The Effects of Facial and Text-Based Emotions on Social Media Engagement

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Abstract

The use of images and text within online word of mouth (WOM) has become a fundamental component of firm generated content (FGC); however, much extant research primarily focuses on the textual elements of online WOM. This research examines the use of textual and visual content, particularly the faces within images, to determine how the emotional valence of the two content elements drive consumer engagement. Our findings reveal that the extent to which the two elements are congruent or incongruent can influence the number of comments FGC receives and the emotional valence of consumer comments. We find that a moderate mismatch between emotional valence of textual and visual content can increase total comments for FGC. Additionally, results show that a complete mismatch between the emotional valence of the text and visual elements decreases the number of comments the FGC receives. Notably, results indicate that this negative effect is reversed, leading to higher consumer engagement, for exciting brands in contrast to sincere brands. Content incongruence is also shown to impact the emotional valence of consumer responses similarly. These results offer actionable and concrete implications for marketers developing digital content strategies.

Introduction

Social media has become an important part of brand equity in terms of helping to build awareness, increase sales, and understand consumers' sentiments towards brands. Firm spending on social media advertising increased more than 50% between 2013 and 2014 from roughly $11 billion to $18 billion (eMarketer 2015). Brands have begun to embrace social media and develop branded social media pages to disseminate content to consumers. Within social media, a brand may choose to create content that is more textually dense or include imagery that focuses on the brand or persons. Anecdotally, marketers assume that providing images with the text can help capture consumers' attention and help firms' content to "get noticed." Despite the pervasive use of imagery in social media, the empirical marketing literature has focused on the text elements primarily, leaving a gap in our understanding of visual content. The rise in platforms such as Instagram and Pinterest suggest that imagery is a fundamental component of social media content, and that deriving approaches to analyze both text and visual elements is critical to informing our knowledge on social media engagement. How do the two elements influence consumer engagement? How do they influence the positive or negative nature of consumer responses? This research considers the influence of both text and imagery within firm generated content (FGC) to provide insights into how the two elements jointly influence consumer engagement.

In an online context, Berger and Milkman (2012) showed that emotional textual content, specifically high arousal text content, gets shared more. Others have also shown that emotional textual reviews are considered more diagnostic and affective banner ads obtain higher click-through rates (Lohtia et al. 2003; Yin 2014). While this literature clarifies our understanding of how text drives consumer engagement, little is known about the influence of images on consumer engagement. In the content marketing domain, research has examined the effects of images in print advertisement. The advertising literature has shown that the use of pictorial elements and faces within advertisements can influence consumers' perceptions, attitudes towards the advertisement, and product evaluations (Pieters and Wedel 2004; Xiao and Ding 2014). Given the importance of pictorials and faces in print advertising, do these elements influence consumer behaviors in an online context? While research has examined the visual content of print advertising, limited work has been conducted on their effect as a component of online WOM content on consumer engagement.

This research explores the use of text and visual content to determine how the emotionality within the two elements drive consumer engagement. In light of what literature has shown about the effects of emotionality of text in an online context and the use of faces in print advertising, we explore the emotionality of FGC, drawing a distinction between the text and visual components. We explore how the emotional valence of FGC on Facebook influences consumer engagement, measured in terms of both the volume and valence of consumer comments. We leverage machine learning via Amazon's Rekognition facial recognition software to measure positive and negative emotional facial expression within images. We construct a measure of emotional valence for pictures using the emotions (happy, calm, sad, and angry) from facial expressions within the images. Utilizing text analysis, we measure emotional valence (positive/negative) of the text components of FGC. By measuring the emotional valence of text and image content, we show that the extent to which the two elements are (in)congruent influences the volume of comments and the emotional valence of comments.

Our analysis reveals that when the emotional valence of the text is incongruent with the emotional valence of visual elements, firm-generated posts experience fewer consumer comments. Alternatively, we find that a moderate mismatch between emotional valence of text and visual elements can significantly increase comment volume. Examining the potential moderating role of brand personality, we find that a mismatch in the emotional valence of text and visual elements can lead to higher consumer engagement for exciting brands, whereas sincere brands experience a decrease in consumer engagement. This suggests that there is not a single "playbook" that all brands can employ as to how to engage consumers with social media. Additionally, our results suggest that contrary to anecdotal claims, adding an image to a firm's social media post, in some cases, can reduce the number of comments it receives if the two elements are incongruent. Lastly, in exploring the emotional valence within the content of consumer comments, results show that content congruence increases the amount of positive emotional language used within consumer comments for sincere brands. In contrast, a content mismatch increases the amount of positive emotional language used within comments for exciting brands. These findings have implications for marketing managers who develop digital and social media marketing strategies.

Given the significant financial and strategic emphasis placed on online engagement and social media, understanding how content influences the volume and content of consumer responses is beneficial. The approach we use to capture emotional valence of visual content can be useful in future research exploring the influences of images in the context of online word of mouth (WOM). We also extend the content marketing literature on the role of faces within print advertisement to a social media context. This analysis is among the first to explore the emotional valence of imagery within social media. Given recent findings of content emotionality's influence on consumer liking, clicking, and sharing behaviors (Berger and Milkman 2012; Lohtia et al. 2003; Agnieszka et al. 2018), images provide a rich data source that convey emotion beyond the text components.

The remainder of this article is structured as follows. First, we discuss related literature and the intended contribution of our analysis. We then present the data and describe the measures used in the analysis. Lastly, we detail the analysis and present the results. We conclude with a discussion of the implications of our work for managers and researchers.

Related Literature

Our study examines the impact of FGC on consumer engagement via the volume and emotionality of comments. We describe FGC using both textual and visual components and score the emotional valence of each element to evaluate the impact of congruent versus incongruent content. This research draws on three streams of literature: online WOM, content marketing, and brand personality. First, we discuss research of online WOM, focusing on articles related to content emotionality. Second, we discuss content marketing and the role of faces within advertisements. We then provide an overview of the literature related to (in)congruence and specify our expected outcomes when FGC is (in)congruent. Additionally, we briefly discuss brand personality and how it may moderate the way consumers respond to content (in)congruence.

Online WOM

Recent work by Kumar et al. (2013) suggests that brands embrace social media as it can potentially have a positive impact on sales, new customer acquisition, brand awareness, and consideration set formation (Kumar et al. 2013; Kumar et al. 2016; Goh et al. 2013; Sunghun et al. 2015). Research in social media and online WOM has shown that WOM can influence firm performance indicators such as sales (Chevalier and Mayzlin 2006; Liu 2006; Moe and Trusov 2011), consumers purchase decisions (Leskovec et al. 2007), television ratings (Godes and Mayzlin 2004), product adoption (Trusov et al. 2009), and stock market performance (Tirunillai and Tellis 2014). Others have investigated network effects within social media (Mayzlin and Yoganarasimhan 2012; Trusov et al. 2010) and posting behavior of users (Toubia and Stephen 2013; Moe and Schweidel 2012).

A wealth of literature has begun to employ text analysis techniques to derive meaning from the text of online WOM (e.g., Lee and Bradlow 2011; Tirunillai and Tellis 2014; Buschken and Allenby 2016). In regard to the valence of online WOM, researchers have shown that both positive and negative online WOM influence firms' price fluctuations (Shin et al. 2008). Others have demonstrated that the impact of negative valence content outweighs that of positive valence content (Chevalier and Mayzlin 2006; Luo 2007).

More recently, researchers have begun to investigate how content emotionality influences consumer engagement (e.g. likes, shares, or volume of comments). Literature has shown a link between high arousal emotionality and social transmission (Berger and Milkman 2012). A recent study by Agnieszka et al. (2018) found that the informative versus emotional appeal of FGC impacts consumer engagement. Tellis et al. (2019) examine digital advertisements in the context of YouTube and find that positive emotional content is shared more. The researchers find a negative relationship between sharing and informational content except in cases where informational ads were examined in a risky context (Tellis et al. 2019). Lee et al. (2018) find that including brand personality attributes (e.g., humor and emotion) in FGC positively influences consumer engagement while informative content (e.g. prices) is negatively associated with consumer engagement. Lohtia et al. (2003) find that emotional appeal in online banner ads leads to higher click through rates (CTR). Despite research into the emotional content of FGC and online WOM, limited work has investigated the role of visual content (Liu et al. 2017). To the best of our knowledge, our research is among the first to consider the emotional valence of visual content in social media.

Visual Elements of Content Marketing

Research has shown that verbal and visual information within advertisements have separate influences on consumers' brand attitudes and product evaluations (Rossiter and Percy 1983; Mitchell 1986; Pieters and Wedel 2004). Mitchell (1986) classified pictures as positive, neutral and negative, and found that affect-laden photographs influenced consumers' brand attitudes. The results suggested that images categorized as negative resulted in less favorable attitude than those categorized as positive or neutral. Pieters and Wedel (2004) use eye tracking and gaze duration to examine the surface size of pictorial, text and brand appearance in print advertisements and find that the pictorial elements capture the most attention. Similarly, Pieters et. al (2007) use bounding boxes to examine the size of design elements: brand, text, pictorial, price, and promotion and find that surface size influences attention capture. Pieters et al. (2010) distinguish between visual and design complexity within advertisements and find that feature complexity is negatively associated with attention and attitude towards the ad whereas design complexity is positively associated with attention and attitude towards the ad.

