AMERICAN MARKETING ASSOCIATION

Article

Journal of Marketing Research
2020, Vol. 57(1) 1-19

DOI: 10.1177/0022243719881113
journals.sagepub.com/home/mrj
SAGE

Is a Picture Worth a Thousand Words? An Empirical Study of Image Content and Social Media Engagement

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Abstract

Are social media posts with pictures more popular than those without? Why do pictures with certain characteristics induce higher engagement than some other pictures? Using data sets of social media posts about major airlines and sport utility vehicle brands collected from Twitter and Instagram, the authors empirically examine the influence of image content on social media engagement. After accounting for selection bias on the inclusion of image content, the authors find a significant and robust positive mere presence effect of image content on user engagement in both product categories on Twitter. They also find that high-quality and professionally shot pictures consistently lead to higher engagement on both platforms for both product categories. However, the effect of colorfulness varies by product category, while the presence of human face and image–text fit can induce higher user engagement on Twitter but not on Instagram. These findings shed light on how to improve social media engagement using image content.

Keywords

image processing, natural language processing, social media analytics, user-generated content, visual marketing

Online supplement: https://doi.org/10.1177/0022243719881113

The past few years have witnessed a shift in social media platforms from text-centric to visual-oriented experience. The trend toward visual social media is partially driven by the changing habits of social media users, thanks to the popularization of smartphones and improved mobile internet experience. As people engage with social media through apps on their smartphones, they quickly learn that taking a picture "on the go" using a high-resolution phone camera is much easier than typing a status update on a tiny keyboard. According to Meeker (2016), social network users shared an average of 3.2 billion digital images each day in 2015 on Snapchat, Facebook, Instagram, and WhatsApp combined. It is no coincidence that Instagram and Pinterest, two image-centric social media apps, have quickly risen to become the second- and fourth-largest social networks in the United States by user penetration (eMarketer 2018). The old idiom "A picture is worth a thousand words" has become the new maxim among social media marketers.

While many studies have examined the determinants that drive virality or effectiveness in the context of user-generated content (UGC), the vast majority of these studies focus on text content (e.g., Chevalier and Mayzlin 2006; Chintagunta, Gopinath, and Venkataraman 2010; Tan, Lee, and Pang 2014), leaving the role of image content a largely unexplored question. Is it true that including pictures in a post always leads to higher user engagement on social media platforms such as Facebook and Twitter, as some industry studies seem to suggest (eMarketer 2011; Vavrek 2012)? More importantly, do pictures with certain image characteristics induce more interaction and propagation than other pictures? And if so, what are these characteristics? Answers to these questions will help marketing practitioners and researchers better understand user engagement in the current visual-oriented social media sphere.

In this study, we aim to answer these questions by quantifying the impact of image content on social media engagement.[1] Drawing from the extant literature on visual marketing, we propose three effects of image content:

[1] We use "image content," "image," and "picture" interchangeably in this article.

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1. "Mere presence effect" (for general social media platforms where both text-only and text-and-image posts coexist): The image content in a social media post helps the post stand out from the media clutter when the majority of online content is text-based. Furthermore, some social platforms allow users to share a hyperlink to a picture posted on other social platforms. We specifically distinguish these linked pictures from the immediately viewable pictures in our analysis to capture the benefit of exhibiting image content directly in a post.
2. "Image characteristics effect": The image content in a social media post may provide informational, aesthetic, or self-enhancement value independent of the text content and therefore may increase the total appeal of the post. However, an image with uninteresting content or low quality may backfire and lead to lower user engagement. In this study, we identify four image characteristics—colorfulness, the presence of human face and emotional state, image source, and image quality—and evaluate their effects on social media user engagement.
3. "Image–text fit effect": Both imagery and text content in a social media post are employed by the author to express a particular viewpoint. Research has shown that irrelevant pictures in print ads create extra difficulty for readers to comprehend the main message and thus lead to worse ad recall and less favorable attitudes toward the ad (Heckler and Childers 1992; Lee and Mason 1999). We contemplate that a similar image–text fit effect may also be present in the context of social media.

To empirically examine the proposed effects of image content, we collect data on social media posts related to different product categories from two leading social networking platforms. Among the three data sets used in our research, two are collected from Twitter, a microblogging social media platform for sharing short news and status updates. The first data set includes 18,790 tweets mentioning at least one of the nine major U.S. airlines posted in September 2015. The second data set consists of 14,959 tweets mentioning at least one of the ten major compact sport utility vehicle (SUV) models posted in the same month. Both data sets contain rich information about the text content, image content (if any), posting time, and account characteristics for each tweet. We follow the standard industry practice to measure the engagement level of each tweet using the number of likes and retweets. Our third data set is collected from Instagram, an image-heavy social media platform. It includes a random sample of 2,044 Instagram photos posted between January 16 and February 15 in 2018, concerning the same nine airlines in our airline tweets data set. This data set contains the same set of information about the content (image and text) and user account for each Instagram post, except that the user engagement level is measured using the number of likes because sharing is not readily available on Instagram.

