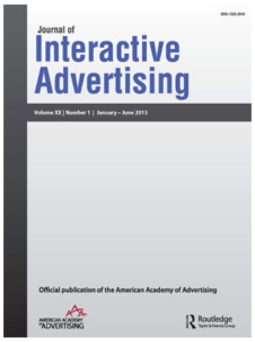

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ABSTRACT

This study assesses brand messages on Twitter (i.e., tweets broadcasted by a brand) and the contributory engagement a tweet receives. It presents a typology for brand messages that accounts for 92.6% of messages found. Findings offer mild support for self-concept and self-enhancement as drivers of engagement. This research also tests assumptions made by marketers regarding social content. Brand messages that promoted giveaways positively influenced engagement, giving support to Berger's (2012) behavioral residue claim. Brand messages that mentioned popular culture events and current holidays positively influenced engagement, suggesting that brands that humanize do see benefits. Finally, promotional messages negatively influenced engagement, suggesting that consumers are skeptical of product information that comes directly from brands.

KEYWORDS

Social media marketing; brand management; social networking; consumer engagement; promotion

Almost every popular consumer brand now has a social media (i.e., social networking) presence. Following Facebook in 2006, Twitter gained popularity as a microblogging service. Twitter differentiates itself in two ways: Messages are public and brief (Kwak et al. 2010). Twitter has placed an emphasis on being a public medium by calling itself "a platform for you to influence what's being talked about around the world" (Twitter 2016). It is no surprise, then, that brands broadcast messages on Twitter. As of 2015, 91% of the largest consumer brands had active Twitter accounts (Yesmail 2015). Scholars have studied the use of Twitter by brands and companies, in areas such as brand personality (Kwon and Sung 2011), feedback and discussion (Lin and Peña 2011), promotions (Parsons 2011), and corporate social responsibility (Etter 2013). Yet no study has cumulatively cataloged and attempted to define a typology in which to classify the entirety of messages that a brand broadcasts. Moreover, no study has constructed a broad view of how consumers engage with these different types of content. This study aims to better understand brand content through lenses that predict the amount of engagement that content will receive.

In particular, self-concept and self-enhancement—which posit that consumers will disclose personal information when presented with an opportunity to do so—are considered in terms of brand engagement (e.g., Wojnicki and Godes 2008; Taylor, Strutton, and Thompson 2012). This study also addresses commonly held marketing adages. Giveaways and sweepstakes are assessed for their ability to create online "behavioral residue," a question not yet definitively answered in the literature (e.g., Berger 2012). Engagement is also addressed as it pertains to two types of brand messages that initial evidence suggests may be received with skepticism: promotional materials and corporate social responsibility. Content from brands that contain practical information, such as tips and advice, are assessed for their engagement (e.g., Berger 2012). Similarly, news stories that brands curate and rebroadcast are also assessed for their ability to engage (e.g., Berger and Milkman 2011). Finally, this analysis touches on the recent tendency of brands to mention popular culture events and holidays as a part of humanizing their social media accounts, and whether the practice bolsters engagement, as modern marketing wisdom suggests.

By analyzing the amount of engagement these content types receive, marketers can develop best practices and tailor messages appropriately. This study draws on a large sample of tweets from major brands with established Twitter followings and classifies messages based on content. It then tests different content types and assesses whether they are share more (or less) than average.

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Literature Review

A Behavior Based View on Social Media Engagement

Advertising literature remains fragmented on a unified definition for social media engagement, but most definitions agree that it stems from interactive experiences consumers have via social media with brands, products, or services (Brodie et al. 2011). These experiences have cognitive, affective, and behavioral components (Brodie et al. 2013). This study incorporates a novel data-mining approach using publicly available data from Twitter. As such, it is limited to publicly viewable behaviors on the service (i.e., customer engagement behavior). In review of such behaviors, Dolan, Conduit, and Fahy (2016) update Muntinga, Moorman, and Smit's (2011) seminal model and suggest a construct of six behaviors that consumers exhibit in participating with brands. The behaviors include creating, contributing, consuming, dormancy, detachment, and destruction. This construct contains various intensities in which consumer behavior can be observed (low, moderate, and high) and two valences (positive and negative).

Differing behaviors have been shown to better assess different business outcomes (Murdough 2009). The present analysis leveraged two instances of contributing behavior, which is considered to be a moderate, positively valenced type of engagement: retweets and likes. These behaviors have been thought to "deepen relationships with customers" and "increase reach" for brands (Murdough 2009, p. 95). These engagement behaviors were chosen given the constraints of what is publicly available via the Twitter API. Other engagement metrics exist, and it would be beneficial to study them all (e.g., replies, views, and so on).

Many engagement typologies treat the behaviors of retweets and likes similarly (e.g., Dolan, Conduit, and Fahy 2016; Brodie et al. 2013). Both are positively valenced ways of responding to a brand message. The key difference between a retweet and a like is the intentional sharing function that comes with retweeting (Kwak et al. 2010). When a user performs a retweet, that message is rebroadcast. Twitter allows users to provide a comment with their retweet. As such, users often share their take on the message they are rebroadcasting (Twitter 2016). This sharing function allows additional users, ones following the person who just performed the retweet, to see that tweet in their timelines. When this interaction occurs for a brand, its organic reach grows (Murdough 2009). The more retweets a brand generates for a message, the more people see it, at no cost to the brand. Free diffusion of brand content is of interest to marketers (Kim 2016). Solis and Li (2013) found that the most widely shared goal of social media strategists was to market their content as widely as possible to consumers.