Recent advancements in machine learning have provided automated ways to analyze images. Liu et al. (2017) use deep neural networks to train image classifiers to predict brand attribute measures (e.g. rugged, glamorous, fun and healthy). Klostermann et al. (2018) use description tags of images via Google Cloud Vision API to cluster images based on contents (e.g. products) and context (e.g. scenery/situations). The authors suggest this method as means for brands to determine consumer's brand perceptions. Research leveraging automated approaches to process images in a social media context is in its nascency. Our research contributes to this emerging stream by incorporating the valence expressed in both textual and visual content. To the best of our knowledge, our work is among the first to examine how text and images jointly influence consumer engagement. By differentiating between certain visual attributes, we aim to provide insights into how visual elements within FGC influence volume and emotional valence of consumer comments, and thus consumer engagement.

Relevant to the use of images in content marketing, research has also examined the impact of faces in visual elements of marketing content. Facial expressions provide additional non-verbal cues to the intent or meaning of communications. Researchers have found that attractiveness of models and persons in advertisements can influence product perceptions and consumer behaviors (e.g., Solomon et al. 1992; Bower and Landreth 2002;). Literature investigating faces has shown that faces can influence election results (Todorov et al. 2005) and trust perceptions (Gorn et al. 2008; Tanner and Maeng 2012). Small and Verrochi (2009) analyze faces within charity advertisements and find that sad faces elicit greater donations compared to happy or neutral faces. Xiao and Ding (2014) examine the effect of facial features in print advertising and find that faces have a substantial effect on consumer attitude towards the brand, advertisement and purchase decisions. Their results reveal that people showed preference towards certain facial traits in advertisements compared to others (e.g. attractiveness and trustworthiness) with some heterogeneity across individuals and product categories. Others have shown that emotional facial expressions capture attention in various settings (Lundqvist and Ohman 2005; Oatley and Jenkins 1996). As content emotionality has been found to drive online engagement, the emotionality expressed on the faces within FGC provides another avenue through which brands can communicate with consumers. Given the importance of faces in print advertising, we examine their impact within FGC on social media.

Content Matching Expectations

Consumer behavior and psychology literature provide insights into how (in)congruency influences consumers' perceptions. Some scholars suggest that congruent stimuli are perceived more favorably through schema-based positive affect transfer compared to incongruent stimuli (Sujan 1985; Fish and Pavelchak 1986). Subsequent research found that positive affect transfer extended to situations where mild incongruence was present (Meyers-Levy and Tybout 1989). Mandler (1982) found that moderate incongruence in contrast to completely congruent or incongruent, generated more favorable product evaluations. The author contends that the process of responding to incongruency is different than that required to process congruence, yielding more affective processing. Bosman (2006) explores the incongruence of ambient scent with the product category and finds that pleasant ambient scents that are congruent are more effective at increasing consumer product evaluations. Lee and Thorston (2008) investigate the impact of celebrity-product incongruence on purchase intentions to find that a moderate mismatch was better than either a complete mis-match or complete match. In some instances, extreme incongruity has been shown to decrease product evaluations as consumers work to reconcile the discrepancy. Moderate incongruity can be viewed as interesting and has been shown to elicit positive curiosity from the "unexpected-ness" of the information (Meyer-Levy et al. 1994; Mandler 1982).

Prior research has illustrated that pictorial and textual elements offer distinct influences on consumer's attitude, perception, and attention in the context of print advertisements. In this research, we investigate the joint impact of textual and visual elements within social media to determine how the two components drive consumer engagement. We focus on the emotional valence (positive and negative) of the text and facial images. To the extent that the emotional valence of the text conflicts with the emotional valence represented by faces within the image, we expect that (in)congruency effects may influence consumer engagement.

We consider positive (negative) valenced content paired with congruent positive (negative) valenced content to be indicative of a complete match. A complete match can occur in two ways: when both textual and visual content are positively valenced (e.g. positive valence text paired with a happy face) or when both textual and visual content are negatively valenced (e.g. negative valence text paired with angry/sad faces). We anticipate positive impacts of congruency on consumer engagement.

H1a: A complete match between textual and visual content within FGC will be associated with an increase in volume of comments.

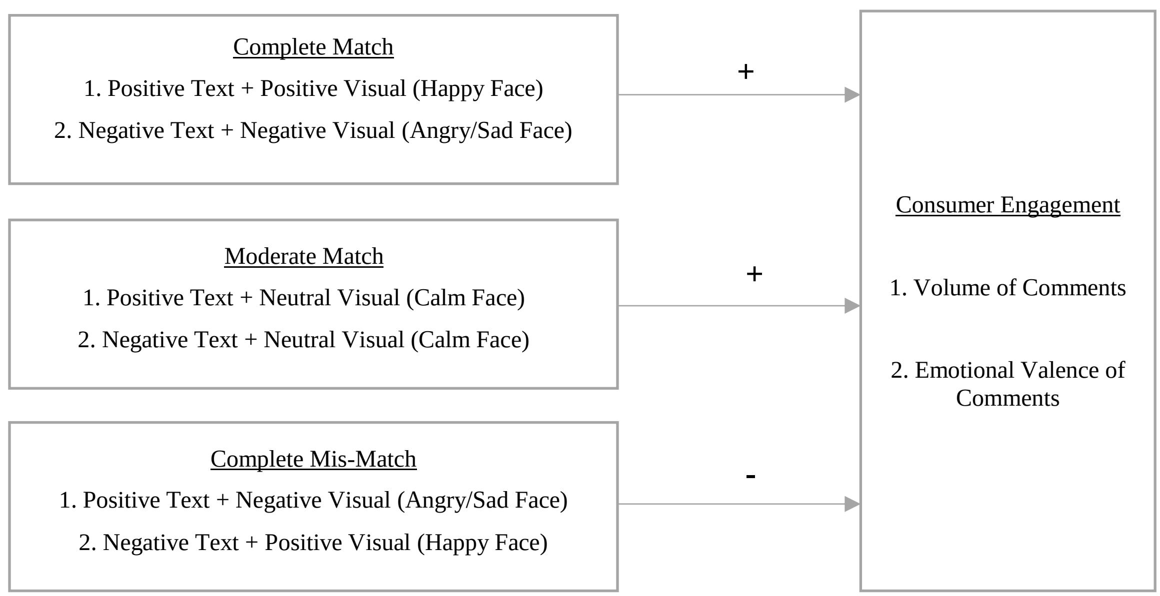
We consider positive (negative) valenced textual content combined with incongruent negative (positive) valenced visual content to be indicative of a complete mismatch. This incongruity can appear in two ways: positive valenced text content paired with negative valenced visual content (angry/sad faces) or, negative valenced text content paired with positive valenced visual content (happy face). We expect that FGC containing a complete mismatch between visual and textual content to evoke unfavorable consumer responses (e.g., fewer comments). The greater the distance between the emotional valence of the text and images may result in consumers extending more effort to reconcile the difference. This heightened cognitive processing may lead to consumers losing interest and/or fewer comments.

H1b: A complete mismatch between text and visual content within FGC will be associated with a decrease in volume of comments and positive emotionality of comments.

For the moderate match condition, we examine positive/negative valence emotion paired with neutral valenced content. This can occur when either positive or negative valenced text is paired with neutral visual content (calm face). Given the advantages of moderate incongruency we expect that a moderate match between the emotional valence of the text and the image will evoke more favorable responses from consumers. When the distance between the emotional valence of the textual and visual element of firm's post is moderate, we suspect that the content may be viewed as more interesting and arouse curiosity leading to greater comments. Figure 1 denotes the content match pairs, congruency conditions and expected results.

H1c: A moderate match between textual and visual content within FGC to be associated with an increase in volume of comments.

Figure 1: Expected Influence of Content Match Pairs



Brand Personality

In addition to congruency between components of FGC we also examine how brand personality may moderate how consumers respond to in(congruency) in the firm's content. To the extent that certain brand personalities are more associated with incongruency than others, we contend that consumers may respond differently when presented with mismatched content from a particular type of brand.

Aaker (1997) defined brand personality as "the set of human characteristics associated with a brand." Brand personality has been used to capture the way consumers feel about brands along dimensions typically associated with a person. Aaker (1997) developed the Big Five brand personalities widely used in research (sincerity, excitement, competence, sophistication, and ruggedness). Scholars and marketers have suggested that brand personality is important in distinguishing a brand from competitors (Aaker 1997), building brand equity (Keller 1993), forming preferences for the brand (Biel 1993), influencing brand loyalty (Sung and Kim 2010), and facilitating consumer-brand relationships (Sung and Tinkham 2005).

In the marketplace, two brand personalities (sincere and exciting) make up most of the variation in brand personalities (Aaker 1997; Caprara et al. 2000). Sincere and exciting brand personalities are fundamental in the marketing landscape (Aaker et al. 2004). Prior research suggests that sincere brands are advantageous in fostering long term consumer relationships as they are associated with traits such as honest, wholesome, down-to-earth, family-oriented, friendly and sentimental which have been linked to greater relationship strength (Aaker et al. 2004; Robbins et al. 2000). Brands such as Dove, Coca Cola, and Hallmark are associated with sincere personalities (Harvey 2017; Aaker 1997). Brands such as MTV and Virgin are considered to portray an exciting personality exhibiting traits such as daring, cool, young, unique, independent, and trendy (Aaker 1997). Researchers indicate that exciting brand personalities are advantageous in attracting young consumers, cultural vitality and generating interest (Harvey 2017; Altschiller 2000).

