	7,865 (80.09)	7,837 (79.82)	7,864 (80.09)	7,836 (79.81)
Cov	-0.0002 (0.0001)	-0.0001 (0.0001)	-0.0002 (0.0001)	-0.0001 (0.0001)
Rho	0.0036	0.0038	0.0037	0.0039
-2*log likelihood	228,513	228,445	228,511	228,442

Notes: Standard errors are in parentheses. Var (u_i) indicates the standard deviation at the group level (brand), whereas Var (intercept e_{0j}) indicates the standard deviation at the individual level (message). Rho indicates the percentage of the variance explained by the group level (brand). Control variables included in the model but not reported. * p < .05, ** p < 0.01

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We decided to include message characteristics that did not yield significant results in the full model, e.g. emotional cues and hashtags. This was done specifically to check whether significant interaction effects would occur with other variables, leading to higher volumes of retweets. When including interaction terms in a model, it is necessary to also include the main variables.

The results (see Table 3) indicate that the combination of the three characteristics (informational, emotional and traceability cues) creates an interaction effect on retweeting. In particular, messages have significantly more retweets when product cues are combined with emotional cues, links to the brand website, and hashtags. Combining these four message characteristics in the same message increased the number of retweets by 37.2. However, one particular combination – hashtags, product cues and emotional cues – yielded significantly fewer retweets in the model analyzing the effects of links to the brand website.

To further understand how the combination of different characteristics influences the number of retweets, we also created a predictive model for combinations of cues with links to the brand website. The highest number of predicted retweets is achieved when product cues, emotional cues, links to the brand website and hashtags are combined in the same message: 64.07 retweets if the combination is present, versus 20.02 retweets when product cues, emotional cues, links to the brand website and hashtags are not present in the message. Table 4 shows the predicted number of retweets for each combination of message characteristics.

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Table 3
Combination of Cues by Type of Link (n = 19,343)

Parameter	Brand Website	Photo or Video	SNS	News
Fixed Effects				
Intercept	-5.45 (4.08)	-6.41 (4.01)	-7.27 (4.01)	-6.24 (4)
Emotional Cues	-0.71 (2.8)	-0.42 (2.29)	-1.55 (2.32)	-0.61 (2.26)
Product Cues	2.82 (3.64)	6.93 (2.72)*	7.23 (2.74)**	6.91 (2.77)*
Link	-0.25 (2.48)	0.88 (4.9)	6.85 (4.36)	-3.85 (4.45)
Hashtag Presence	-0.93 (2.2)	-0.95 (1.88)	-0.56 (1.89)	-0.57 (1.85)
Prod * Emo	13.99 (6.42)*	9.55 (5.21)	12.55 (5.29)*	11.15 (5.21)*
Prod * Hashtag	6.78 (4.7)	5.55 (3.69)	6.88 (3.67)	6.07 (3.67)
Prod * Link	8.15 (5.27)	-7.15 (12.26)	-7.51 (10.67)	-2.97 (9.57)
Emo * Link	0.39 (4.54)	-2.82 (9.04)	10.18 (7.8)	3.29 (3.37)
Emo * Hashtag	2.66 (3.97)	3 (3.48)	5.52 (3.53)	-3.42 (11.85)
Hashtag * Link	1.65 (3.76)	6.08 (6.37)	0.81 (6.04)	2.86 (7.64)
Prod * Emo * Hashtag	-23.43 (8.38)**	-9.53 (7.06)	-12.47 (7.1)	-11.53 (6.92)
Prod * Emo * Link	-6.37 (10.51)	26.36 (23.79)	-20.2 (18.96)	-13.24 (25.32)
Prod * Hashtag * Link	-0.73 (7.2)	7.62 (14.29)	-11.65 (13.9)	-4.17 (14.68)
Emo * Hashtag * Link	2.8 (7.44)	3.08 (11.99)	-21.32 (10.68)*	-0.72 (20.7)
Prod * Hashtag * Emo * Link	37.2 (14.44)*	-27.84 (27.74)	16.96 (24.27)	12.84 (37.41)
Random Parameters				
Var (u _i)	32.47 (11.31)	32.43 (11.25)	31.83 (11.08)	31.60 (11.09)
Var (intercept e _{0j})	7,821 (79.65)	7,838 (79.83)	7,831 (79.76)	7,839 (79.84)
Cov	-0.0001 (0.0001)	-0.0001 (0.0001)	-0.0001 (0.0001)	-0.0001 (0.0001)
Rho	0.0041	0.0041	0.0040	0.0040
-2*log likelihood	228,408	228,447	228,433	228,450

