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Published in:
Journal of Advertising Research

DOI:
10.2501/JAR-2015-009

What Motivates Consumers To Re-Tweet Brand Content?

The Impact of Information, Emotion, And Traceability on Pass-Along Behavior

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How do certain cues influence pass-along behavior (re-Tweeting) of brand messages on Twitter? Analyzing 19,343 global brand messages over a three-year period, the authors of this article found that *informational* cues were predictors of higher levels of re-Tweeting, particularly product details and links to a brand's website, social network sites, and photos or videos. And, although *emotional* cues did not influence re-Tweeting on their own, they reinforced the effects of informational cues and *traceability* cues (hashtags) when combined in the same message. In other words, Twitter users especially are interested in messages that are rich in informational content.

INTRODUCTION

Consumers increasingly use social network sites (SNSs) to engage in brand-related activity. This activity includes consuming and creating content about brands (Muntinga, Moorman, and Smit, 2011) and spreading messages about (or from) the brand (Jansen, Zhang, Sobel, and Chowdury, 2009). Brands stimulate this type of activity, often inviting customers to share information with their friends (Araujo and Neijens, 2012). For brands, one of the key advantages of this phenomenon is the ability to stimulate positive word of mouth (WOM) and extend the reach of the brand message (comScore, 2011). Another advantage is the higher credibility of messages from consumers—or, alternatively, messages validated by consumers—compared with advertising (Goldsmith and 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,

Management Slant

- Consumers actively pass along brand messages on Twitter through re-Tweets and help extend brand reach by exposing a message to new audiences.
- When passing along brand messages to many followers in a public manner, consumers prefer rich information content about the brand and its products.
- Emotional cues and hashtags (traceability cues), when combined with informational cues, lead to an even higher level of re-Tweeting.
- Providing relevant, specific, and information-rich messages, therefore, becomes one important manner in which brands can stimulate pass-along behavior of their content on Twitter.

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Consumers increasingly use social network sites (SNSs) to engage in brand-related activity. This activity includes consuming and creating content about brands and spreading messages about (or from) the brand.

and Yongjian, 2012). Up to 80 percent of the Twitter users involved in a 2014 study habitually mentioned brands in their Tweets (Nagy and Midha, 2014).

One of the features of Twitter that may explain this behavior is the ability to re-Tweet. Re-Tweeting has emerged as a key mechanism for information diffusion (Boyd, Golder, and Lotan, 2010; Suh, Hong, Pirolli, and Chi, 2010). A re-Tweet happens when a user decides to republish a message received from either an individual or a company. By republishing the message, the user passes it along to her or his own followers on Twitter. It still is unclear, however, 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 WOM (De Bruyn and Lilien, 2008), scholarly work on electronic-referral marketing and viral advertising suggests that the manner in which messages are designed can influence consumers' disposition to pass them along. The emotional tone or emotional cues in the message can stimulate pass-along behavior by creating an emotional connection between the consumer and the message (Dobele, Lindgreen, Beverland, Vanhamme, and van Wijk, 2007; Eckler and Bolls, 2011).

The informational value of a message also can stimulate pass-along behavior, as consumers more likely will pass along information they find useful (Chiu, Hsieh, Kao, and Lee, 2007). Emerging research on the diffusion of general (*i.e.*, not brand specific) information on Twitter also indicates that elements such as hashtags, that make the message more findable or traceable, are related to higher levels of re-Tweeting (Suh *et al.*, 2010).

Researchers, however, still do not fully understand how these message characteristics influence pass-along behavior, specifically for brand messages on Twitter. This area is a particularly pressing gap, because message characteristics comprise some of the few elements that marketers can control to stimulate pass-along behavior.

What Motivates Pass-Along Behavior?

The current study

- reviewed reasons for online pass-along behavior identified by electronic-referral marketing and viral-advertising literature, and by emerging research on information diffusion via Twitter, identifying message characteristics that may help stimulate pass-along behavior;
- tested whether earlier findings were applicable to Twitter content. In particular, this study investigated the influence of emotional, traceability, and informational cues on pass-along behavior of brand content on Twitter.

