The Effect of Sentiment and Complexity on Consumer Engagement With Brand-Themed User-Generated Content

Eunhee Ko
Northwestern University
Douglas Bowman
Emory University

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Abstract

We study consumer engagement (*likes, comments*) with brand-themed user-generated content – image-based social media posts tagged with *#brandname* – an increasingly common way that consumers engage with brands. We describe consumer engagement using characteristics (sentiment and complexity) of the image and the text of a post, and characteristics of the focal brand, while controlling for the extent of the user's (individual who posted) social media network size and activity. We study over 84,000 Instagram posts collectively hashtagged with over 150 product brand names. First, we find a positive effect for both visual and text sentiment. Second, while too much information from either images or text attenuates consumer engagement, around the middle of the range of visual complexity there is an optimal level that makes a post rich and engaging. Finally, we find that brand visibility and brand involvement are positively associated with higher levels of consumer engagement.

Keywords: *brand-themed posts, consumer engagement, visual content*

Track: *Digital Marketing & Social Media*

1. Introduction

Users are becoming authors of brand stories (Gensler et al. 2013), and brand-themed posts on social media – tagged with *#brandname* (e.g. *#bmw*; *#cocacola*) – are an emerging way that consumers express their relationships with brands. They can result from a user's intrinsic desire to express their relationship with the brand, possibly motivated by the self-presentation purpose often underlying social media posting behavior (Jensen Schau and Gilly 2003). In addition, marketers encourage brand-themed user-generated content (UGC) in a number of ways including experiential marketing campaigns, by collaborating with general users in social media, and by conducting influencer campaigns, seeking various benefits such as content authenticity and cost efficiency.

We study consumer engagement, measured as the number of likes and comments, with a brand-themed social media post on Instagram. Higher engagement with a brand-related social media post is associated with more visits to the brand's website (Socialbakers, 2014), which can help drive sales. Earned social media engagement volume affects brand awareness and purchase intent (Colicev et al. 2018), and it elicits a positive causal effect on offline behavior (Mochon et al. 2017). Conversations (online and offline) among consumers about brands drive about 19 percent of purchases (Fay et al. 2019).

A large body of literature has investigated the relationship between UGC components (e.g. content, volume) and relevant outcomes (e.g., product sales, virality, engagement) (e.g., Lee et al 2018). While numeric (e.g., number of hashtags, review ratings) and textual information has been studied, visual characteristics are a relatively new area of consideration. To date, the limited number of marketing studies considering visual content have been mostly of marketer-generated content (e.g., de Vires, Gensler, and Leeflang, 2012, Kumar et al. 2016), exceptions being Li and Xie (2019), and Zhang, Vir Singh and Srinivasan (2017) who also include UGC.

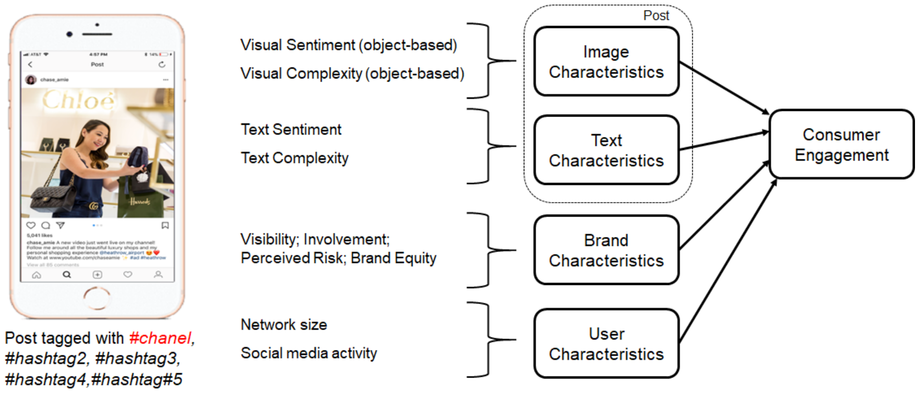
2. Conceptual Framework

We conceptualize consumer engagement with a brand-themed user-generated post on social media as a function of three broad drivers: characteristics of the post (*content*), characteristics of the brand (*motives*), and characteristics of the user (*network structure*). Our framework is presented in Figure 1.