Prior literature supports the hypothesis that the interaction of brand personality and disconformatory actions by the firm may influence consumer brand relationships. Sudar and Noseworthy (2016) explore negative sensory disconfirmation (when touch disconfirms visual expectations) and brand personalities. They find that negative sensory disconfirmation by exciting brands can be perceived favorably as consumers view the disconfirmation as more authentic of an exciting brand personality in contrast, sensory confirmation is preferred for sincere brands (Sudar and Noseworthy 2016). In this analysis, we explore congruence between textual and visual elements within FGC on consumer engagement. We differentiate between sincere and exciting brand personalities to examine the moderating role that brand personalities exhibit on consumers' responses to (in)congruence.

Aaker et al. (2004) suggest that consumers expect a degree of relationship disconfirmation and unpredictability with exciting brands and associate sincere brands with more dependable and consistent actions. We contend that content mismatch is more aligned with the exciting brand personality while consumers may expect content congruence with sincere brands. Incongruent content may be misaligned with consumer perceptions of consistency of sincere brands. We anticipate that sincere brands may be viewed more unfavorably compared to exciting brands when there is a mismatch between the emotional valence of images and the valence of the brand's text. We expect that content mismatch from exciting brands may be viewed more favorably by consumers who expect a certain level of spontaneity and disconfirmation for exciting brands.

H2a: A content mismatch for sincere brands will be negatively associated with volume of comments.

H2b: A content mismatch for exciting brands will be positively associated with volume of comments.

In terms of emotional valence of consumer comments, we expect that a content match for sincere brands will evoke more positively valenced comments while content mismatch for exciting brands will evoke more positively valenced comments.

H3a: A content is match for sincere brands to be associated with an increase in positive emotional comments from consumers.

H3b: A content is mismatch for exciting brands to be associated with an increase in positive emotional comments from consumers.

Data & Measures

We collect social media data from Facebook brand pages for 15 brands, presented in Table 1. We use the Facebook graph API to download all available activities made by a brand, such as posts (text and images) and all user comments for a given posts. The raw dataset includes all activity starting from the day the brand page was created on Facebook through October 31, 2018. Brands in our data started Facebook pages as early as January 2009 to February 2012 with Crest and Louis Vuitton being among the first to start Facebook pages and Colgate being the last. We analyze 23,605 Facebook post and aggregate over 2.38 million Facebook comments. Among brands, we find that Gucci has the largest number of post and Nike has the fewest number of brand post. In terms of consumer comments, we see that Chanel garners the most comments of brands in our dataset followed by Covergirl. Cosmetic brand Loreal, has the least number of comments. In terms of product categories, we find that luxury brands have the most comments of all product categories while oral hygiene products have the least (Table 3). Similarly, luxury products have the most brand post and oral hygiene has the least number of posts.

Table 1: List of Brands in Analysis

Brand	Start Date	Product Category	Num. of Post	Num. of Images	Num. of Comments
Adidas	2011-02-17	Sport Apparel	899	434	70,536
Chanel	2009-11-17	Luxury	1,462	837	494,693
Coach	2009-06-15	Luxury	1,795	1,123	124,922
Colgate	2012-02-15	Oral Hygiene	455	229	31,774
Covergirl	2009-06-22	Cosmetics	1,890	807	277,958
Crest	2009-01-01	Oral Hygiene	765	456	20,813
Estee Lauder	2009-06-24	Cosmetics	2,091	952	106,086
Gain	2010-02-11	Household Goods	1,258	432	138,853
Gucci	2009-01-17	Luxury	4,594	2,918	262,256
Loreal	2009-12-31	Cosmetics	903	618	10,401
Louis Vuitton	2009-01-01	Luxury	1,218	733	174,945
Maybelline	2009-07-15	Cosmetics	2,410	1,.83	249,702
New Balance	2009-12-14	Sports Apparel	2,262	1,281	50,506
Nike	2010-06-03	Sports Apparel	369	117	113,493
Tide	2010-06-03	Household Goods	1,234	434	257,471

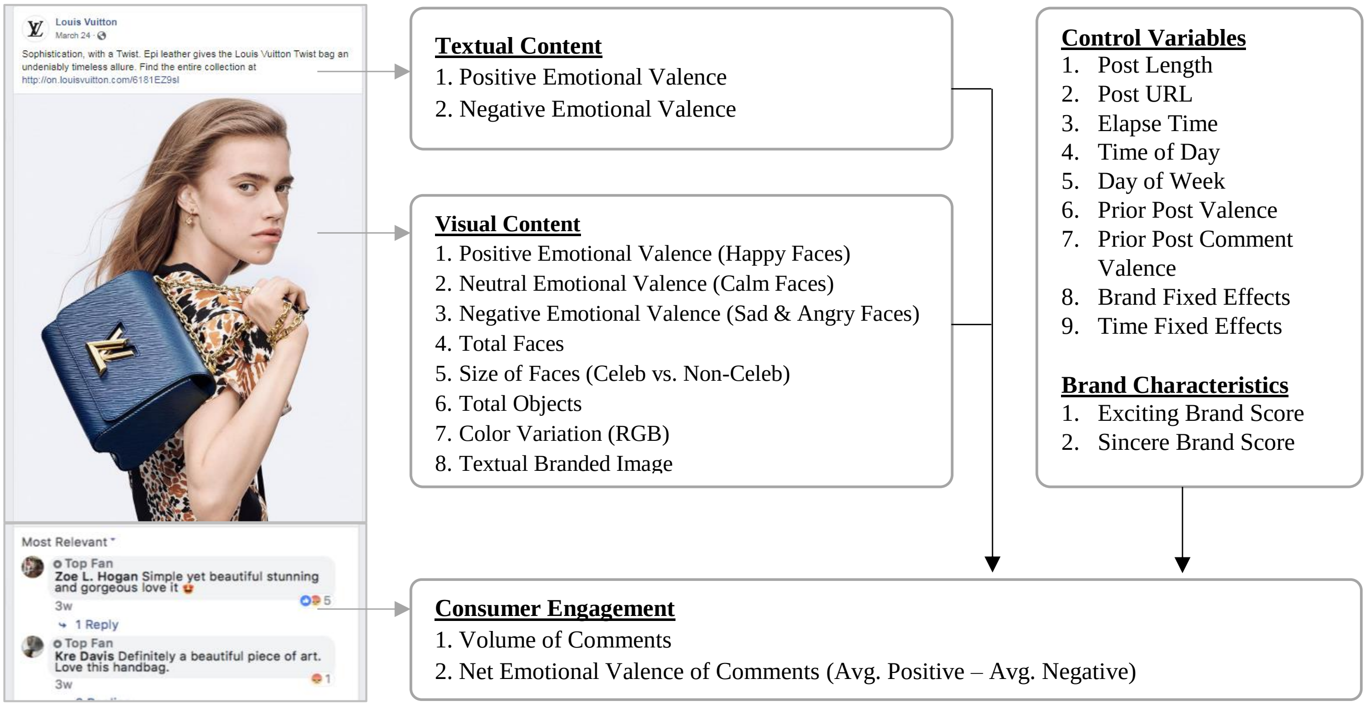
For each firm post we capture the date of the post, time, text and images if any are used in the post. We also capture individual user comments in response to the brand’s post. For each comment we capture the comment date, time, and the text of the comment. Figure 2 summarizes the measures used in the analysis. Table 2 details the description for the measure used in our analysis and data sources. We employ LIWC text analysis software to measure the emotional valence of the text and Amazon Rekognition API to analyze images. Each approached is described in subsequent paragraphs.

Table 2: Measures used in Analysis

Variable	Description	Source/Operationalization
Total Comments	Total number of comments a post receives	
<u>Post Text Content</u>		
Post Pos	Percetange of words in post that are associated with positive valence emotions	Text Analysis via NRC emotionality dictionary
PostNeg	Percetange of words in post that are associated with negative valence emotions	Text Analysis via NRC emotionality dictionary
<u>Post Image Content</u>		
TotalFaces	# of human faces in a image	Amazon Image API
NonCelebFaceSize	Percentage of image that contains non celebrity face(s)	Amazon Image API
CelebFaceSize	Percentage of image that contains celebrity face(s)	Amazon Image API
FacePos	Weighted percentage of image with a face containing positive emotion (happy face)	Amazon Image API
FaceNeg	Weighted percentage of image with a face containing negative emotion (angry or sad face)	Amazon Image API
FaceNeu	Weight percentage of image with a face containing neutral emotion (calm face)	Amazon Image API
TotalObjects	number of objects types in image	Amazon Image API
Red	Average red channel among top 10 most prevalent colors within a given image	Google Image API*
Blue	Average blue channel among top 10 most prevalent colors within a given image	Google Image API*
Green	Average green channel among top 10 most prevalent colors within a given image	Google Image API*
TextualBrandedImage	Indicator that denotes if image contains brand name	Amazon Image API
<u>User Comments Content</u>		
CmmtPos	Average of expressed positive valence emotions among all comments for a given firm post	Text Analysis via NRC emotionality dictionary
CmmtNeg	Average of expressed negative valence emotions among all comments for a given firm post	Text Analysis via NRC emotionality dictionary
Net Emotional Valence	CmmtPos - CmmtNeg	
<u>Brand Characteristics</u>		
Exciting	Percetage of respondents who checked “energetic” as it relates to the brand	BAV Lovett et al. 2013 dataset
Sincere	Percetage of respondents who checked “authentic” as it relates to the brand	BAV Lovett et al. 2013 dataset
<u>Controls</u>		
Time of day		
Day of week		
Post Text Length		
Post URL		
Elapse Days between Post		
Sentiment Prior Post		
Comment Sentiment Prior Post		

* Google Image API is used to determine the dominate color variation within images as Amazon’s Image API (Rekogntion) does not offer this functionality.