Furthermore, the authors of the current paper believe they have advanced emerging literature on the diffusion of information through Twitter specifically by investigating brand messages and their diffusion processes. They also studied the influence of message characteristics on pass-along behavior using a sample composed exclusively of messages created by brands, instead of general messages.

Finally, the authors have outlined recommendations for marketers on how to extend the reach of brand messages on Twitter.

LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

The Role of Emotion

Messages triggering emotions tend to be passed along the most by consumers (Dobele *et al.*, 2007; Phelps *et al.*, 2004); these triggers frequently are used in viral advertising, especially in online videos (Golan and Zaidner, 2008; Porter and Golan, 2006). Only content that is somehow extraordinary (Porter and Golan, 2006) and that links emotion to the message (Dobele *et al.*, 2007) will capture the attention of consumers enough for them to pass it along.

Similarly, the presence of emotions or different types of emotional tone in e-mail messages (Eckler and Bolls, 2011) significantly influences pass-along behavior, especially when these messages are more hedonic in nature (Chiu *et al.*, 2007).

The earlier research prompted the current authors to assess whether or not emotional cues influence pass-along behavior of Twitter messages. The authors believed this investigation was necessary because

- Twitter messages mainly are composed of short texts, yet viral-advertising scholars primarily have focused on online videos. It is unclear in existing literature whether emotional cues exert the same influence when the type of content is changed.
- Electronic-referral marketing and viral-advertising studies have focused on pass-along behavior through e-mail,

which allows consumers to target who they want to see a given message. When consumers decide to pass along brand messages by re-Tweeting, they pass the message to all their followers on Twitter—usually in a public manner.

The current authors, therefore, proposed the following hypothesis:

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

The Role of Information

Scholarly investigation of electronic-referral marketing has indicated that people more likely will pass along an e-mail based on their ability to evaluate the message as valuable or helpful (Huang, Lin, and Lin, 2009) and when the message contains useful content (Chiu *et al.*, 2007). Moreover, users actively consider whether the content will be useful to their audience when re-Tweeting (Boyd *et al.*, 2010).

The question then becomes: What would be considered "useful" content in the context of brand messages? Providing information about the product or brand is one of the reasons electronic-referral marketing and viral advertising are used (Golan and Zaidner, 2008; Porter and Golan, 2006). Earlier scenarios 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 (Kwon and Sung, 2011).

The current authors defined 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 proposed the following hypotheses:

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

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

Links may be considered "redirecting-informational cues" (Kwon and Sung, 2011), as they provide additional information. In addition, with regard to the diffusion of general information on Twitter, the presence of links is a predictor of increased levels of pass-along behavior (Petrovic, Osborne, and Lavrenko, 2011; Suh *et al.*, 2010). Moreover, Twitter messages linking to different types of websites have been associated with varying levels of re-Tweets (Suh *et al.*, 2010).

Because prior research has not determined the types of links leading to higher numbers of re-Tweets, the current authors proposed the following set of four related subhypotheses in regard to types of links related to brand activity on Twitter:

H4a: Brand messages that contain links to a brand website will be re-Tweeted more often than messages that do not contain links to a brand website.

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

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

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

The Role of Traceability

Elements related to how messages are displayed on Twitter—and how easily they can be found—also affect pass-along behavior (Boyd *et al.*, 2010; Suh *et al.*, 2010). One element that increases the traceability of Twitter messages is the use of hashtags (#)—or traceability cues—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), leading the current authors to the following hypothesis:

H5: Brand messages that contain hashtags will be re-Tweeted 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, for example, can 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 the current hypotheses, the authors expected that combining these characteristics (linearly) would reinforce pass-along behavior. It was possible, however, that these combinations also would create interaction or synergy effects.

In other words, the authors did not always expect that the combination of two characteristics would simply add main effects. One possible interaction effect would be that a characteristic (*e.g.*, emotional cues) only had a significant effect when used in combination with another characteristic (*e.g.*, product-information cue).