<u>Characteristics of the Post</u>

Posts are described through image content - visual sentiment, visual complexity, and the types of objects contained in the image; and, their text content - text sentiment, text complexity.

Figure 1: Conceptual Framework – Drivers of Consumer Engagement with a Brand-Themed Social Media Post



Visual Sentiment. Visual content contains cues about affect, emotion, and sentiment. For example, eyes can be described as "beautiful", "glaring", or "sad". These are individual components of an image, which collectively determine the image's overall sentiment. We expect that the more positive the overall image is, the higher is consumer engagement.

Visual Complexity. Taken together, Pieters, Wedel and Batra's (2010) finding of a positive effect of low feature complexity and Berlyne's (1960) argument for an intermediate effect suggest a bimodal effect of visual complexity. This is consistent with the photography industry which advocates two dominant approaches for constructing an engaging photo. The first, called the isolation effect, is to take a simple photo in which the focal object stands out from everything around it. The second follows from the belief that an engaging photo contains a degree of richness and complexity that draw attention to it. Eventually, however, clutter takes hold making an image hard to process.

Text Sentiment. Emotionally divergent text may be associated with cognitive attention or arousal-related effects. Extant research suggests a positive relationship between the divergence aspects of text sentiment and viral behavior in social media (Stieglitz and Xuan 2013). We expect that more emotionally divergent text is associated with higher consumer engagement.

Text Complexity. On one hand, relevant text that is concise and to the point should lead to higher consumer engagement. On the other hand, a moderate amount of complexity may be associated with higher consumer engagement since it may better capture the richness of a post and contain elements that appeal to a wider audience. However, too much text can lead to information overload or indicate lack of focus or purpose, which should attenuate engagement.

Object Types (control variable). We succinctly account for the various object types included in the visual content of a post. Pets (or living things in general) have long been known to generate heavy engagement volume. Furthermore, posts that include people involve their networks, which are predisposed to engaging with the post.

Brand Characteristics

Lovett, Peres and Shachar (2013) find that more visible brands and higher involvement brands have more online/offline word-of-mouth. In-depth interviews we conducted also revealed that perceived risk and brand equity may affect engagement.

Visibility. We expect a synergy between the public nature of social media and the inherent visibility of the brand; a brand-themed post in which the focal brand is perceived as more visible or observable to consumers should elicit higher engagement.

Involvement. Involvement refers to the degree of importance that consumers attach to a brand, and higher involvement brands should elicit higher engagement.

Perceived Risk. Perceived risk is associated with more cautious behaviors implying that consumers will be more cautious about engaging with a brand-themed post concerning a brand with higher perceived risk.

Brand Equity. Aspects of brand equity that relate to the self-presentation purpose often found in social media engagement (Jensen Schau and Gilly, 2003) should affect engagement: differentiation refers to a brand's defining characteristics and distinctiveness.

User Characteristics

Network Size. Users with larger networks on social media platforms have a larger number of followers with an *a priori* affinity for engaging with their content.

Network Activity. On one hand, users with more experience posting on social media have had the opportunity to learn which of their posts engage consumers. On the other hand, it is easy to imagine users who post excessively as lacking relevance and alienating others.

3. Data

We began by creating a list of brands to study. We began with Lovett, Peres and Shacher's (2014) published dataset of almost 700 of the leading U.S. national brands, filtering out brands that corresponded to movie names and common-noun names. We then selected two samples: a random sample of 90 brands; and, then to understand brands with extreme ratings, the top 30 brands on each of three distinct brand-image dimensions – Fun, Glamorous, and Rugged.

The social media data were collected from Instagram.com. Our unit of analysis is a post, and hashtags with brand names are the source tags. We excluded posts generated by firms. The raw data are post-related factors, including images, hashtags, mentions, comments, and the number of likes, while user-related variables include number of followers and number of Instagram posts the user has made to date. We then appended each brand's characteristics data from the dataset posted online by Lovett et al. (2014).