Figure 2: Summary of Measures used in Analysis



Emotional Valence of Text and Comments

We analyze the text of user comments using Linguistic Inquiry and Word Count (LIWC), which has been used in prior literature to capture emotional valence of the text (Berger and Milkman 2012). It analyzes text by parsing through each comment one word at a time. Using the NRC emotion lexicon, LIWC processes each word within a comment by searching the dictionary file for a match and incrementing the appropriate emotional category (Pennebaker et al. 2007; Mohammad et al. 2013). We quantify emotional valence as the percentage of words within the comment associated with positive/negative emotion within the dictionary.

For each brand post, we capture the emotional valence (positive and negative) of the text element. Using the same approach, we capture the emotional valence for each user comment for a given post. We exclude comments that do not contain words and successive duplicate comments. We aggregate the emotional valence measures for comments by brand post such that we have total comments and the average emotionality (positive and negative) of comments for each brand post in our dataset. Table 3 shows the summary statistics of emotional valence measures in the dataset. Similar to prior literature, we find that on average brands score higher on positive related emotionality than negative content.

Table 3: Summary of Post and Comment Emotionality Measures

Variable	N	Mean	Std Dev.	Min	Mix
Post Positive	23,605	6.24	6.88	0.00	100.00
Post Negative	23,605	1.79	3.61	0.00	66.67
Comment Positive	23,605	8.59	8.49	0.00	100.00
Comment Negative	23,605	1.67	3.10	0.00	100.00
Post Word Count	23,605	28.25	36.02	0.00	3,176.00
Total Comments per Post	23,605	101.01	397.35	0.00	20,132.00

Image Data

In addition to the textual content of brand posts on Facebook, we analyze images posted in conjunction with the text. Our data contains 12,710 images across 15 brands. We find that nearly 54% of FGC posts in our data contain an image, with some variation across product categories. For instance, luxury (62%) and oral hygiene (56%) include more pictures on average compared to other brands. Interestingly, cosmetic brands (49%) rank 4th of the 5 product categories in terms of percentage of post containing images. Table 4 provides a description of the number of images and the characteristics we examine in our analysis.

Table 4: Total Number of Measures by Product Category

Category	Post	Comments	Images	Face	Celebrity Face	Textual Branded Image
Cosmetics	7,294	644,147	3,560	1,519	692	960
Household	2,492	396,324	1,022	356	78	454
Luxury	9,069	1,056,816	5,611	3,007	1,593	609
Oral Hygiene	1,220	52,587	685	367	114	336
Sports Apparel	3,530	234,535	1,832	745	308	283
Total	23,605	2,384,409	12,710	5,994	2,785	2,642

Note: Face, Celebrity Face and Textual Branded Imaged denotes the number of images that contain a face, a celebrity face and the brand name respectively.

There are several tools to analyze image content (Computer Vision System Toolbox via MATLAB, OpenCV, Deep Neural Networks) which have been explored in the computer information science field (Corke 2005; Liu et al. 2018; Klostermann et al. 2018). Cloud services such as Google Cloud, Amazon Rekognition and Microsoft Azure offer a computer vision API to aid with object detection and facial recognition. We utilize Amazon's Rekognition application to process image content. Given our focus on emotional facial expressions within images, Amazon's API provides a robust set of tools that can be used in a scalable means by researchers. Moreover, its identification of facial expressions provides more granular measures of facial expressions.

Our research examines the emotional valence of the text component of FGC in addition to the emotional valence of faces within visual components of firm-generated content. We categorize the affect within images as positive, negative and neutral valence via facial expressions within the image (Mitchell 1986). Using an image processing API, we determine the extent to which a face within a given image exemplifies positively valenced emotions (happy), negatively valenced emotions (anger and sad) and neutral emotional valence (calm). We also consider the size of the face compared to the overall size of the image in our investigation. Prior literature has found that surface size can influence visual attention (Pieters and Wedel 2004;

Koch and Ullman 1985; Itti 2005). Larger surface size has been linked to greater "pop out" as it facilitates figure-ground segmentation which can lead to higher salience and attention (Itti 2005). Next, we describe the Amazon Rekognition API in detail and explain how we derive the image covariates.

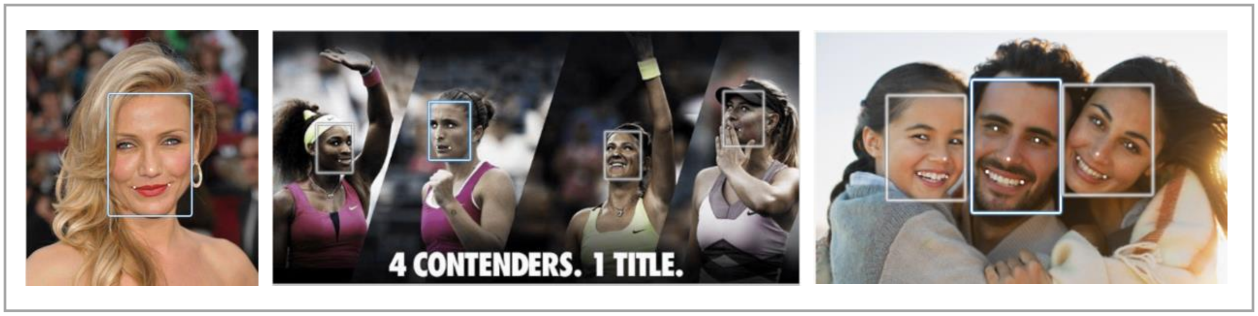
Number and Size of Faces. We examine the number of faces present in the image and the size of the faces as control measures. Using Amazon's facial recognition feature, we can determine the number of faces within a given photo and the relative size of the faces within an image. The API is designed to determine if there is a face within an image by looking for key facial features such as eyes, nose and mouth (Amazon 2019). In the affirmative, the facial detection application provides face details including a bounding box of the face, facial landmarks (e.g., coordinates of eye and mouth), emotions, sunglasses detection, and beard and mustache detection (Amazon 2019). The bounding box is a rectangle surrounding the face only. For each face, the API provides normalized width and height values of the bound box. Figure 3 provides examples of the bounding box functionality. We create two facial measures: a count of the number of faces that appear in an image and the fraction of the image that contains a face. The former allows us to control for multiple faces within an image and the ladder allows us to control for the proportional size of the faces within a given image.

Using the bounding box width and height metrics, we calculate the fraction of the image occupied by each face and sum across all the faces within a given image to determine the total percentage of the image that contains a face. Specifically, we operationalize size of faces as:

$$NonCelebFaceSize_j = \sum_{i=1}^{F_j} Width_{ij} * Height_{ij} \qquad (1)$$

where j denotes image j=1,…,12710, F_j denotes the total number of faces in image j, and $Width_{ij}$ and $Height_{ij}$ are normalized measures associated with face i in image j.

Figure 3: Facial Recognition Bounding Box



Celebrity Faces. We control for the number of celebrity faces within a given image and the size of the celebrity face in the photo. Prior literature has documented the positive effects of celebrity endorser on brand attitude, box office performance, and product sales. Given the positive impact of celebrity endorsers in prior research we expect that having a celebrity face within a firm's social media post may influence consumer engagement.

Amazon's API uses a database of celebrity faces from a range of categories (e.g., sports, business, politics, and entertainment) along with facial recognition software to determine if the face within an image is a celebrity and an associated confidence measure (Amazon 2019). The software has the ability to match celebrity faces in a variety of settings and conditions such as makeup and alter egos (e.g., Johnny Depp dressed as Jack Sparrow from the film *Pirates of the Carribean*) (Amazon 2019). Similar to non-celebrity faces, we code for the number of celebrities faces in an image along with the fraction of the photo that contains a celebrity face.

$$CelebFaceSize_j = \sum_{i=1}^{F_j} Width_{ij} * Height_{ij} \quad (1)$$

where j denotes image j=1,…,12710, F_j denotes the total number of celebrity faces in image j, and $Width_{ij}$ and $Height_{ij}$ are normalized measures associated with celebrity face i in image j.

Emotional Valence of the Face. Because an image can potentially convey many emotions, we operationalize emotionality as the fraction of the image that conveys a particular emotional valence. This fraction approach is similar to the text analysis approach which considers the fraction of words within a text corpus associated with a given emotion. To the extent that the faces may be the driving influence in determining the overall emotionality of the entire image, we suspect that our operationalization may provide conservative estimates.

Consistent with prior literature, we capture positive, negative and neutral valance of images to determine how the different levels of emotional valence impact consumer engagement (Mitchell 1986). We capture emotion conveyed on faces across four emotional measures (happy, calm, sad, and angry) as an indication of the level of emotional valence represented within an image. We measure happy, sad, and angry as they denote positive and negative emotions, while calm represents a neutral emotion. We utilize Rekognition to rate each face across the four emotional measures. Using an internal algorithm, Rekognition determines the emotion (on a scale of 0-100) within faces detected for an image. Table 5 provides examples of Rekognition's facial emotionality measure for different images.