Moreover, Twitter now filters content from consumer news feeds in an attempt to deliver "the most popular content first" (Newton 2016). Initial evidence suggests that engagement metrics such as likes and retweets may be used as proxy for measuring how popular people find content to be. Taken together, these metrics may increasingly dictate not only the number of free impressions a brand receives for its content but perhaps the number of times content is seen by its followers. In summary, retweets and likes are beneficial to marketers in novel ways. For these reasons retweets and likes warrant analysis.

Scholarship in psychology, marketing, advertising, and public relations offers predictions for how differing types of brand content will be engaged with online. The following sections review different types of messages that brands create on social media in an attempt to unify the literature into a typology. Focus is given to literature that offers predictions on engagement.

Self-Disclosure and Self-Enhancement

Research has shown that electronic word of mouth (eWOM) generated by consumers predominantly pertains to personal information that relates to the individual from whom the content originates (Java et al. 2007). These conversations usually consist of private experiences or personal relationships with friends. One study of Twitter found that 80% of all user content contained personal updates (Naaman, Boase, and Lai 2010). These users, dubbed "meformers" (as opposed to "informers"), "typically post messages relating to *themselves* or *their thoughts*" (p. 192). Psychologists suggest that the tendency for individuals to self-disclose information stems from its central role in the development and maintenance of relationships: People who disclose personal information are liked more by peers (Collins and Miller 1994).

Beyond this, recent neural research shows that self-disclosure is intrinsically rewarding (Tamir and Mitchell 2012). Sharing information with others leads to the release of dopamine and is associated with positive affect. In the same study, Tamir and Mitchell showed that this effect alters behavior to such a degree that individuals were willing to forgo small amounts of money for the opportunity to talk about themselves, as opposed to talking about others.

Self-enhancement theory asserts that, when given an opportunity, people enjoy talking, both offline and online, about themselves (Berger 2014; Ko and Chen 2009). Self-enhancement is defined as "the tendency to seek experiences that improve or bolster the self-concept, for example by drawing attention to one's skills and talents" (Wojnicki and Godes 2008, p. 8). This disclosure is used to enhance an individual's sense of personal worth and as such involves a preference for positive over negative self-views. Self-enhancement is acknowledged as a key motivator of human behavior (Fiske 2001). Wojnicki and Godes (2008) demonstrated that consumers' propensities to generate word of mouth (WOM) are affected by their motivation to self-enhance. Other studies have concluded that consumers aim to associate themselves with products and brands that are symbolic of their identity (Berger and Heath 2007). Moreover, consumer brands and products have been shown to be positively associated with consumer social groups (Berger 2012). Consumers discuss the use of products to better identify with social circles. Moving beyond discussion and use of products and services, research shows that consumers share marketing material from brands when they feel the content matches their idea of self-concept (Taylor, Strutton, and Thompson 2012). In their study of viral videos, Taylor, Strutton, and Thompson (2012) found "the likelihood that they share online advertisements depends on the degree to which consumers perceive that the ad enables them to express their identity" (p. 23).

Along these lines, the present research calls into question social media content. Drawing from self-disclosure and self-enhancement, it stands to reason that messages generated by brands encouraging consumer expression should receive more engagement. Messages that act as a cue for consumers to respond with personal information, thoughts, or opinions can also be thought of as a call to disclose self-concepts and perform self-enhancement. This type of content, *which seeks input or expression from reader*, is the first one of interest to the present study. These messages clearly seek interaction with current and potential customers. When brands seek to engage consumers by asking them to express portions of their self-concept, consumers may be compelled to engage (Fiske 2001).

From the literature, two measurable changes in behavior are suspected. First, given the functionality of Twitter to retweet messages with the ability to "add a comment" (i.e., a nugget of personal information), it is suspected that users will retweet a message to respond to the information. This type of engagement is suspected over simply replying to the message, because replies are not displayed in friends' news feeds. If users want to reply to messages from brands in a way that can prominently be seen by their friends, retweeting messages provides an opportunity for the messages to be seen. Retweets allow consumers to share their ideas of self-concept in a way that is more publicly viewable to their followers than replies would allow.

H1a: Brand messages that seek interaction with current and potential customers will foster more retweets than messages that do not.

In addition, this study posits that when brands provide the opportunity for consumers to disclose personal information, a more positive evaluation of the message will be observed. As Tamir and Mitchell (2012) show, disclosing personal information comes with a tangible intrinsic satisfaction (e.g., a dopamine release). The self is a fundamentally positive stimulus, and people implicitly associate the self with positive affect (Greenwald et al. 2002; Tamir and Mitchell 2012). As previous research on Twitter has shown, people tend to "like" content that they would respond to with positive affect (Youyou, Kosinski, and Stillwell 2015; Hansen et al. 2011). Given that people tend to enjoy self-disclosure, they too will tend to like messages that encourage such behavior.

H1b: Brand messages that seek interaction with current and potential customers will foster more retweets than messages that do not.