Constructing Measures From the User Post Data

Visual Sentiment Measure. We applied *DeepSentiBank* (Chen et al. 2014), a CNN network based on Plutchik's Wheel of Emotions (Plutchik 1980), as a classifier to detect sentiment from our image data.

Visual Complexity Measure and Object Types. We operationalized visual complexity as the number of objects in an image (e.g., Xiao and Ding 2014; Li and Xie, 2019) obtained using Microsoft's (Azure) computer vision API for object recognition. We created indictor variables to describe the types of objects in the image (e.g., living things, food, scenery). Finally, we counted the number of faces in each image.

Text Sentiment Measure. We employed *SentiStrength* (Thelwall et al. 2010), commonly used in text mining, to capture the degree of positive and negative sentiment strength of the text data.

Text Complexity Measure. Following Dong and Zhou (2012), we computed text complexity as the number of unique hashtags (compound hashtags were first tokenized into separate words).

4. Empirical Analysis and Results

A brand-related post on Instagram received, on average, 245 likes and 4 comments, though both are highly skewed and their median values are 34 and 1, respectively. Almost all the posts received at least one like (99.5%), while 62.3% elicited one or more comments.

We estimated a negative binomial regression for *LIKES* and a zero-inflated negative binomial regression for *COMMENTS*. A log-linear model showed similar results.

Consumer Engagement and Image Content

Visual Sentiment. Higher visual sentiment is associated with more likes ($p<.0001$) and more comments ($p<.0001$).

Visual Complexity. Over the range of our data, we find that the relationship between visual complexity and number of likes is bimodal, with a strong positive effect at the minimum and just past the middle of the scale, no effect for modest values, and a strong negative effect at high levels of visual complexity. A third-order relationship fits the data best.

Consumer Engagement and Text Content

Text Sentiment. Consumer engagement is higher when a post includes more divergent emotions in its text content ($p<.0001$).

Text Complexity. We find a positive relationship at low and at moderate levels of text complexity, and a negative relationship at high levels of text complexity. Consumers are more engaged when a post contains a small number of unique words in its hashtags, but not when the post contains too much information.

Consumer Engagement and Brand Characteristics

Visibility; Involvement. Higher engagement is associated with more visible (p<.0001) and higher involvement brands (p<.0001). Consumers engage more heavily with higher involvement brands offline, and this carries over to their social media activity.

Perceived Risk. Brands viewed as having higher perceived risk earn fewer likes with a brand-themed user post (p<.0001), however, the effect is relatively modest compared with involvement.

Brand Equity. All other things being equal, Differentiation (p<.0001) and Knowledge (p<.0001) are positively associated with a brand-themed post achieving more engagement.

Consumer Engagement and User Characteristics

The size of the user's network has a significant effect on consumer engagement with their posts. A larger number of followers is associated with more engagement (p<.0001). The number of posts the user has created to date has a negative effect on engagement (p<.0001). Users with an excessive number of posts could be flippantly posting without much thought as to their relevance.

Robustness Checks

We conducted several robustness checks, finding that the substantive conclusions are robust. First, we examined alternative operationalizations of brand equity derived from the Brand Asset Valuator variables reported by Lovett et al. (2014). Second, we examined a model which took the log form (ln(X); i.e., nonlinear, monotone) for the explanatory variables with skewness over two. Third, we estimated models using only the middle 98% of the data to exclude posts with a very large number of likes and/or comments. Fourth, we estimated our model on a subset of the data that excluded posts from accounts that were likely commercial in intent (9% of the posts were from a user description that contained words such as order, shipping, shop, price). Fifth, using manual inspection, we estimated our model on a subset of the data that excluded (as best we could) posts with hashtags for multiple brands. Finally, we examined first-, second-, and third-order forms of the four focal variables that describe a post (visual sentiment, visual complexity, text sentiment, and text complexity) using both within-sample and out-of-sample assessment.

5. Managerial Implications and Conclusions

The results from this study support that consumer engagement with brand-themed image-based user posts (Instagram) is affected by the visual and text characteristics of the post, characteristics of the focal brand, and characteristics of the user, and for the most part, in a manner we predicted. Some brand-themed posts are made because of a user's desire to express their relationship with a brand. Others may be the result of efforts by marketers that include experiential marketing, collaborating with general users, and influencer campaigns.