Table 5: Examples of Emotional Facial Expressions

	Example 1	Example 2	Example 3
Image			
Happy	14.08	94.20	0.93
Calm	71.72	0.06	9.98
Sad	2.47	0.23	3.46
Angry	1.86	1.37	81.05

* Values range from 0-100

For each emotion we calculate a weighted average of the emotion across the number of faces within the image accounting for facial size. For example, if there are two faces within an image; one that occupies 30% of the picture and another that occupies 10% of the picture, the emotionality on the face is weighted proportional to the size of the face such that the emotions on the face that occupies 30% of the picture is weighed higher than the emotions on the face that occupies 10% of the picture. Equation 2 denotes the derivation of the emotion measure for each photo in our analysis:

$$wEmotion_{je} = \sum_{i=1}^{F_j}(Width_{ij} * Height_{ij} * Emotion_{ije}) \quad (2)$$

where *j* denotes image j=1,…,12710, *e* denotes a given emotion (e=1,…,4) across the four emotions, F_j denotes the number or total faces within image *j*, $Width_{ij}$ denotes the width of face *i*, $Height_{ij}$ denotes the height of face *i*, $Emotion_{ije}$ indicates the emotional measure for face *i* in image *j* along emotional dimension *e*. Effectively, for each photo within our data that contains a face, we have a weighted measure for each emotionality (happy, calm, sad and angry) which provides a measure of the fraction of the image that contains emotional content related to the four emotions of consideration in our analysis. *FacePositive* represents the emotional measure for happy faces. *FaceNeutral* represents the emotional measure for calm face. *FaceNegative* represents the emotional measure for both sad and angry faces.

Number of Objects. To control for the number of types of objects within an image we rely on object and scenery detection tools within Amazon's API. Rekognition's object detection uses deep learning to generate description tags that decipher the objects and scenery within a given image. The API can detect objects (e.g. tree, flower, table), events (e.g. graduation, wedding, party), and concepts (e.g. nature, evening, landscape) (Amazon 2019).

Recognizing the scenery and objects within images is a fundamentally challenging task within the image analysis domain. Drawing on prior research (Klosterman et al. 2018; Ho 2019; Girshick et al. 2016), we use object detection tags in conjunction with part of speech (POS) tagging, to identify descriptors tags that are nouns as nouns denote objects in linguistic text (Straka and Straková 2017). Table 6 provides examples of images, the corresponding tags produced by the API and the measure of the total number of object types.

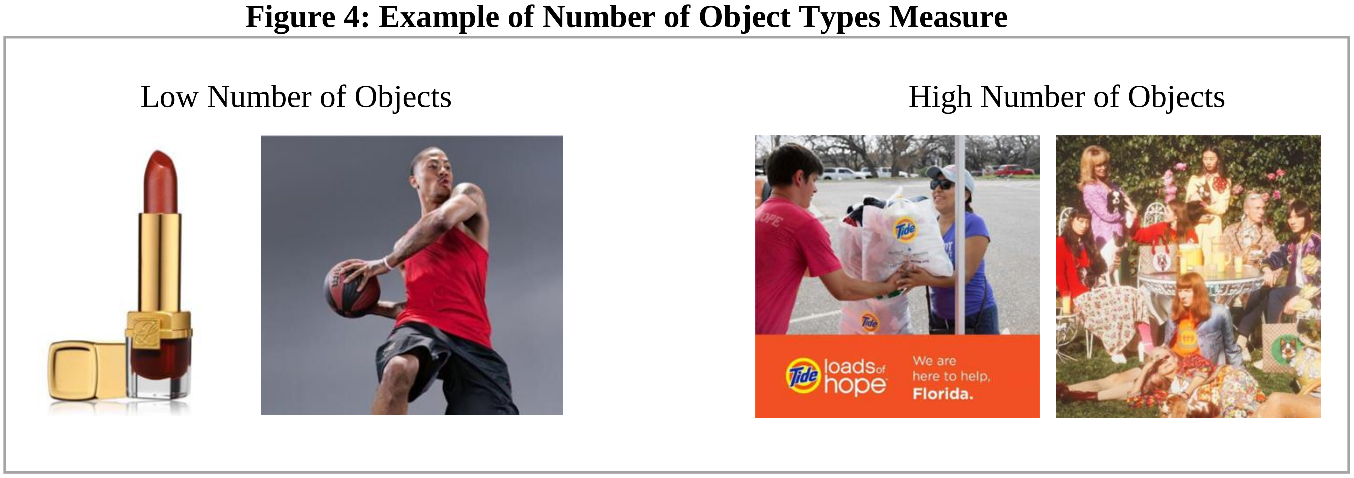
Table 6: Examples of Object and Label Detection Results

Image	Image Description Tags	Number of Objects
	**Person, Human, Apparel, Footwear, Shoe, Clothing, Pedestrian, Path, Building, Urban, Town, Metropolis, City, Shorts, Vehicle, Automobile, Transportation, Car, Road, Skin, Street, Tarmac, Asphalt, Bike, Bicycle, Downtown, Pavement, Sidewalk, Wheel, Machine, Pants, Sleeve, Office Building,** Architecture, **Flooring**, **Intersection, Walkway, Long Sleeve,** Walking, **Sport**, Working **Out**, **Exercise**, **Fitness**	43
	**Tool, Brush, Mascara, Cosmetics**	4

* Bold denotes labels that are categorized as nouns, plural nouns and proper nouns using parts of speech (POS) tagger.

We operationalize number of objects as the number of unique nouns associated with an image. This approach is consistent with approaches within the image analysis and offers a reasonable proxy for the number of objects types within an image. Our approach offers a reasonable summary measure of the number of objects within an image based on sophisticated machine learning algorithms (Klosterman et al. 2018, Girshick et al. 2016). Figure 4 shows examples of images with low number of objects and high number of objects using our approach.

Figure 4: Example of Number of Object Types Measure



Textual Branded Images. Advertising design strategy has urged firms to display the brand prominently on marketing materials. Some suggest that the presence of the brand logo or name helps garner interest among consumers and increases awareness. Amazon's API recognizes any text within an image and reports the textual content. As a control measure, we denote images that contain the brand's logo or name. To the extent that the brand logo contains the name of the brand or consistent lettering, we are able to parse the text within a given image to determine if it contains the brand's name. We construct an indicator variable denoting if the image contains the brand name. Figure 5 provides examples of instances where the brand name and/or logo can be identified. In cases such as Nike (e.g. Nike's swoosh), in which the branding/logo does not contain text, we are unable to indicate branded image. To this degree we suspect that our approach to identifying branded images will result in a conservative estimate of the influence of branded images on consumer engagement and emotionality.

Figure 5: Example of Branded Images in Data

Control Variables. We account for time of day, day of week, the emotional valence of the brand's prior post, the emotional valence of prior comments, post word count, and if the post contains a URL. For time of day we denote 6:00 AM -11:59 AM as morning, 12:00 PM– 5:59 PM as afternoon, 6:00 PM – 11:59 PM as evening and 12:00 AM – 5:59 AM as night (Kanuri et al. 2018). For day of the week, we distinguish between weekdays (Monday-Friday) and weekends (Saturday and Sunday). Prior post emotional valence captures the positive and negative emotional valence of the prior post by the brand to Facebook. Prior comment emotional valence is constructed as the average positive and negative emotional valence of comments from the previous post. We also include a measure of the amount of time (in days) that has elapsed since the brand's previous post. We incorporate a linear and quadratic term to allow for a non-linear effect of time since the last post.

Empirical Analysis and Results

This analysis investigates two dependent measures: total comments a post receives and the net emotionality of consumer comments. For the former, we estimate a negative binomial regression based on equation (4). For the latter, we estimate a linear regression as the net emotionality takes on continuous values that may be either positive or negative. We model both total comments and net emotionality as a function of firm textual and visual content characteristics:

$$y_i = \alpha + \sum_{j=1}^{n} \beta_{1j} * \text{PostTextContent}_{ij} + \sum_{j=1}^{k} \beta_{2j} * \text{PostImageContent}_{ij}$$
$$\sum_{j=1}^{n} \beta_{3j} * \text{PriorPostTextContent}_{ij} + \sum_{j=1}^{p} \beta_{4j} * \text{PriorPostCommentSentiment}_{ij}$$
$$\sum_{j=1}^{k} \gamma_j * \text{ControlVariables}_{ij} + \varphi_b + \delta_y + \varepsilon_i \tag{4}$$

where y_i denotes the number of comments for post i, β_{1j} denotes a vector of coefficients of the post's text attributes (positive and negative emotionality), β_{2j} denotes a vector of coefficients of the image characteristics (FacePositive, FaceNeutral, FaceNegative, total number of faces, size of faces in image (celeb and non-celeb), number of objects, textual branded image), β_{3j} denotes a vector of coefficients for prior post's emotional valence (positive and negative emotion), β_{4j} denotes a vector of coefficients for prior comments' emotional valence (positive and negative). γ_j denotes a vector of coefficient for control variables (time of day, day of week, elapsed time, elapsed time^2, URL indicator, post length). φ_b and δ_y denote brand-specific fixed effects and year fixed effects, respectively. Table 7 presents the full model results.

We begin our discussion of the results by first examining the influence of emotional valence of content on total comments. Next, we examine the influence of firm content characteristics on net emotional valence of consumer comments offering insight into what content characteristics are indicative of positive or negative consumer responses.