One of the biggest challenges in analyzing online UGC, well documented in previous literature (Netzer et al. 2012), is to convert the overwhelming quantity of unstructured data into quantifiable measures. Thanks to the advancement in automated text-mining techniques, several recent studies have utilized the information contained in text data beyond simple volume to derive useful insights from UGC (for two reviews of relevant studies, see Pang and Lee [2008] and Purnawirawan et al. [2015]). Following this literature, we apply supervised learning algorithms to code the text content in social media posts. However, the emergence of the visual web has presented us with new challenges in mining image data. In this study, we employ Google Cloud Vision API (application program interface), which encapsulates powerful deep learning models, together with manual coding, to extract information from image data.

We develop a bivariate zero-inflated negative binomial (BVZINB) model to examine how image content affects the number of likes and retweets for the two Twitter data sets. The zero-inflation component in the proposed model is intended to handle the presence of excess zeros in the number of likes and retweets in our two Twitter data sets. The inclusion of image content in a tweet can be a deliberate decision by the poster, which may depend on factors that also influence user engagement with the post. To alleviate the endogeneity concern, we rely on the propensity score matching method to create a pseudo "treatment" group and a "control" group that are matched 1:1 on the basis of post and account characteristics, and we use the matched sample for our model estimation. For the analysis of the Instagram data set, because the number of likes is the sole engagement measure and all posts in our Instagram data set received at least one like, we use a log-linear regression to quantify the "image characteristics" and "image–text fit" effects.

Our findings lend support for all three proposed effects of image content on social media engagement. First, we find a significant and robust positive mere presence effect on both types of user engagement for both product categories on Twitter. The inclusion of an immediately viewable image in a tweet increases the number of retweets by 119.15% and the number of likes by 87.26% for tweets related to air traveling. For tweets related to SUVs, the size of the mere presence effect is +213.12% on the number of retweets and +151.56% on the number of likes. However, our analysis of the airline tweets also reveals that "linked" pictures have an adverse effect: tweets with picture hyperlinks receive 78.18% fewer retweets and 66.2% fewer likes than tweets without any pictures. Second, we find that high-quality and professionally shot pictures consistently lead to higher engagement for both categories on both platforms. We also find that pictures with human faces tend to attract more attention and induce higher user engagement on Twitter but not on Instagram. Picture colorfulness affects user engagement on both platforms. However, its effect heavily depends on product categories: colorful pictures lead to higher engagement for air-travel-related social media posts, but less colorful pictures tend to induce more sharing for SUV-related posts. Finally, our analysis reveals that the fit between image and text content in a social media post increases liking for airline-related posts on Twitter but not on Instagram.

First, our research contributes to the rapidly growing literature on social media content effectiveness. Given the rapid rise of visual social media, it is timely that we expand the current knowledge on social media content effectiveness by exploring how image content affects social media engagement. Our results highlight the similarities and differences in the effects of image content on social media engagement across product categories and social media platforms. Therefore, our article offers essential managerial implications to social media content creators aiming to enhance their content effectiveness as well as companies trying to improve the efficiency of their brand-related social media listening efforts. These insights are especially useful for companies and industries in which customers increasingly voice their concerns and seek service interventions through social media, such as the airline industry. Better identification of potentially influential posts allows these companies to take action before the harmful social buzz becomes viral.

Second, our research also adds to the literature on visual marketing. Extant research has primarily focused on the impact of visual elements on advertising effectiveness. With the spread of smartphones and ubiquitous access to the internet, image content in social media is increasingly created by ordinary users rather than professionals. Content effectiveness metrics in social media are also broadened to include many prepurchase engagement measures in addition to sales. Our research extends the literature on visual marketing from the traditional "paid media" channels to the emerging "earned media" arena. Our findings regarding the mere presence effect and the image characteristics effect are generally in line with previous literature. Our analysis also reveals a significant and positive image–text fit effect on engagement for airline-related posts on Twitter, but not on Instagram. This finding highlights the importance of considering the platform-specific context when evaluating the effectiveness of images on social media.

Background

In this section, we review related literature and discuss how our study builds on and extends the extant literature. We then propose a modeling framework for the determinants of social media post engagement.