Sweepstakes, Contests, and Giveaways

Brands use social media for promotions (Kim 2016). Specifically, giveaways, contests, and sweepstakes have been shown to be common marketing tactics on social media (Parsons 2011). As such, a second type of message is introduced, one that *promotes a sweepstakes, contest, or giveaway*. This type of promotion can vary from brand to brand but, at the heart, publicizes giving something of tangible value to the consumer for free, or at a drastically reduced fee (Parsons 2011). On one hand, it is logical that consumers would share information with friends to give them a chance to receive free things. Leading case studies from such sources as *Harvard Business Review* suggest giveaways and contests are ways to foster social media engagement and increase WOM (Schneider 2015). However, it has been shown that small samples, coupons, and rebates do not lead to increased WOM (Berger 2012). Major brands have observed that "it is getting harder to make much of an impact with small giveaways" (Funk 2012, p. 28). With the amount of content created by brands increasing, smaller promotions can be lost in the sea of promotions that are created daily (Yesmail 2015).

Berger and Schwartz (2011) have shown that certain types tend to be more effective than others. Giving away products or nonproduct extras (e.g., logo hats or recipes) was positively linked to more overall WOM. Expanding on this, Berger (2012) found that when giveaways are publicly visible, promotions generate "behavioral residue." Behavioral residue is a broadly defined concept that encompasses a host of publicly viewable online and offline behavior. Online behaviors include likes, sharing, and online evidence that others can discover later (Gosling et al. 2011). In an analysis of Facebook, Parsons (2011) found that "the like button seems most suited to determining the success of sales promotions such as contests, sweepstakes, and giveaways as participation rates can be compared" (p. 14). With the value of this type of social media promotion in question, it is timely to assess whether these messages garner such engagement. The present study assesses messages that promote sweepstakes, contests, and giveaways and the amount of engagement these messages receive. Berger's (2012) finding (e.g., that promotional giveaways generate behavioral residue) is tested to see whether it applies in a social media context.

H2a: Brand messages that promote a sweepstakes or giveaway will foster more retweets than messages that do not.

H2b: Brand messages that promote a sweepstakes or giveaway will foster more likes than messages that do not.

Pop Culture Events and Current Holidays

Brands strive to stay relevant to their consumers on social networking sites (Yan 2011). Brands tend to leverage the events and daily happenings that consumers engage in as a way to relate to target audiences on social networking sites. For large brands that have consumers in many different demographics, few events encompass large pockets of consumers. Marketers recognize two distinct types of timely events. They are included as the next items in the present typology. The first, labeled *pop culture events*, includes messages that reference events ranging from the Oscars to the Super Bowl. Pop culture events are typically large and align with the tastes of the brand's target audience (for a good review, see Sashittal, Hodis, and Sriramachandramurthy 2015). Messages that mention *current holidays and seasons* emerge as another common theme. These events include nontraditional holidays, such as Pi Day, and are discussed by brands as they are also relevant to the consumer's lived experience (Lehmann et al. 2012). The frequency of this second message type appears to be rising, as brands have begun to create "fake" holidays around products and services (e.g., National Cookie Day, International Whisky Day) (Murrow 2016).

In a study of Facebook, 8% percent of all brand messages included references to traditional holidays (Coursaris, Van Osch, and Balogh 2013). Another 10% were dedicated to events such as sports and pop culture happenings. Marketers have noted that creating messages around these types of events can yield positive effects (Murrow 2016). Given Twitter's focus on timely cultural events, consumers appear to be more captivated by the service during these times (Twitter 2016). Some scholars have begun to assert that brands should mention these types of events as part of an "entifying process" (Sashittal, Hodis, and Sriramachandramurthy 2015). The proposition is that brands that act as entities, or human individuals, will garner more engagement because they are treated more like a celebrity on the social media service and less like a brand. Despite these claims and the recent popularity of these event-based messages by brands, no known research empirically tests these types of messages for effective engagement. As such, these types of messages are ripe for initial analysis.

H3a: Brand messages that relate to current holidays or seasons will foster more retweets than messages that do not.

H3b: Brand messages that relate to current holidays or seasons will foster more likes than messages that do not.

H4a: Brand messages that relate to popular culture events will foster more retweets than messages that do not.

H4b: Brand messages that relate to current holidays or seasons will foster more likes than messages that do not.

Promotion of the Brand, Product, or Service

Brands also broadcast marketing materials on social media (Kwon and Sung 2011). These messages "are designed to stimulate immediate or near future purchases through [minor] monetary incentives" and to "build product knowledge, understanding and existence" (Coursaris, Van Osch, and Balogh 2013, p. 8). As such, this study adds the category *promotion of the brand, product, or service* to the typology. These messages use social media as a platform to deliver information, such as attributes or details about a certain product or service offered by the brand (Borhani 2012). Whenever brands directly present informational content about products and services, skepticism becomes an issue (Obermiller, Spangenberg, and MacLachlan 2005). Research shows that consumers are now skeptical of advertising that comes directly from brands via Twitter and Facebook (Saprikis 2013). Advertising is becoming increasingly avoided on social media (Kelly, Kerr, and Drennan 2010). Kim (2014) credits the expanding role advertising is taking in the Internet landscape and the increased pervasiveness of such ads as possible causes of the increased resistance. Funk (2012) warns that consumers are now skeptical of social media content from brands and suggests that brands not produce "uninspired promotional spam," as consumers are likely to ignore these messages entirely. Adopting this view, it is expected that when a brand mentions products or services with no major incentives (e.g., a giveaway), the message will receive less engagement when compared to other types of messages (p. 149).