Total Comments

We estimate three models: (1) a base model, (2) a model that incorporates two-way interaction between emotional valence of text and faces to examine the potential influence of content (in)congruency on consumer engagement, and (3) a model that also incorporates a 3-way interaction between visual emotional valence, text emotional valence and brand personality to examine how brand personality may moderate the effects of content (in)congruency. Comparing models 1 and 2, the likelihood ratio test is χ^2=38.4 (d.f.=6, p<.01), indicating a statistically significant interaction between text and visual emotional valence. Comparing models 2 and 3, the likelihood ratio test is χ^2=65.7 (d.f.=22,p<.01), indicating a significant 3-way interaction between brand personality, text-based emotional valence and visual emotional valence.

Base Model. From the base model, our results show that positive and negative emotionally valenced text have a positive impact on the number of comments for a firm post. For visual elements, we use the emotional facial expressions (happy, calm, sad and angry) within the image as a measure of the emotional valance for visual content. The significant and positive effect of *FacePos* suggests that happy faces within firm Facebook post are positively associated with total comments. Conversely, the significant negative coefficient estimates for *FaceNeu* and *FaceNeg* show that calm, angry and sad faces within images decrease volume of comments for a firm's post. We also find that exciting brands are associated with greater consumer comments. These results help to understand how the components of firm generated Facebook post individually influence the number of comments it receives.

We find a non-linear relationship between number of faces and volume of comments. The *TotalFaces* covariate is significant and positive while the quadratic term is significant and negative. The size of the face seems to only matter when it is a celebrity face shown by the positive significant parameter estimates for *CelebFaceSize* covariate and lack of significance for the *NonCelebFaceSize* parameter. We find a negative correlation between number of objects and total comments, indicating that the more objects within an image the fewer comments it receives. This could be a result of consumer's attention being disjointed causing the image to stand out less leading to fewer comments. In controlling for color variation that exist within images we find that the level of red channel within an image is positively association with total comments. Given recent literature denoting time of day effect on consumer engagement (Kanuri et al. 2018; Gullo et al. 2018) we control for time of day the brand posted the content to Facebook. We find that compared to firm post at night, firm post in the morning garner more comments while firm post in the afternoon garner significantly less comments. This suggest that firms should consider timing post in the morning in contrast to the afternoon or night. Results show that FGC posted during the week (Mon-Fri) are associated with higher volume of comments. Other content measure such as word count and presence of a URL link are shown to significantly reduce the number of comments a firm's post receives.

Table 7: Result of Covariates on Total Comments

	Equations					
	(1)		(2)		(3)	
	Base Model		Text X Face		Text X Face X Personality	
	Est.	Std. Err.	Est.	Std. Err.	Est.	Std. Err.
PostPos	0.003*	(0.001)	0.003*	(0.002)	0.011	(0.009)
PostNeg	0.019**	(0.003)	0.021**	(0.003)	-0.026	(0.020)
FacePos (Happy Face)	0.024**	(0.004)	0.025**	(0.006)	0.040	(0.064)
FaceNeu (Calm Face)	-0.018*	(0.008)	-0.024	(0.018)	-0.129	(0.167)
FaceNeg (Sad/Angry Face)	-0.013*	(0.005)	-0.003	(0.007)	-0.076	(0.053)
Sincere	0.023	(0.026)	0.024	(0.026)	0.021	(0.026)
Exciting	0.200**	(0.045)	0.200**	(0.045)	0.196**	(0.045)
PostPos x FacePos			0.000	(0.001)	0.010	(0.007)
PostPos x FaceNeu			-0.001	(0.002)	0.014	(0.019)
PostPos x FaceNeg			-0.001*	(0.001)	0.005	(0.005)
PostNeg x FacePos			-0.005**	(0.001)	0.016	(0.014)
PostNeg x FaceNeu			0.003*	(0.001)	-0.019	(0.035)
PostNeg x FaceNeg			-0.000	(0.001)	0.011	(0.009)
PostPos x Sincere					-0.000	(0.001)
PostNeg x Sincere					0.002	(0.002)
PostPos x Exciting					-0.001+	(0.000)
PostNeg x Exciting					0.003**	(0.001)
FacePos x Sincere					-0.000	(0.005)
FaceNeu x Sincere					0.006	(0.014)
FaceNeg x Sincere					0.007	(0.005)
FacePos x Exciting					-0.001	(0.004)
FaceNeu x Exciting					0.006	(0.012)
FaceNeg x Exciting					0.001	(0.004)
PostPos x FacePos x Sincere					-0.000	(0.001)
PostPos x FaceNeu x Sincere					-0.001	(0.002)
PostPos x FaceNeg x Sincere					-0.001*	(0.001)
PostNeg x FacePos x Sincere					-0.002*	(0.001)
PostNeg x FaceNeu x Sincere					0.003	(0.003)
PostNeg x FaceNeg x Sincere					-0.001	(0.001)
PostPos x FacePos x Exciting					-0.001**	(0.000)
PostPos x FaceNeu x Exciting					-0.000	(0.001)
PostPos x FaceNeg x Exciting					0.001*	(0.000)
PostNeg x FacePos x Exciting					-0.000	(0.002)
PostNeg x FaceNeu x Exciting					-0.001	(0.003)
PostNeg x FaceNeg x Exciting					-0.000	(0.000)
TotalFaces	0.050**	(0.008)	0.051**	(0.008)	0.051**	(0.008)
$TotalFaces^2$	-0.001**	(0.000)	-0.001**	(0.000)	-0.001**	(0.000)
NonCelebFaceSize	0.040	(0.238)	0.062	(0.241)	-0.032	(0.254)
CelebFaceSize	0.448*	(0.207)	0.583**	(0.218)	0.602**	(0.224)
TotalObjects	-0.022**	(0.002)	-0.022**	(0.002)	-0.023**	(0.002)
BrandedImage	0.005	(0.033)	0.008	(0.033)	0.007	(0.033)

RedColorChannel	0.003**	(0.001)	0.003**	(0.001)	0.004**	(0.001)
GreenColorChannel	-0.002	(0.001)	-0.002	(0.001)	-0.002	(0.001)
BlueColorChannel	-0.001	(0.001)	-0.000	(0.001)	-0.000	(0.001)
ElapseTimeDay	0.036**	(0.003)	0.035**	(0.003)	0.036**	(0.003)
ElapseTimeDay^2	-0.000**	(0.000)	-0.000**	(0.000)	-0.000**	(0.000)
Morning	0.238**	(0.057)	0.243**	(0.057)	0.244**	(0.057)
Afternoon	-0.095*	(0.041)	-0.092*	(0.041)	-0.094*	(0.041)
Evening	-0.075+	(0.041)	-0.068+	(0.041)	-0.064	(0.041)
Weekend	-0.056*	(0.027)	-0.056*	(0.027)	-0.073**	(0.027)
PostUrl	-0.298**	(0.023)	-0.299**	(0.023)	-0.289**	(0.023)
PostWC	-0.003**	(0.000)	-0.003**	(0.000)	-0.003**	(0.000)
L_PostPos	-0.001	(0.001)	-0.001	(0.001)	-0.001	(0.001)
L_PostNeg	0.004	(0.003)	0.004	(0.003)	0.004	(0.003)
L_cmtemo_postive	-0.005**	(0.001)	-0.005**	(0.001)	-0.005**	(0.001)
L_cmtemo_negative	0.012**	(0.004)	0.012**	(0.004)	0.012**	(0.004)
2010	0.498**	(0.084)	0.496**	(0.084)	0.494**	(0.084)
2011	0.798**	(0.082)	0.796**	(0.082)	0.796**	(0.082)
2012	0.849**	(0.082)	0.849**	(0.082)	0.850**	(0.082)
2013	0.880**	(0.082)	0.881**	(0.082)	0.886**	(0.082)
2014	0.555**	(0.084)	0.554**	(0.084)	0.555**	(0.084)
2015	0.784**	(0.085)	0.781**	(0.085)	0.750**	(0.085)
2016	0.358**	(0.084)	0.350**	(0.084)	0.353**	(0.084)
2017	0.276**	(0.083)	0.275**	(0.083)	0.277**	(0.083)
2018	0.143+	(0.082)	0.142+	(0.082)	0.145+	(0.082)
Chanel	3.258**	(0.384)	3.254**	(0.384)	3.253**	(0.384)
Coach	2.252**	(0.444)	2.250**	(0.444)	2.239**	(0.443)
Colgate	1.153**	(0.348)	1.148**	(0.348)	1.145**	(0.348)
Covergirl	1.930**	(0.318)	1.926**	(0.317)	1.930**	(0.317)
Crest	0.191	(0.337)	0.185	(0.337)	0.190	(0.336)
Estee Lauder	1.674**	(0.412)	1.671**	(0.412)	1.658**	(0.411)
Gain	1.796**	(0.323)	1.796**	(0.322)	1.797**	(0.322)
Gucci	1.796**	(0.430)	1.793**	(0.429)	1.797**	(0.429)
Loreal	-0.729**	(0.241)	-0.726**	(0.240)	-0.736**	(0.241)
Louis Vuitton	1.968**	(0.295)	1.964**	(0.294)	1.964**	(0.294)
Maybelline	1.838**	(0.354)	1.828**	(0.354)	1.821**	(0.353)
New Balance	-1.558**	(0.148)	-1.558**	(0.148)	-1.529**	(0.148)
Nike	1.001**	(0.111)	1.002**	(0.111)	1.063**	(0.112)
Tide	2.586**	(0.375)	2.583**	(0.374)	2.594**	(0.374)
_cons	0.784	(0.583)	0.773	(0.582)	0.809	(0.586)
lnalpha	0.764**	(0.008)	0.763**	(0.008)	0.761**	(0.008)
N	23589		23589		23589	
Parameters	55.000		61.000		83.000	
Log Likelihood	-118808.750		-118789.533		-118756.687	

**,*,+ denotes p<0.01, 0.05, 0.10 respectively. The baseline time of day is night, the baseline year is 2009, the baseline time of day is Weekdays (Mon-Fri), the baseline brand is Adidas.