These interaction effects, however, seldom have been investigated, as most studies about electronic-referral marketing and viral advertising have focused on either emotional or informational cues and not on their combination. In light of the lack of earlier literature, the authors proposed the following research question (RQ):

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

METHOD

Sample

The current study used 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 range of markets, customer segments, and brand characteristics, thus, increasing the generalizability of the results.

The data collection followed two steps (See Figure 1):

- Identify brand profiles.
- Collect brand messages.

Identify Brand Profiles

The first step of the data collection was to determine which of the 100 top brands were actually present on Twitter. Brands may 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 and alternative names by which the brand is known. For example, for American Express, the authors also searched for "Amex." They 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; because their emphasis was not on brand content, they were not relevant to the pass-along behavior that this study was investigating. Examples of profiles that were eliminated included not only the music-video cable channel 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 the study's 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 process 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 re-Tweets from each of the 27,846 brand messages. The oldest Tweet in the sample was from 2009, and the newest from 2012.

Collect Brand Messages

Of these messages, 31 percent 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 percent of the messages were replies)
- HTC (89 percent)
- Kellogg's (88 percent)
- Gap (85 percent).

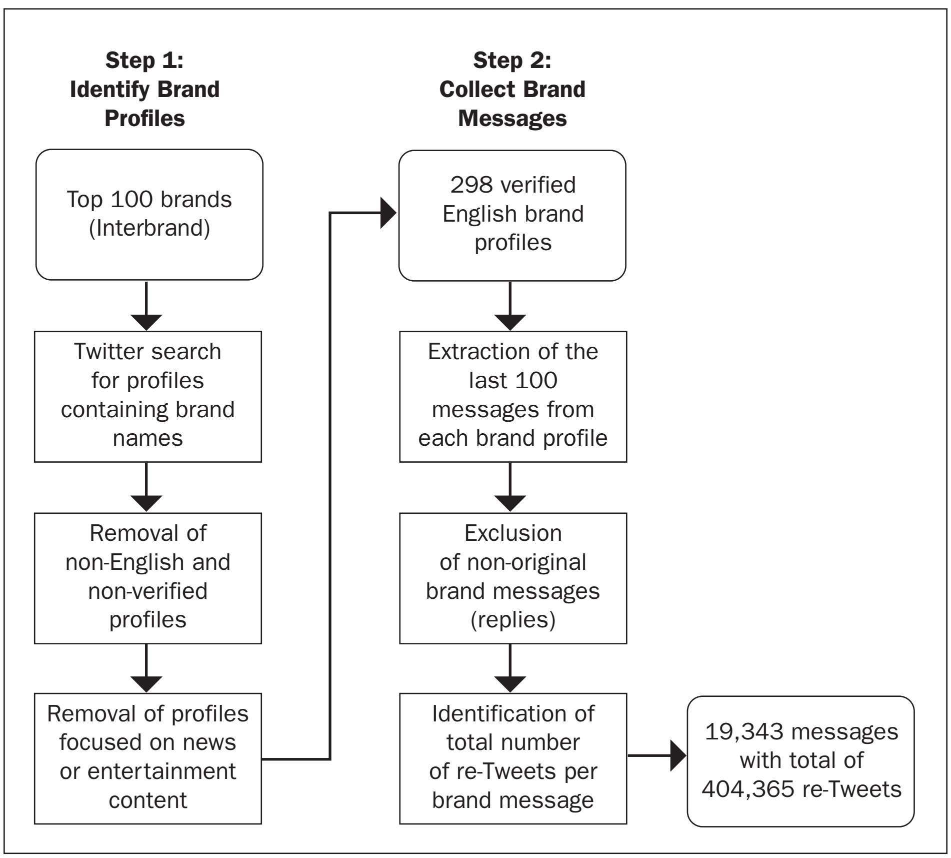

Figure 1 Data Collection Summary

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:

- 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 were to write a public reply, this message would be less interesting to the general public than original brand messages.

- Reinforcing the first point: The sample showed a significantly higher level of re-Tweets for original brand messages (on average 20.9 re-Tweets per message; SD = 96.01) than for replies to users (on average 0.45 re-Tweets per message; SD = 3.22).