H5a: Brand messages that promote the brand, product, or service will foster fewer retweets than messages that do not.

H5b: Brand messages that promote the brand, product, or service will foster fewer likes than messages that do not.

Mentions a Charity or Goodwill Effort (Corporate Social Responsibility)

It has become commonplace for brands to mention charities and other goodwill programs they are involved with as a part of their social media campaigns (Kim 2016). Therefore, the category *mentions a charity or goodwill effort* was added to the typology. Etter (2013) has found the engagement levels of online corporate social responsibility (CSR)–related messages to be typically lower than other types of brand messages. The author cites the lack of willingness to engage with consumers and discuss issues of potential sensitivity as the primary driver of the lack of interest from consumers. Etter (2013) surmises that if brands were to openly engage with stakeholders about CSR issues in social media, brands would then open an arena for possible criticism and face the risk of attracting critical stakeholders. He concludes that brands appear to be unwilling to write engaging content in this area and instead appear to send one-way messages that are informational and self-promoting. As mentioned in the previous section, these types of promotional messages are now evaluated with skepticism on social media (Saprikis 2013). Consumers may evaluate such content as overtly promotional (Funk 2012). Therefore, this study points hypotheses in the same direction as was specified for promotional content.

H6a: Brand messages that mention a brand's charity work will foster fewer retweets than those that do not.

H6b: Brand messages that mention a brand's charity work will foster fewer likes than those that do not.

Interesting News and Content With Practical Value

Brands also share information that could be of practical use to their consumers (Berger 2012). This includes tips and advice, and can be generally thought of as information that consumers may find practically useful (Coursaris, Van Osch, and Balogh 2013). Therefore, the category *gives advice or useful information* was added to the typology. Similarly, brands curate news and interesting articles from a variety of media and share them with consumers via social media (Berger 2012). Thus, the category *mentions a news story or interesting article* was also added to the typology. Berger and Milkman (2011) performed an analysis of news articles that appeared in the most-shared list of the *New York Times*. The researchers looked at how featured, practical, interesting, and surprising the content was. The early premise was that practical and interesting content would be shared the most. Through several rounds of analysis, this was not the case. The most dominating factor in the analysis was whether the content included arousing (activating) emotions. Similarly, Peters, Kashima, and Clark (2009) used survey responses to show that students were more likely to share social anecdotes about other students that contained interest, surprise, disgust, and happiness. Anecdotes that did not contain arousing emotions garnered little attention, and students were not likely to pass them on to others.

Berger (2012) concedes that consumers do sometimes share information of practical value with one another. However, he suggests they are motivated to do so only when (1) the information is highly unique and (2) the information is of specific use to a friend. Given the broad consumer focus of the brands studied here, it is logical to think that practical information shared by large brands will not be as unique and specific as necessary to facilitate broad engagement across large demographics. Along with these findings, this study expects to find that practical content alone will not be enough to garner increased engagement in brands' social media messages.

H7a: Brand messages that give advice and useful information will foster fewer retweets than those that do not.

H7b: Brand messages that give advice and useful information will foster fewer likes than those that do not.

H8a: Brand messages that link to a news story or an interesting article will foster fewer retweets than those that do not.

H8b: Brand messages that link to a news story or an interesting article will foster fewer likes than those that do not.

Method

Selection of the Brands

Myriad popular consumer brands exist. Brands from multiple product categories were chosen. Due to the low infectivity of messages on Twitter, the most popular consumer brands were chosen (Goel, Watts, and Goldstein 2012). This was done to ensure that sharing (i.e., the number of times those brand tweets are retweeted) was prevalent enough to observe. AdAge (2012) "mega brands" were used as a measure of the most popular consumer brands. Brands are not separated into product categories. To address this issue, brands were assigned to a corresponding product category. At least 20 major categories emerged. To limit the scope, only brands with at least three other parity products were considered. Four categories had at least four brands (refer to

Table 1. Brands included in study.

Insurance Companies	Banks	Cable and Satellite Companies	Department Stores
Progressive	Citibank	Comcast	Macy's
Nationwide	Bank of America	Time Warner Cable	JCPenney
Liberty Mutual	Wells Fargo	DirecTV	Kohl's
Allstate	PNC	Dish	Sears
State Farm			

Table 1 for the brands included in the study by category). In all, 17 brands were selected.

Retrieving Tweets from Twitter

Python was used to access the Twitter API. An API is a way for third-party services to connect to Twitter and call its functions. This study used the Twitter API (Version 1.1) to retrieve tweets. It was queried using the statuses/user_timeline call. Tweets sent from these 17 brand accounts were downloaded for 92 days. The tweets ranged from October 12, 2013, to January 12, 2014. To initiate the data collection process, 3,200 recent tweets per each of the 17 brands were downloaded. Tweets that were newer than two weeks were discarded and retrieved later when they had reached two weeks of age. Then, every two weeks, a new crawl was conducted for each brand, retrieving only new tweets from that brand that were at least two weeks old. This action was taken under the premise that the majority of retweets and likes would happen within the first two weeks of a tweet being published. By waiting two weeks to collect a tweet's metadata, this study hoped to capture the majority of that tweet's all-time diffusion (i.e., retweets). When the same three-month period of data was harvested for each brand, the data collection concluded. With each tweet came its accompanying metadata. This included the number of times the tweet was retweeted.