Text and Imagery Interaction Effects. Model 2 incorporates the interaction between content elements, enabling us to draw inferences about the effects of a match vs. mismatch in textual and visual elements on consumer engagement. Consistent with the base model, we find that the main effects of positive and negatively valenced text is still positive and significant on volume of comments. For the visual content measures, we see that only positive (happy) faces remain significant and positive; we no longer find significant main effects for neutral (calm) or negative (angry/sad) emotionally valenced faces as the variation is now explained by interaction terms.

In examining the interaction terms, we find that positively valenced text paired with negatively valenced images decrease the total number of comments FGC receives. Similarly, negatively emotionally valence text paired with positively valenced visual stimuli is also negatively associated with total number of comments FGC receives. Taken together, our results support H1b, indicating that a mismatch between the text and visual elements of the brand's post decreases consumer engagement. Effectively, model 2 shows that angry and sad faces significantly lower consumer comments when paired with text that has positive emotional valence. Similarly, happy faces significantly decrease consumer comments when paired with negatively valenced text.

The interaction between negative valence text and neutral visual imagery is positive and significant suggesting that moderate incongruency between text and visual imagery is associated with greater consumer comments. Thus, we find support for H1c. This finding is consistent with prior literature that showed moderate incongruency could lead to favorable consumer responses. We do not find evidence to support H1a, that a complete match between emotional valence of text and visual content significantly influences consumer engagement. It could be that consumers expect text and images to match and when matching occurs in a social media context it doesn't elicit consumer action.

We find qualitatively similar results among control variables in the text and imagery interaction model as we did in the base model.

Text, Imagery and Brand Personality Interaction Effects. Model 3 allows us to test H3a and H3b by examining the interaction between content elements (visual and text) and brand personality measures. The 3-way interaction provides insights into how consumers' responses to (in)congruency between content elements may differ for certain brand personality types. In examining the model fit using log likelihood we find that Model 3 has better fit compared to Model 2 (χ^2=65.7,d.f.=22,p<.01), indicating that the inclusion of the 3-way interactions better fits the data.

Results from Table 7 show no significant main effects of emotional valence of text nor visual elements as the variation is now captured with interaction terms. Across all three models, we find a significant and positive effect for exciting brands on total number of comments for FGC. In examining the interactions with sincere brands, we find that content mismatch has a significant negative effect on total comments for FGC as evident by the negative parameter estimate for *PostPos x FaceNeg x Sincere* and *PostNeg x FacePos x Sincere* interaction terms. When positive emotionally valenced text is paired with negative valenced visual elements (e.g. angry/sad faces) we show a significant decrease in the number of comments for a sincere brand. Similarly, when negatively valenced text is paired with positive valenced visual elements (e.g. happy faces) we also find a significant decrease in volume of comments. These results suggest that consumers respond less favorable (e.g. fewer comments) to incongruences in FGC posted by sincere brands, supporting H2a.

In exploring the interactions with exciting brands (*PostPos x FaceNeg x Exciting*), we find that a mismatch between emotional valence of text and visual content has a significant positive impact on total comments. Specifically, results show that while positive valenced text paired with negative valenced imagery (angry/sad faces) decreases comments for sincere brands there is a significant and positive effect for exciting brands. Interestingly, we find that a complete match (*PostPos x FacePos x Exciting*) between emotional valence of text and visual content leads to a reduction in total comments for exciting brands. These findings suggest that consumers may respond more favorably to incongruences in FGC by exciting brands and may even expect a certain degree of incongruence from exciting brands. We find support for H2b.

In Model 3, we do not find evidence of a positive impact of moderate (in)congruence in visual and text content for either sincere or exciting brands. This may be a natural result of consumers more readily recognizing when FGC is either consistent or inconsistent with the brand personality. Among other control variables in the model, we find consistent results in the brand personality interaction model as we did in the base model.

Summary. The results from Models 1-3 suggest that imagery and text jointly affect the volume of consumer engagement with FGC. Our results reveal that both positive and negative emotionally valenced text content increases the volume of consumer engagement. Among visual elements, we find that happy faces increase consumer engagement while calm, sad, and angry faces reduce consumer engagement. When negatively valenced text is paired with positively valenced visual content (e.g. a happy face), FGC experiences a significant decrease in the number of comments. Similarly, positively valence text paired with negatively valence visual content (angry/sad faces), can also reduce the number of comments FGC receives. Our results show that brand personality moderates this negative effect. Our findings indicate that sincere brands experience lower consumer engagement with content incongruence however, this negative effect is reversed for exciting brands, such that total comments increase with incongruence between text and visual content.

Net Emotional Valence of Comments

Next, we examine the influence of text and visual content on emotionality expressed within consumer comments. Table 8 details the results of Models 1 – 3. A positive parameter estimate can be interpreted as an increase in positively valenced emotional consumer responses while a negative parameter estimate can be interpreted as a decrease in positive emotionally valenced consumer responses (e.g. an increase in negatively valenced consumer responses). As was the case for the volume of comments, in comparing Models 1 and 2, we see that the incorporation of the 2-way interaction between text and visual emotional valence improves model fit (χ^2=26.0, d.f.=6, p<.01). We also find that the addition of the 3-way interaction between text, visual and brand personality in Model 3, compared to Model 2 which omits the 3-way interaction, also improves model fit (χ^2=59.1, d.f.=22, p<.01).

The particular covariates of interest are the 3-way interaction terms between text, visual and brand personality, as they allow us to test H3a and H3b. Our results suggest that a match between emotional valence of text and visual elements is associated with an increase in net emotional valence for sincere brands as evidenced by the *PostPos x FacePos x Sincere* covariate. Coupled with the findings regarding the volume of comments, our results suggest that positively valenced text paired with happy faces may not increase the number of comments a post receives but it does increase the amount of emotionally positive language within the content of consumer comments for sincere brands. Additionally, we find a marginally significant (p<0.1) positive effect of *PostNeg x FaceNeg x Sincere* on the net emotional valence of consumer responses. These results support H3a suggesting that on average, consumers may respond favorably when text and visual content from sincere brands are congruent. In looking at the interaction *PostNeg x FaceNeu x Sincere*, we see that the moderate mismatch between emotional valence of text and images is associated with an increase in the net emotional valence of responses from consumers for sincere brands. This is consistent with the sincere brand personality and the notion that consumers may respond for favorably to consistency from sincere brands and less favorably to inconsistency.

For exciting brands, we find one notable significant interaction, *PostNeg x FacePos x Exciting*, which is associated with an increase in the net emotional valence of consumer comments. Thus, we find support for H3b, revealing that content mismatch for exciting brands is associated with more positive emotional comments. This is consistent with our prior results that show incongruence from exciting brands is associated with greater number of comments. Taken together, the results from net emotionality and total comments suggest that for exciting brand, a mismatch between emotional valence of text and images can lead to greater total comments and greater positively valenced consumer responses.

Other covariates such as textual branded image, positively valenced text, total objects and positive emotionality of comments from the firm’s prior post are also associated with increase in positively valenced emotionality of consumer responses. This suggest that while textual branded image do not increase total number of comments, the presence of the brand name/logo does help to foster positive consumer responses.

Table 8: Result of Covariates Impact on Net Emotional Sentiment of Consumer Comments