- Certain message characteristics strongly and significantly were correlated to the type of message (original message or reply), in particular the presence of links ($\phi = 0.60$, $p < 0.001$) and hashtags ($\phi = 0.31$, $p < 0.001$). The 8,503 replies from brands to other users were removed from the sample, and only the 19,343 original brand messages were kept—that is, the messages that brands actually created for all consumers to read.

Dependent and Independent Variables

This study's unit of analysis was the individual brand message (Tweet); the dependent variable was the number of re-Tweets 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, and 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, the authors used two strategies to maximize the accuracy of the automated content analysis:
  - ✧ The use of WordNet-Affect 1.0 domain (Strapparava and Valitutti, 2004) to identify texts containing nouns, adjectives, or verbs associated with emotion in the English language.
  - ✧ Identifying messages that contained emoticons, or punctuation (such as exclamation marks) associated with emotions, in line with earlier research on blog texts (Aman and Szpakowicz, 2007).

Of all Tweets included in the sample, 27.69 percent contained emotional cues.

- **Informational Cues:** The authors followed an earlier investigation of the content that brands post on Twitter (Kwon and Sung, 2011) and adopted two types of informational content cues: brand and product cues.

  - ✧ *Brand cues*: Brand cues combined two categories from the earlier scholarly work (Kwon and Sung, 2011): 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 also was mentioned in the Tweet. The authors of the current study built a custom vocabulary of product names using two strategies:
    - – 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").
    - – 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 often are nonstandard (*e.g.*, "CS6" for Adobe or "VW Beetle" for Volkswagen). Words for which the function in the phrase was not clear also were selected for further inspection, as product names sometimes are made of English words (*e.g.*, "Windows" for Microsoft). All these words then were reviewed so that product names could be identified and included in the custom vocabulary associated to specific brands. This custom vocabulary then was used to determine which messages had at least one product cue.

Of all Tweets in the sample, 21.30 percent had brand-information cues, and 24.89 percent had product-information cues.

Presence of Links

Each message automatically was analyzed to determine whether there was a link in the text. When a link was found, the study used 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 then was categorized using a custom dictionary to determine whether the website belonged to the brand, an SNS (*e.g.*, Facebook), a video or photo-sharing site (*e.g.*, YouTube, Flickr, Vimeo), or news medium (*e.g.*, Huffington Post, NYTimes).

Certain sites were categorized differently depending on which brand referred to them (*e.g.*, Flickr was considered a brand website for Yahoo, which owns it, but a photo- or video-sharing site for Disney). The variable first was operationalized generically—namely, whether the message had any links at all—and then specifically by type of link. Of all Tweets in the sample,

- 35.39 percent were to the brand website,
- 9.22 percent to SNS,
- 8.47 percent to photos or videos, and
- 5.25 percent to news media.

Hashtag (Traceability Cues) Presence: This variable was operationalized as the occurrence of at least one hashtag (#) in the message. Automated content analysis was used to identify the hashtags, present in 48.15 percent of the Tweets.

Control Variables

Four control variables were introduced:

- *Brand equity*: Interbrand's (2011) brand valuation (M = 27,693.52, SD = 20,062.50) 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:
  - ✧ 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).
  - ✧ The number of followers indicated the number of Twitter users who tended to see the brand message first, and, therefore, affected the absolute number of potential re-Tweets—a consequence pointed out in earlier studies on general content (Petrovic, Osborne, and Lavrenko, 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 (M = 35.24, SD = 52.91). 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.

All 19,343 messages were categorized using the automated procedures. To determine the reliability of the automated procedures, four independent coders and one of the study's authors 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, and 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 agreed 72 percent for emotional cues, 84 percent for brand-information cues, and 75 percent for product-information cues (the kappa statistics were 0.35, 0.40, and 0.47, respectively); 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 because of its ability to isolate the individual characteristics of each message from potential effects coming from the brands themselves—for example, a more popular or appealing brand may elicit more re-Tweets than other brands.