Messages starting with the "at" symbol (i.e., @) were excluded from this analysis. This decision was made based on the limited exposure that these types of messages receive. Twitter's news feed is designed to not show these messages by default. As a result, a substantially smaller percentage of people see these tweets. Given the limited audience of these messages, the retweet distribution for these messages is inevitably different and therefore confounding to this analysis. As such, this study is limited to broadcast messages on Twitter, not personal responses (such as customer service). Similarly, tweets starting with "RT" were labeled as retweets and removed from the analysis because these retweets originated from other accounts and are not messages that the brand authored. Retweet counts are reflective of the original author and would skew the results. Removing these retweets greatly reduced the skew of the variable and reduced the standard deviation to a more normal distribution. These adjustments resulted in a final corpus size of 7,447 tweets. The large reduction in tweet count was due to the majority of tweets starting with @. All tweets matching the aforementioned parameters were used in the analysis.

Brands sent 4.87 tweets per day ($SD = 4.22$). The range was rather large. On average, any given brand's tweet was retweeted eight times ($SD = 25.75$). For a complete picture of the descriptive statistics, see Appendix 1.

Developing a Typology

All of the concepts brought forward in the literature review were inspired by previous content analyses of brand messages on Facebook and Twitter (Coursaris, Van Osch, and Balogh 2013; Berger 2012; Lin and Peña 2011; Kwon and Sung 2011). To determine the final content types included in the typology, two researchers reviewed the aforementioned previous content analysis studies. They then looked at random samples of 500 tweets from the data set. As they saw similar types of messages occur, they made note of the categories. The two researchers then met and discussed the content categories they had inferred. While the researchers had varying names for categories (i.e., advertising versus promotion; corporate social responsibility versus charity), they were easily able to agree on eight key message types. These types were then used to identify messages. The researchers surmised that, if the content categories were sufficient, they would be able to label the majority of brand tweets with at least one type. They then assigned 250 random tweets according to the typology: 91.2% of all tweets were assigned at least one category. The researchers settled on the eight content types, citing that adding more content types would make manual content analysis more cumbersome and expensive, and that no one category would offer substantial improvement on the total percentage of labeled tweets. The final content categories, a brief explanation, and an example for each type can be found in Appendix 2.

Data Annotation Via Amazon Mechanical Turk

A total of 496 Amazon Mechanical Turk (MTurk) workers were each paid \$4 to annotate 48 tweets according to the typology. In total 7,447 tweets were analyzed and used in this study. To scale this approach across all of the tweets, the researchers developed an online service that loaded the entire corpus of tweets and randomly generated web pages with tweets for workers.

The data was annotated according to Sorokin and Forsyth's (2008) three distinct aspects of quality assurance for using Amazon MTurk. First, to ensure the workers understood the requested task, the coders were greeted with the following message: "This survey contains tweets from popular brands. Your job is to determine which of the following categories applies to each tweet. Choose as many categories per tweet as applies. Some tweets will have multiple categories. The categories are as follows …" The workers then saw the typology in full with the example messages shown in Appendix 2. Each tweet was accompanied by the typology as a series of checkboxes. At the top of each page, an explanation of the typology was provided for reference (as seen in Appendix 2). The tool asked workers to determine which of the following categories applied to each tweet. They were instructed to choose as many categories per tweet as applicable and informed that some tweets would have multiple categories.

In keeping with Sorokin and Forsyth's (2008) second and third aspects of quality assurance, gold-standard data was used to screen out errors and to prevent cheating the Amazon MTurk system. In every batch of 48 tweets, each worker saw three tweets. Those tweets each had eight possible categories that were either present or absent (one for each item in the typology). This equals a total of 24 correct decisions (annotations). If a worker did not correctly identify at least 23 of the 24 correct annotations, that worker's annotations were deemed to be inaccurate and the data were disregarded. This means that only those workers whose data had 95.83% pairwise agreement ($\alpha = .833$) or better were included in the data set. Each tweet was read three times by three different workers. In the end, the majority classification for each of the eight categories was adopted for each tweet. These measures enabled researchers to be confident that the results were valid, accurate, and the majority opinion of the workers. In total, 22,341 annotations were made.

Concerning data quality, it is worth noting that only workers with the designation of "Categorization Master Workers" were used in this study. This was chosen through multiple rounds of comparing the various criteria options available through MTurk. Each time, results were compared to gold-standard data. Master Workers far outperformed any other criteria. Amazon defines Master Workers as

> elite groups of workers who have demonstrated accuracy on specific types of HITs [Human Intelligence Tasks] on the Mechanical Turk marketplace. Workers achieve a Masters distinction by consistently completing HITs of a certain type with a high degree of accuracy across a variety of requesters. Masters must continue to pass our statistical monitoring to remain Mechanical Turk Masters. (Amazon Mechanical Turk 2016)

In all, the typology was able to assign at least one class to 92.6% of tweets studied. This suggests the typology was broad enough to cover the large domain of brand messages exhaustively while being succinct and straightforward in its classifications. Each brand's content mix was derived by dividing the number of items found for each item in the typology by the total number of tweets found for that brand. For a review of the content mixes by brand and overall, refer to Table 2.