	Equations					
	(1) Base Model		(2) Text X Face		(3) Text X Face X Personality	
	Est.	Std. Err.	Est.	Std. Err.	Est.	Std. Err.
PostPos	0.111**	(0.008)	0.112**	(0.009)	0.373**	(0.055)
PostNeg	-0.070**	(0.016)	-0.065**	(0.016)	-0.042	(0.113)
FacePos (Happy Face)	0.017	(0.023)	-0.008	(0.033)	0.384	(0.244)
FaceNeu (Calm Face)	-0.146*	(0.059)	0.120	(0.100)	-1.094	(0.835)
FaceNeg (Sad/Angry Face)	-0.002	(0.030)	-0.023	(0.038)	-0.074	(0.277)
Sincere	-0.067	(0.150)	-0.062	(0.150)	0.016	(0.152)
Exciting	0.244	(0.233)	0.238	(0.233)	0.306	(0.233)
PostPos x FacePos			0.002	(0.002)	-0.059*	(0.023)
PostPos x FaceNeu			-0.010	(0.009)	-0.053	(0.074)
PostPos x FaceNeg			0.000	(0.003)	0.014	(0.025)
PostNeg x FacePos			0.004	(0.006)	-0.102+	(0.060)
PostNeg x FaceNeu			-0.053**	(0.011)	0.430**	(0.161)
PostNeg x FaceNeg			0.009*	(0.004)	-0.036	(0.034)
PostPos x Sincere					-0.021**	(0.005)
PostNeg x Sincere					-0.002	(0.010)
PostPos x Exciting					-0.006**	(0.002)
PostNeg x Exciting					-0.001	(0.005)
FacePos x Sincere					-0.032	(0.020)
FaceNeu x Sincere					0.135+	(0.074)
FaceNeg x Sincere					0.002	(0.026)
FacePos x Exciting					-0.006	(0.020)
FaceNeu x Exciting					-0.032	(0.051)
FaceNeg x Exciting					0.007	(0.018)
PostPos x FacePos x Sincere					0.006**	(0.002)
PostPos x FaceNeu x Sincere					0.001	(0.007)
PostPos x FaceNeg x Sincere					-0.001	(0.003)
PostNeg x FacePos x Sincere					0.003	(0.004)
PostNeg x FaceNeu x Sincere					-0.036*	(0.014)
PostNeg x FaceNeg x Sincere					0.006+	(0.003)
PostPos x FacePos x Exciting					-0.001	(0.002)
PostPos x FaceNeu x Exciting					0.006	(0.005)
PostPos x FaceNeg x Exciting					-0.000	(0.001)
PostNeg x FacePos x Exciting					0.011*	(0.006)
PostNeg x FaceNeu x Exciting					-0.015	(0.011)
PostNeg x FaceNeg x Exciting					-0.003	(0.002)
TotalFaces	-0.091+	(0.047)	-0.101*	(0.047)	-0.118*	(0.047)
$TotalFaces^2$	0.001	(0.001)	0.001	(0.001)	0.001	(0.001)
NonCelebFaceSize	0.740	(1.344)	0.201	(1.354)	0.257	(1.366)
CelebFaceSize	1.132	(1.175)	0.677	(1.179)	0.815	(1.186)
TotalObjects	0.049**	(0.011)	0.049**	(0.011)	0.049**	(0.011)
BrandedImage	0.456*	(0.191)	0.453*	(0.191)	0.440*	(0.191)
RedColorChannel	0.007	(0.004)	0.007	(0.004)	0.006	(0.004)
GreenColorChannel	0.005	(0.007)	0.005	(0.007)	0.005	(0.007)
BlueColorChannel	-0.009	(0.006)	-0.009	(0.006)	-0.008	(0.006)
ElapseTimeDay	-0.008	(0.012)	-0.008	(0.012)	-0.009	(0.012)

ElapseTimeDay^2	-0.000	(0.000)	-0.000	(0.000)	-0.000	(0.000)
Morning	0.392	(0.315)	0.391	(0.315)	0.368	(0.314)
Afternoon	0.014	(0.233)	0.009	(0.233)	-0.007	(0.233)
Evening	0.257	(0.238)	0.249	(0.238)	0.243	(0.238)
Weekend	0.078	(0.151)	0.075	(0.151)	0.075	(0.151)
PostUrl	0.148	(0.129)	0.147	(0.129)	0.157	(0.129)
PostWC	-0.004*	(0.002)	-0.004*	(0.002)	-0.004*	(0.002)
L_PostPos	-0.009	(0.008)	-0.009	(0.008)	-0.006	(0.008)
L_PostNeg	0.010	(0.016)	0.010	(0.016)	0.009	(0.016)
L_cmtemo_postive	0.063**	(0.007)	0.062**	(0.007)	0.063**	(0.007)
L_cmtemo_negative	0.008	(0.018)	0.008	(0.018)	0.005	(0.018)
2010	0.198	(0.487)	0.211	(0.487)	0.176	(0.487)
2011	-0.064	(0.473)	-0.050	(0.472)	-0.109	(0.472)
2012	-0.388	(0.477)	-0.366	(0.477)	-0.380	(0.477)
2013	-0.070	(0.478)	-0.059	(0.478)	-0.078	(0.477)
2014	-1.056*	(0.488)	-1.041*	(0.487)	-1.076*	(0.487)
2015	-1.310**	(0.488)	-1.290**	(0.488)	-1.310**	(0.488)
2016	-2.972**	(0.483)	-2.961**	(0.483)	-3.013**	(0.482)
2017	-4.574**	(0.477)	-4.561**	(0.477)	-4.595**	(0.477)
2018	-5.825**	(0.475)	-5.812**	(0.474)	-5.864**	(0.474)
Chanel	8.538**	(2.023)	8.479**	(2.022)	8.779**	(2.023)
Coach	8.578**	(2.278)	8.525**	(2.278)	8.905**	(2.277)
Colgate	3.969*	(1.789)	3.936*	(1.788)	4.137*	(1.788)
Covergirl	5.578**	(1.620)	5.534**	(1.619)	5.735**	(1.619)
Crest	3.130+	(1.742)	3.100+	(1.741)	3.285+	(1.741)
Estee Lauder	7.351**	(2.082)	7.299**	(2.081)	7.476**	(2.080)
Gain	7.196**	(1.632)	7.162**	(1.632)	7.284**	(1.631)
Gucci	7.192**	(2.228)	7.129**	(2.228)	7.525**	(2.228)
Loreal	5.391**	(1.206)	5.373**	(1.206)	5.472**	(1.210)
Louis Vuitton	7.159**	(1.598)	7.113**	(1.598)	7.331**	(1.597)
Maybelline	5.960**	(1.805)	5.899**	(1.805)	6.130**	(1.805)
New Balance	0.848	(0.791)	0.863	(0.791)	0.796	(0.792)
Nike	0.008	(0.620)	-0.019	(0.620)	-0.012	(0.621)
Tide	3.443+	(1.894)	3.394+	(1.894)	3.672+	(1.893)
_cons	0.351	(2.892)	0.369	(2.891)	-1.163	(2.915)
N	23589		23589		23589	
Log Likelihood	-84209.052		-84196.077		-84166.537	

**,*,+ denotes p<0.01, 0.05, 0.10 respectively. The baseline time of day is night, the baseline year is 2009, the baseline time of day is Weekdays (Mon-Fri), the baseline brand is Adidas.

Discussion

FGC on social media platforms use a combination of textual and visual content. Much extant empirical research focuses more on the text of online WOM and less on the visual components. This study examines the individual and combined effects of textual and visual elements of firm generated content on consumer engagement. We leverage machine learning via an image processing API to capture emotions using facial recognition software. Using the emotions from facial expressions, we construct a measure of emotional valence of images. We employ text analysis to construct a measure of emotional valence of the textual component within firm generated content. By measuring the emotional valence of both text and visual elements, we show that the extent to which the two elements are (in)congruent can influence the number of comments a social media post receives and the emotional valence of consumer comments. Our method can be replicated by researchers and marketers with relative ease to assist with understanding how pictorial elements influence consumer responses in online WOM.

This research adds to the nascent social media research that incorporates image analysis. Given the proliferation of social media platforms such as Instagram, Pinterest and Snapchat which are dominated with images, this is an area of potential for firms and marketers. To the best of our knowledge, this research is among the first to examine the influence of both text and visual content (specifically faces) within a social media context. Additionally, we offer an approach for measuring the emotional valence within images utilizing facial recognition tools. Given the burgeoning literature related to consumers' emotional responses to brands and the influence of emotionality on social media engagement, images offer another dimension on which brands can convey emotionality.

Our results offer content marketing insights for digital marketers. Contrary to what conventional practitioners may believe, adding images to social media posts can potentially reduce consumer engagement in cases where there is a complete mismatch between the text and visual content. For example, our results suggest that pairing positively valenced text with negatively valenced visual content (angry/sad faces) can lead to a decrease in number of comments while a moderate mismatch leads to increases in number of comments. For marketers focused on increasing consumer engagement our findings provide concrete insights into how to craft digital media content and informs content marketing strategies.

Our research suggests that the decision to match or mismatch should be informed by brand attributes and that brand personality can influence how consumers respond to FGC. There is no “one size fits all” approach to social media marketing strategy; what works for one brand may not work for another brand, and marketers should be cognizant of this when implementing digital media strategies. We find that for sincere brands, consumer engagement is negatively associated with a mismatch between textual and visual content components, but exciting brands experience a significant increase in user comments when the text and visual content is mismatched. We also show that consumers’ net emotional response to FGC from sincere brands is significantly more positive when there is a match between text and visual content and significantly more negative when there is a content mismatch. For exciting brands, consumers’ net emotional responses are more positive when there is a mismatch between text and visual elements.

Our research is not without limitations. As image analysis is a developing stream of literature there are numerous ways to measure various elements within images, we offer one approach, but others can work to develop alternative approaches. With innovations in machine learning and deep learning there are other approaches that currently exist, and new tools being built that may offer additional methods to analyze image content. While we measure emotions based on facial expressions, one direction to pursue would be to leverage the combination of text and images to infer the emotions associated with other objects in images. Another avenue for future researchers to consider is the extent to which color variation may arouse emotions.

Similarly, there may be other ways to measure color variation that deviates from how it is operationalized within this analysis.

Our research employs Facebook posts from a limited number of product categories. Future research may investigate if our findings generalize to other product categories and across other social media platforms such as Instagram and Twitter. While we determine emotional facial expressions using happy, sad, angry and calm, researchers may also explore identifying other emotions and the degree of arousal in an image. While we make use of field data to investigate the impact of content (in)congruence in FGC on online consumer engagement, future research in a laboratory setting may allow one to identify the boundary conditions of our findings. While we investigate how content characteristics drive consumer engagement, future studies should also seek to move beyond understanding drivers of online WOM to identify how content affects metrics such as website traffic and sales (e.g., Akpinar and Berger 2017; Fossen and Schweidel 2019).

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