Notes: Standard errors are in parentheses. Control variables included in the model but not reported. Var (u_i) indicates the standard deviation at the group level (brand), whereas Var (intercept e_{0j}) indicates the standard deviation at the individual level (message). Rho indicates the percentage of the variance explained by the group level (brand). * p < .05, ** p < 0.01

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Table 4
Predictions of Retweets for Interactions with Links to the Brand Website

Product cues	Emotional cues	Hashtag	URL to the brand website	Predicted number of Retweets	95% Confidence Interval
No	No	No	No	20.02 (2.85)	14.44 – 25.61
Yes	No	No	No	22.85 (4.08)	14.85 – 30.85
No	Yes	No	No	19.32 (3.35)	12.75 – 25.89
No	No	Yes	No	19.09 (2.85)	13.50 – 24.68
No	No	No	Yes	19.78 (3.08)	13.74 – 25.81
Yes	Yes	No	No	36.13 (5.39)	25.55 – 46.70
Yes	No	Yes	No	28.70 (3.51)	21.81 – 35.58
Yes	No	No	Yes	30.76 (4.22)	22.49 – 39.02
No	Yes	Yes	No	21.05 (3.37)	14.44 – 27.65
No	Yes	No	Yes	19.46 (3.97)	11.69 – 27.24
No	No	Yes	Yes	20.50 (3.39)	13.85 – 27.14
Yes	Yes	Yes	No	21.21 (4.54)	12.31 – 30.12
Yes	Yes	No	Yes	38.06 (7.29)	23.78 – 52.35
Yes	No	Yes	Yes	37.53 (3.96)	29.77 – 45.29
No	Yes	Yes	Yes	25.65 (5.18)	15.50 – 35.80
Yes	Yes	Yes	Yes	64.07 (6.23)	51.87 – 76.28

Note: Standard errors are in parentheses.

DISCUSSION

The present study aimed to understand how emotional, informational and traceability cues can influence pass-along behavior of content published by brands on Twitter. We tested findings or assumptions drawn from earlier ERM and viral advertising research, as well as from studies on pass-along behavior of general (non-brand specific) messages on Twitter. We used a large sample of messages from top global brands, a sampling strategy with the advantage of measuring retweeting behavior of brand content on Twitter in an actual setting. This complements earlier studies, which, particularly in ERM, have mostly been based on experiments or surveys inquiring about potential behavior.

Our first important finding is that Twitter users are highly focused on informational cues when deciding whether to retweet brand messages. This extends earlier findings on ERM, reinforcing that pass-along behavior is highly dependent on utilitarian reasons. While this was previously known for one-to-one e-mail communications, this is now also confirmed for one-to-many communication of brand messages on Twitter. Twitter users are, however, not motivated by all kinds of brand information. A message simply about the brand, containing brand cues, is not more likely to be retweeted by users. Only messages that specifically contained information about products from the brand were associated with higher levels of retweeting, indicating that consumers have a high level of expectation about the brand message's content.

Links, also considered informational cues (Kwon & Sung, 2011), were found to predict higher levels of retweeting as well. Not all links, however, are predictors of retweeting: For original brand

messages (i.e., not replies to other users), only links to the brand website, to SNSs or to photos or videos were associated with higher levels of retweeting. These findings add to the existing empirical research on generic Twitter content (e.g. Petrovic et al., 2011; Suh et al., 2010), clarifying which types of links influence retweeting specifically for brand content. Moreover, these findings also point to a methodological contribution by highlighting the importance of explicitly investigating pass-along behavior only for original brand messages and not including replies. Considering that replies are associated both with lower levels of retweeting and lower frequency of links, including replies in the sample would have artificially increased the effects of any type of link in pass-along behavior because of their correlation with original brand messages, that attract more retweets.