Least Absolute Shrinkage and Selection Operator Regression

To determine which elements of the brand typology most affected each engagement behavior, two least absolute shrinkage and selection operator (LASSO) regressions were created in Python using the LASSOLarsCV module in sklearn. The module created a cross-validated LASSO, using the LARS algorithm. LASSO is a form of regularized regression that assesses the combined effect of many correlated

Table 2. Occurrences of content types (in percentages) by brand.

Brand	Pop Culture	News	Holiday	Useful Information	Goodwill	Seeks Input	Giveaway	Product/Service
Allstate	6%	29%	29%	60%	4%	7%	5%	13%
Bank of America	4%	40%	1%	14%	5%	1%	1%	34%
Citibank	4%	12%	18%	24%	4%	18%	6%	53%
Comcast	7%	52%	8%	6%	4%	1%	0%	56%
DirectTV	15%	7%	9%	3%	1%	30%	12%	57%
Dish	9%	5%	18%	4%	0%	15%	4%	83%
JCPenney	3%	6%	30%	7%	5%	14%	4%	56%
Kohl's	20%	5%	24%	6%	1%	18%	12%	62%
Liberty Mutual	25%	17%	13%	12%	2%	24%	31%	12%
Macy's	14%	7%	36%	3%	7%	14%	7%	55%
Nationwide	5%	13%	15%	34%	9%	10%	8%	21%
PNC	3%	15%	21%	18%	4%	35%	4%	13%
Progressive	2%	59%	3%	16%	2%	10%	2%	8%
Sears	2%	4%	39%	11%	0%	30%	13%	42%
State Farm	1%	26%	18%	68%	2%	5%	4%	12%
Time Warner Cable	18%	13%	7%	3%	1%	12%	27%	56%
Wells Fargo	3%	25%	12%	38%	5%	15%	4%	31%
Average overall	11%	15%	18%	14%	2%	16%	13%	47%

variables through a sparsity-driven L^1 penalty (Tibshirani 2011). Alphas were determined automatically by the model, and 20% of the data was used as the testing set. Because of its automatic feature selection, LASSO is generally preferred over stepwise regression and is used in cases where many predictor variables exist (Hindman 2015). To prepare each engagement metric for modeling, values that were more than two standard deviations from the mean outcome variable were replaced with the cutoff value. This was done only for regression analysis to reduce squared error caused by extreme outliers. In each model, the number of Twitter users that followed each account and the type of brand the content originated from were used as control variables.

Results

To investigate the hypotheses, a LASSO regression was fitted for both independent variables. For a review of the coefficients from the model, refer to Table 3. Overall, the explanatory power of the like model ($r^2 = .418$) was stronger than the retweet model ($r^2 = .212$).

When considering hypothesis 1a, brand messages *that sought input with current and potential customers* positively predicted retweet counts ($b = .336$, $p < .05$). When considering hypothesis 1b, brand messages *that sought interaction with current and potential customers* did not positively predict like counts ($b = .000$). Marginal support is given to hypothesis 1a but not to hypothesis 1b.

When considering hypothesis 2a, brand messages *that promoted a sweepstakes or giveaway* positively predicted retweet counts ($b = 2.075$, $p < .05$). When considering hypothesis 2b, brand messages *that promoted a sweepstakes or giveaway* positively predicted like counts ($b = 1.029$, $p < .05$). Support is given to hypothesis 2.

When considering hypothesis 3a, brand messages *that related to current holidays or seasons* positively predicted retweet counts ($b = .502$, $p < .05$). When considering hypothesis 3b, brand messages *that related to current holidays or seasons* positively predicted like counts ($b = .264$, $p < .05$). Support is given to hypothesis 3.

When considering hypothesis 4a, brand messages *that related to a popular culture event* positively predicted retweet counts ($b = .351$, $p < .05$). When considering hypothesis 4b, brand messages *that related to a popular culture event* positively predicted like counts ($b = .750$, $p < .05$). Support is given to hypothesis 4.

When considering hypothesis 5a, brand messages *that promoted the brand, product, or service* negatively predicted retweet counts ($b = -.710$, $p < .05$). When considering hypothesis 5b, brand messages *that promoted the brand, product, or service* negatively predicted like counts ($b = -.509$, $p < .05$). Support is given to hypothesis 5.

When considering hypothesis 6a, brand messages *that mentioned a brand's charity work* positively predicted retweet counts ($b = 1.396$, $p < .05$). When considering hypothesis 6b, brand messages *that mentioned a brand's charity work* positively predicted like counts ($b = .400$, $p < .05$). Hypothesis 6 is rejected.

When considering hypothesis 7a, brand messages *that gave advice and useful information* positively predicted retweet counts ($b = .977$, $p < .05$). When considering hypothesis 7b, brand messages *that gave advice and useful information* negatively predicted like counts ($b = -.267$, $p < .05$). Hypothesis 7a is rejected and hypothesis7b is accepted.