Images are now a dominant media format, driven by both psychology (taking photos increases the enjoyment of experiences [Diehl, Zauberman and Barasch 2016]) and technology (cameras are ubiquitous; self-expression is easy; curating content is simple; sharing is quick). Moreover, marketers see tremendous potential for image-based posts involving brands: "What am I doing filming cars driving through the desert when brands are being built on Instagram (Jeffery Dachis, Razorfish co-founder, Wall Street Journal, 2018)?"

We find that more positive visual sentiment is associated with higher consumer engagement. Visual sentiment, which to date has received limited attention by marketing researchers, is critical to understanding consumer engagement with brand-themed posts in social media.

We find that visual complexity, operationalized as the number of objects in an image, positively affects consumer engagement at its low or moderate levels, with an optimal point that drives the most consumer engagement somewhere in the middle of the scale, and then quickly becomes negative in its effect after a certain threshold. Visual complexity has been frequently studied in the contexts of advertising and web interface design. Several of those studies suggest that an optimal level of visual complexity drives the most positive responses (Geissler et al. 2006; Reinecke and Bernstein 2013). We find a similar relationship. Consumers are engaged the most around the midpoint of visual complexity and become distracted by too much visual information.

Consistent with popular discussions, we find that including living objects such as people or pets in user-generated posts earns higher engagement.

Emotionally charged text content in user-generated brand-themed posts is more likely to drive consumer engagement compared with neutral content. We find that text sentiment is positively related to consumer engagement with a user-generated brand-themed image-based post. Emotionally charged text may activate cognitive attention or the arousal effect shown to impact viral behaviors.

We find a strong effect for text complexity on consumer engagement with a user-generated brand-themed post. Similar to the effect of visual complexity, we find that simple text (low text complexity) is positively associated with consumer engagement, and there is a second peak around the middle of the scale, and a strong negative effect for too much text information. Information overload has been widely studied in consumer contexts, and numerous studies have found a negative relationship between the amount of information and responses (e.g., Townsend and Kahn 2014) mainly due to an individual's limited capability to process information (Newell and Simon 1972; Payne 1976).

Including *#brandname* in a social media post is an emerging way that consumers engage with brands. We find that brands can benefit from encouraging this form of expression by users. We find that more visible brands and higher involvement brands earn more consumer engagement with user image-based posts on social media. These findings are consistent with Sprott, Czellar and Spengenberg (2009) who find that brand visibility increases consumers' attitudes towards products and Lovett et al. (2013) who reveal that brand visibility as a component of social drivers stimulates word-of-mouth. Different from Lovett et al. (2013), we find a positive relationship between brand involvement and consumer engagement, which is consistent with their expected hypothesis (i.e., a positive relationship between brand involvement and word-of-mouth).

This article makes several contributions. First, we discover that visual sentiment affects consumer response, which has seen only limited attention in marketing literature. And, we find this using large-scale observational data. Prior studies characterized visual sentiment through only a few aspects of images (e.g. facial expressions), and the analyses typically examined a small number of observations in a laboratory setting. Employing a technique that has been developed recently in the computer science literature (Deep CNNs), we can extract visual sentiment from large-scale, real-world data and connected it with a critical social media metric (consumer engagement), which firms are increasingly incorporating into their social media strategies.

Second, this article empirically accounts for visual complexity, text sentiment based on emotional divergence, and text complexity. All have received relatively little attention in marketing. Our results with large-scale field data illustrate an interesting *S*-shaped relationship that implies the existence of an optimal point around the midpoint of our visual complexity scale to drive the most consumer engagement and a threshold where consumer engagement rapidly decreases, presumably due to information overload on visual complexity and text complexity. We also find a positive relationship between consumer engagement and higher levels of text sentiment that may be the result of more cognitive attention or higher emotional arousal.

Third, to the best of our knowledge, this is the first study to investigate how brand characteristics affect consumer-engagement behaviors to user-generated social media posts. A number of studies have linked brand characteristics and various consumer behaviors, but little attention has been paid to the effect of brand properties on consumer engagement, an emerging behavioral metric in social media.

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