Interestingly, emotional cues were not associated with higher levels of retweeting. This is not in line with expectations from earlier research on ERM and viral advertising. Earlier studies indicated that fun, entertainment, or emotional tone or content in messages stimulate pass-along behavior (Chiu et al., 2007; Golan & Zaidner, 2008; Porter & Golan, 2006). This may be because studies on ERM have generally focused on one-to-one communication like email, while communication within SNSs is generally one-to-many, with retweets aimed at a larger audience (Boyd et al., 2010). This may also be partially because earlier studies have focused on online videos instead of text-based content such as Twitter; in addition, users may have different expectations of content on Twitter, especially brand content, compared to online video websites. Also unlike earlier research, hashtags were not found to be predictors of retweeting – probably because only original brand messages were analyzed, with replies excluded from the sample.

However, emotional cues and hashtags yield significant positive influence on the number of retweets when combined with product information, and links to the brand website. This finding not only reinforces the idea that information usefulness is an important factor for pass-along behavior on Twitter, but also indicates that messages with high informational value benefit from the presence of emotional cues, and by the use of hashtags to make the message more findable.

At the same time, however, messages containing just product information, hashtags and emotional cues but without a link to the brand website are associated with significantly lower levels of retweeting. Further analysis indicated that such a negative influence leads only to a slightly different number of predicted retweets when compared to messages without this combination. Future research should not only investigate in more detail the role of hashtag use on brand content but, given the findings of this study, investigate in more detail the role of interaction effects.

In summary, our results strongly suggest that the type of communication (one-to-one versus one-to-many), modality (video versus text) and type of information (generic information versus brand content) influence pass-along behavior on SNSs. When passing along brand messages to many followers on a public manner, and when this message is mostly composed of short texts with links, consumers prefer rich information content about the brand and its products. Future research should investigate this further, and in particular compare brand message characteristics and their influence on pass-along behavior across different types of SNSs.

MANAGERIAL IMPLICATIONS

The current study provides some clear warnings for brands when creating content for Twitter, among them:

- Twitter users seem to be highly aware that their actions happen in a public or semi-public manner, so they retweet brand messages more for their informational value than for other reasons.
- To fully leverage the pass-along behavior and see their messages spread, brands should consider SNS users not only as targets for brand messages, but also as gatekeepers of personal networks. As gatekeepers, they decide, based on the message characteristics, whether they want to associate themselves publicly with the brand message. Providing relevant, specific and information-rich messages therefore becomes one important manner through which brands can stimulate pass-along behavior of their content on Twitter.
- Emotional tone or cues can stimulate pass-along behavior when supporting or complementing informational content.

LIMITATIONS

While this study contributes to research with several important findings that help shed light on brand content pass-along behavior, certain limitations need to be considered. First, even though we used real life data of top global brands, and measured actual consumer behavior, the sample did not include all brands that are active on Twitter. Second, while the study analyzed some message characteristics that are more relevant and more specific to brand communication than earlier studies, these characteristics were still generic because of the diversity of brands and market segments in the study. Also, we did not include all message characteristics found in brand activity on Twitter, and about 1600 brand messages (8% of the sample) did not have any of the characteristics included in this study. Future research could build upon these findings to further investigate how message characteristics specific to a given segment (e.g., specific types of product information cues for one specific segment) may influence pass-along behavior, and investigate on a deeper level the role of interaction effects based on the results of this study. Third, this study investigated the role of emotions by assessing the effects of the presence of emotional cues in the brand Tweets. Future studies could investigate whether tweets that trigger emotional *responses* in consumers using more than just emotional cues in the text would have similar or even stronger effects. Finally, the automated content analysis required some of the independent variables to be operationalized as binary variables, which may have reduced the precision of the results.

Notwithstanding these limitations, this study has provided a strong set of findings, relevant and specific to brand content pass-

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along behavior on Twitter. These findings not only update and advance earlier research in brand content pass-along behavior, but also provide a baseline that can be used by future studies to continue investigating the increasingly strong use that both brands and consumers make of SNSs for their communication activities.