When considering hypothesis 8a, brand messages *that linked to a news story or an interesting article* negatively predicted retweet counts ($b = -.001$, $p < .05$). When considering hypothesis 8b, brand messages *that linked to a news story or an interesting article* negatively predicted like counts ($b = -.267$, $p < .05$). Hypothesis 8 is accepted.

Table 3. LASSO regression "all in" models for retweets and likes.

Predictor	Retweets Coefficient	Likes Coefficient
Followers (control)	.001	.001
Insurance company (control)	.941	.365
Financial institution (control)	.000	−.008
Television providers (control)	−.043	.000
Department stores (control)	.056	.744
Promotes a brand's product or service	−.710	−.509
Promotes a sweepstakes or giveaway	2.075	1.029
Seeks input or feedback from a reader	.336	.000
Mentions a charitable organization	1.396	.400
Gives advice or useful information	.977	−.267
Relates to current holidays or seasons	.502	.264
Mentions (or links to) a news story/ interesting article	−.001	−.267
Relates to a pop culture event	.351	.750
Intercept	−3.682	−1.290
Training data *MSE*	18.115	12.919
Test data *MSE*	18.770	11.246
Training data R^2	.212	.384
Test data R^2	.212	.418

Note. Linear regression coefficients from the models are reported. All effects are statistically significant at the .05 level (two-tailed) per LASSO's specification, excepting those with coefficients equal to 0, which the model removed as a feature selection function.

Discussion

Theoretical Implications

Brand messages that encourage input or participation from consumers appear to positively boost the amount of times those messages are shared (e.g., retweeted). This finding supports what others have observed with self-concept and self-enhancement online: People enjoy talking about themselves and will seize opportunities to do so (Wojnicki and

Godes 2008; Tamir and Mitchell 2012). In the data discussed here, consumers likely self-disclosed and self-enhanced while rebroadcasting (retweeting) the original brand message, thus providing the context of the disclosure to their own followers. This is perhaps the first theoretical link between self-concept and self-enhancement and branded social media content online. As such, this finding is ripe for advancement and further testing.

Interestingly, likes were not positively influenced. The positive affect associated with an opportunity to self-disclose with brand content did not motivate users to like such messages. This lack of affect transfer is interesting and suggests that consumer responses to brand messages that seek input were not always positive. As other scholars have noted, social media engagement is not always positive (Dolan, Conduit, and Fahy 2016). Indeed, consumers can respond to brands in ways that self-enhance but also offer negative opinions (Berger and Heath 2007). Just as it is "cool" to talk about products one likes, it can be "cool" to talk about disliking them. As such, further research into the corresponding affect associated with these types of self-disclosure may reveal more nuanced types of behaviors.

Turning to giveaways and sweepstakes, support for Berger's (2012) behavioral residue hypothesis is given. Social media promotions do appear to generate visible contributory engagement. Here it is important to note that this study counted all promotions equal, small and large. The finding that even small giveaways can bolster engagement goes against the marketing literature (e.g., Funk 2012; Berger 2012). This initial finding may support something that resembles prospect theory: Small monetary gains are perceived with great relative value (for a review, see Goldstein, Martin, and Cialdini 2008). Further research in this area should formally measure the monetary degree of giveaways and sweepstakes to see if the observed engagement varies as monetary value increases. If the intuition of prospect theory does indeed prevail for social media giveaways, diminishing returns may exist.

Managerial Implications

The vast majority of content stemming from brands on Twitter (92.6%) can be summed up into eight different categories (Appendix 2). This shows that while the style, or manner, in which these messages are written can differ, content types across brands are largely homogenous. The typology presented here acts as a "social media playbook." It surmises the most commonly broadcast messages for brands. As such, it is logical that brands looking to develop a social media plan should turn to these message types. This study goes beyond describing content types. It also offers insights as to what types of content typically effect positive engagement. Giving audiences content in which they will engage has never been more vital to social media marketing success. Engagement rates now drive how often content is seen on Twitter (Newton 2016).

Messages that promoted products and services quelled engagement in the observed data. One possible interpretation of this finding is consumer skepticism toward self-promotion. This finding is supported by the growing amount of literature warning of consumer skepticism toward online advertising on social media (Saprikis 2013). As Funk warns (2012), practitioners should be keen not to produce uninspired promotional spam. This analysis suggests one step further: Brands should avoid posting about products and services altogether. However advantageous promotional content might be for brands, it appears that consumers are not engaged in such material. Given that the future of message dissemination on Twitter and other social media will be popularity driven, it is unlikely that these messages will even be seen by large portions of a given brand's followers in the near future (Newton 2016).

As a stark contrast to promotional materials, this study also offers some initial support for the idea of an "entified" (e.g., humanized) brand presence on social media (for an introduction, see Sashittal, Hodis, and Sriramachandramurthy 2015). Brand messages that mentioned popular culture events, holidays, and seasons fostered both types of contributory engagement. The work presented here seems to agree with entification and suggests that consumers want to feel connected and share events with brands. There are few things that brands can experience alongside consumers on a social media platform; the two most salient things found in this study are holidays and pop culture events. This study shows that when brands mentioned pop culture events and holidays, engagement increased. As such, it appears advantageous for brands to engage in these events. The concept of brand entification is new, and further work in this area is likely to yield interesting results, especially as it pertains to social media.