Although 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, *rho* (Rabe-Hesketh and Skrondal, 2008). This strategy also allowed the current researchers 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 the current study, this index, *rho*, 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 re-Tweets, the researchers also created a predictive model. This was done by creating a 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 re-Tweets on average ($SD = 96.01$), with 83 percent of the messages receiving at least one re-Tweet.

The authors first tested the relationship between the dependent variable and each type of cue—emotional, informational, traceability. A full model then was created, including all types of cues and all the control variables. Among the number of re-Tweets that each message characteristic would add to a brand message, the presence of product cues added 11.16 re-Tweets to brand content (See Table 1).

The results provided substantial evidence that informational cues influence the number of re-Tweets a brand message receives. In particular, the presence of product cues was positively associated to the number of re-Tweets, thus providing full support for H3.

Links to additional content on the brand website, on SNS, and to photos or videos also positively influenced the number of re-Tweets, providing support for H4a, H4b, and H4c. Links to news media, however, did not yield significant results, thus not providing support to H4d. Brand cues did not yield significant results, thus, not providing support for H2. The remaining hypotheses found little support in the results. Emotional cues (H1) or hashtag presence (H5) did not yield significant results.

Interaction Effects

The authors next explored the effect of combinations of the informational, emotional, and traceability cues on the number of re-Tweets. 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.

The authors decided to include message characteristics that did not yield significant results in the full model, for example, emotional cues and hashtags. This was done specifically to check whether or not significant interaction effects would occur with other variables, leading to higher volumes of re-Tweets. When including interaction terms in a model, it is necessary to also include the main variables.

The results indicated that the combination of the three characteristics (informational, emotional, and traceability cues) created an interaction effect on re-Tweeting (See Table 2). In particular, messages had significantly more re-Tweets when product cues were combined with emotional cues, links to the brand website, and hashtags.

Combining these four message characteristics in the same message increased the number of re-Tweets by 37.2. However, one particular combination—hashtags, product cues, and emotional cues—yielded significantly fewer re-Tweets 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 re-Tweets, the authors created a predictive model for combinations of cues with links to the brand website. The highest number of predicted re-Tweets was achieved when product cues, emotional cues, links to the brand website, and hashtags were combined in the same message (See Table 3):

- 64.07 re-Tweets if the combination were present, versus
- 20.02 re-Tweets when product cues, emotional cues, links to the brand website, and hashtags were not present in the message.

DISCUSSION

The current study aimed to understand how emotional, informational, and traceability cues could influence pass-along behavior of content published by brands on Twitter. The authors tested findings or assumptions drawn from earlier electronic-referral marketing and viral advertising research, as well as from studies on pass-along behavior of general (nonbrand specific) messages on Twitter.

Furthermore, they used a large sample of messages from top global brands, a sampling strategy with the advantage of measuring re-Tweeting behavior of brand content on Twitter in an actual setting. The authors believe this work complemented earlier studies, which, particularly in electronic-referral marketing, mostly have been based on experiments or surveys inquiring about potential behavior.

FINDINGS

The authors highlighted as their first important finding that Twitter users are highly focused on informational cues when deciding whether to re-Tweet brand messages. This extends earlier findings on electronic-referral marketing, reinforcing that pass-along behavior is highly dependent on utilitarian reasons. Although this previously was known for one-to-one

TABLE 1

Multilevel Models for Number of Re-Tweets 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)
Control variables				
Brand equity	0.0001 (0)	0.0001 (0)	0.0001 (0)	0.0001 (0)
Followers	0.0001 (0)**	0.0001 (0)**	0.0001 (0)**	0.0001 (0)**
Day of the week				
Monday	−1.06 (3.45)	−1.35 (3.45)	−1.13 (3.45)	−1.17 (3.45)
Tuesday	1.00 (3.35)	0.61 (3.34)	0.85 (3.35)	0.76 (3.35)
Wednesday	2.11 (3.34)	1.57 (3.34)	2.00 (3.34)	1.71 (3.34)
Thursday	1.12 (3.35)	0.71 (3.34)	1.06 (3.35)	0.89 (3.35)
Friday	−4.17 (3.38)	−4.24 (3.38)	−4.13 (3.38)	−4.10 (3.38)
Saturday	−2.17 (3.94)	−2.14 (3.93)	−2.30 (3.94)	−2.15 (3.93)
Message age	1.42 (0.29)**	1.37 (0.29)**	1.46 (0.29)**	1.38 (0.29)**
Random parameters				
Var (u_j)	28.09 (9.98)	30.07 (10.62)	29.39 (10.29)	30.98 (10.90)
Var (intercept e_{0ij})	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