Brand messages that contained practical and useful information seemed to foster retweets but not likes. This suggests that brands should continue to generate content in the form of advice and tips but may also may heed a warning that this content is not as interesting as brands may perceive it to be. In addition, brand content that promoted goodwill efforts also fostered positive contributory engagement. This goes against earlier warnings that suggest this content is too one-way and self-promoting to be effective (Etter 2013). It is interesting to note, however, that the goodwill related content was very sparse in this typology, at only 2%.

Beyond creating original material, a stark lack of engagement was found when brands curated and shared news stories. Brands should be aware that, just as Berger and Milkman (2011) found with news stories, interesting news is not enough to foster engagement. Instead, news stories that evoke arousing and activating emotions appear to drive these types of behaviors (for a review of arousing emotional content, see Berger 2012).

Limitations and Future Research

While this study observes consumers' behavior in the form of two engagement behaviors (i.e., retweets and likes) for different brand content types, it falls short of definitively proving the true intrinsic motivations for why audiences chose to share a message. This study offers the literature review as the likely insights into these motivations. However, these motivations are not directly observable with the novel data-mining methodology chosen here. Further studies may advance these findings by interviewing consumers and qualitatively asking them why they share messages. Scholars interested in this line of research may find the theories outlined here, such as self-enhancement and social currency, as a lens for investigation.

It is imperative for advertisers and scholars alike to continue to observe consumer behavior as it pertains to social media engagement. Work in this area is emerging, and the results can yield more than suggestions on what types of content to generate. By advancing some of the evidence presented, scholars can address theories to explain the patterns observed here. In particular, brand entification may positively influence engagement. Deeper research into this phenomenon could reveal insights into the psychological tendencies of consumers' social media engagement with brands.

Conclusion

The emergence of social media has altered the strategies used to communicate with and engage consumers. This study presents an analysis of the role different message types have on two measures of contributory engagement. It can also be thought of as an analysis of the many popular types of messages brands broadcast on social media and their relative effectiveness. In addressing commonly held positions of social media marketers, it is found that brand messages that promoted sweepstakes and giveaways did positively influence engagement. Moreover, brand messages that mentioned pop culture events, current holidays, and seasons also positively influenced engagement. Finally, messages that contained product information negatively influenced engagement.

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Appendix 1

Retweet Counts of Brands Collected

Brands	Average Retweet Count	*SD*
Allstate	3.79	3.24
Bank of America	5.69	6.40
Citibank	4.06	6.35
Comcast	4.12	10.90
DirectTV	4.75	11.38
Dish	7.07	40.45
JCPenney	12.21	27.29
Kohl's	8.04	20.72
Liberty Mutual	7.85	30.63
Macy's	32.36	63.84
Nationwide	2.71	3.73
PNC	0.87	1.63
Progressive	1.75	3.70
Sears	6.36	12.17
State Farm	14.40	44.42
Time Warner Cable	8.83	29.27
Wells Fargo	4.55	6.07
Grand total	7.98	25.75

Appendix 2

The Brand Typology

Type	Description	Examples
Seeks input or expression from reader (via replies or hashtags)	Initiates interaction with current and potential customers. Can include direct responses to followers or questions or surveys.	@DirectTV: Tweet us why you are ready for the season premiere of #TheWalkingDead tomorrow night!
Promotes a sweepstakes, contest, or giveaway	Promotes time-sensitive sweepstakes and giveaways where the brand will award prizes to participants.	@TWC: For Asgard! Enter our @ThorMovies sweeps for a chance to win a trip to LA for upcoming @Marvel premiere: http://t.co/Z1ggaiDlLi
Relates to a pop culture event	Mentions a pop culture event such as the Super Bowl, the Oscars, or other well-known national events.	@Macys: Wow! Andrew McCutchen got really dirty on that slide. Luckily, he can buy a new pair of pants at 30% off this Tuesday at Macys
Relates to current holidays or seasons	Mentions seasons or holidays of that time, including nontraditional holidays such as Pi Day.	@JCPenney: We're pretty pumped for Fall. #jcpStyle http://t.co/7ne18zrH7b
Promotes the brand's product or service	Mentions a certain product or service offered by the brand.	@TWC: Make every game a home game w/NHL Center Ice. Enjoy Early Bird FREE Preview & learn how you can watch 40 games/week: http://t.co/lu9321VFf2
Gives advice or useful information	Provides information that could be of practical use to the reader. Includes tips and advice.	@Nationwide: Planning for the day you say "I do" can quickly add up! Try these #tips for an elegant yet affordable #wedding
Mentions (or links to) a news story or an interesting article	Mentions any story in the news, including print, television, online, and other media.	@Nationwide: Thanks to our associates, @FortuneMagazine recognized us as 1 of the "100 Best Companies to Work For!" #100BestCos for.tn/1CBpAkk
Mentions a charitable organization	Advocates for a charitable organization and/or publicizes the brand's goodwill campaigns.	@JCPenney: It's foot-lanthropy time! Buy a pair of boots & we'll donate $2 to @NBCF thru 10/14! #Bootage http://t.co/Al0lu43469 http://t.co/X67bFpFzlt