Note: Standard errors are in parentheses. Var (u_j) indicates the standard deviation at the group level (brand), whereas Var (intercept e_{0ij}) indicates the standard deviation at the individual level (message). Rho indicates the percentage of the variance explained by the group level (brand).

* $p < 0.05$. ** $p < 0.01$

TABLE 2

Combination of Cues by Type of Link

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 (4.00)
Emotional cues	−0.71 (2.80)	−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 (4.90)	6.85 (4.36)	−3.85 (4.45)
Hashtag presence	−0.93 (2.20)	−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 (4.70)	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)	3.00 (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 (7.10)	−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_j)	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

Note: Standard errors are in parentheses. Control variables are included in the model but not reported. Var (u_j) 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).
* $p < 0.05$. ** $p < 0.01$

e-mail communications, the current study also confirmed for one-to-many communication of brand messages on Twitter.

Twitter users, however, are not motivated by all kinds of brand information. A message simply about the brand, containing brand cues, will not more likely be re-Tweeted by users. In this study, only messages that specifically contained information about products from the brand were associated with higher levels of re-Tweeting, indicating that consumers have a high level of expectation about the brand message's content.

Links, also considered informational cues (Kwon and Sung, 2011), were found to predict higher levels of re-Tweeting as well. Not all links, however, are predictors of re-Tweeting: 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 re-Tweeting. These findings add to the existing empirical research on generic Twitter content (*e.g.*, Suh *et al.*, 2010), clarifying which types of links influence re-Tweeting specifically for brand content.

Moreover, the current 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 re-Tweeting and lower frequency of links, including replies in the sample, would have artificially increased effects of any type of link in pass-along behavior because of their correlation with original brand messages, which attract more re-Tweets.

TABLE 3

Predictions of Re-Tweets for Interactions with Links to the Brand Website

Product Cues	Emotional Cues	Hashtag	URL to the Brand Website	Predicted Number of re-Tweets	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.

It is interesting that emotional cues were not associated with higher levels of re-Tweeting except when combined with informational cues. This finding was not fully in line with expectations from earlier research on electronic-referral marketing 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 and Zaidner, 2008; Porter and Golan, 2006). This finding may be because studies on electronic-referral marketing generally have focused on one-to-one communication like e-mail, whereas communication within SNSs generally is one to many, with re-Tweets aimed at a larger audience (Boyd *et al.*, 2010). This also partially may be 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 with online video websites. Also, unlike earlier research, hashtags were not found to be predictors of re-Tweeting—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 re-Tweets 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 re-Tweeting. Further analysis indicated that such a negative influence leads only to a slightly different number of predicted re-Tweets when compared with messages without this combination.

Future research not only should investigate in more detail the role of hashtag use on brand content but also, given the findings of this study, investigate in more detail the role of interaction effects.

In summary, the authors believe their results strongly suggest that the type of

- communication (one to one vs. one to many),
- modality (video vs. text), and
- information (generic information vs. brand content)

influences pass-along behavior on SNSs. When passing along brand messages to many followers in 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

This 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 re-Tweet 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 AND RECOMMENDED FUTURE RESEARCH

Although 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:

- Even though the authors 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.

- Although 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. The authors did not include all message characteristics found in brand activity on Twitter, and about 1,600 brand messages (8 percent of the sample) did not have any of the characteristics included in this study.

Future research could build on 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. Moreover, 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, the authors believe this study has provided a strong set of findings, relevant and specific to brand content pass-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 communicative activities. JAR

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