User Engagement on Social Media

To understand what drives user engagement on social media, we should first decide how to measure social media engagement. We follow the industry practice of categorizing measures of social media engagement into two broad types. The first type is direct responses to original posts, including likes, comments, and favorites. In this research, we focus on liking, a commonly adopted metric, which enables readers to show enjoyment, appreciation, or endorsement of the content without leaving a comment. For example, Twitter, Facebook, and Instagram have a "like" button, Google+ had "+1," and many blogs have "vote up" or similar measures. The second type concerns sharing or propagation of original posts, which allows the audience to recommend content to their followers. Examples include retweet for Twitter, shares on Facebook and Google+, and repins on Pinterest. Although both types of metrics reflect deeper engagement with social media content than viewing, drivers of liking and sharing behavior can be different as a result of the varying visibility and (un)directed nature of these two actions (Buechel and Berger 2018). Sharing is more socially visible and undirected because the shared content is pushed to all followers of the sharer without addressing anyone in particular. In contrast, liking is more private and directed because it gives a direct affirmation to the posted content but does not propagate the content. Therefore, we treat sharing and liking as correlated yet distinct measures and model them separately.

A large body of research on word of mouth (WOM) suggests that user engagement online can be affected by various factors. Berger (2014) provides a thorough review of the extant research about behavioral drivers of online WOM. Two salient ones are the tendency to self-enhance and the urge to provide useful information. People want to shape how others perceive them through what they say and share online (Chung and Darke 2006); they are also more likely to share useful information to appear smart and helpful (Berger and Milkman 2012). What people say and how they say it also affect user engagement on social media. Peters et al. (2013) propose that content characteristics (e.g., interactivity, vividness, usefulness), content domain (e.g., topic, public vs. personal), and content sentiment (i.e., positive, negative, or neutral) are important text content factors to consider. Berger and Milkman (2012) show that news articles that are higher in emotional intensity and arousal are more likely to go viral. Moore and McFerran (2017) find that the use of emotional, social, cognitive, and descriptive words affect consumer engagement in online WOM. Finally, informative content is shared more than other types of content. Tan, Lee, and Pang (2014) find that the informativeness of the tweet (measured by the number of words, hashtags, and mentions contained in a tweet) performs the best in predicting the popularity of social media content among various lexicon features.

Building on these aforementioned studies, in the current study we consider the influence of the following text content features on social media engagement: (1) two behavioral drivers of sharing as reflected by text content (for self-enhancement and to provide useful information); (2) text sentiment; (3) text topic; (4) linguistic features related to six psychological constructs: affect, social, cognitive, perceptual, biological, and drive; and (5) text informativeness.

Prior research has also suggested that product characteristics and situational factors (e.g., venue format) may moderate the influence of various drivers of customer engagement online. For example, consumers are more likely to engage with content about symbolic products than utilitarian ones to signal identity (Chung and Darke 2006). They are also more likely to express their opinions or complaints online when product quality deteriorates in a concentrated market (Gans, Goldfarb, and Lederman 2017). Moreover, the brand sentiment expressed in social media posts varies significantly with different venue formats (Schweidel and Moe 2014).

To explore the variability of the image content effects in different contexts, we collect data on social media posts related to two product categories, air travel and compact SUVs, from Twitter and Instagram separately. Although both product categories are of high social exposure and are often discussed on social media platforms, air travel is traditionally categorized as an experiential product, whereas a compact SUV is considered by many as primarily a utilitarian product. The difference in major type of benefit provided by these two product categories may induce heterogeneous effects of image content on social media engagement.

Our focal platforms, Twitter and Instagram, are among the leading social networking sites in the United States (Statista 2019). Twitter was originally designed to be a short-message-service (SMS)-based communication platform for sharing short news and status updates. It allows for text-only posts and links to external web pages and had a 140-character limit until November 2017 (when it increased the limit to 280 characters), although users can also post pictures, videos, or GIFs. In contrast, Instagram entirely focuses on media content, especially photos, although users can add a caption to explain and contextualize the subject of the image they post. Moreover, Instagram is famous for its overall high engagement level thanks to its visual nature, user stickiness, and better control over spam, while Twitter has been criticized for its noisiness (Robles 2016). Because of these distinctive features, we speculate that users might have different criteria when deciding what content to engage with on these two platforms.

Consumer Response to Images in Social Media Posts

Social media users are subject to information overload. A post needs to stand out from many others to gain attention from readers before any engagement takes place. This is similar to the challenge faced by banner or print ads, which also need to compete for consumers' attention before any action further down the purchase funnel occurs. In this subsection, we briefly review the literature on visual advertising research and discuss how image content may affect social media engagement.

According to the extant visual advertising literature, imagery components in advertising design can affect cognitive (e.g., attention, attitude, preference) and behavioral (e.g., clicks, purchase intention, sales) outcomes in three ways. First, the mere presence of an image matters. Using eye-tracking methodology, Pieters and Wedel (2004) find that the image component in print ads can capture a superior baseline attention of magazine readers regardless of its size. Various studies on banner ads have also shown that obtrusive ads are more effective because they grab a viewer's attention in the first place (Bruce, Murthi, and Rao 2017; Goldfarb and Tucker 2011). In line with these findings, we expect that the mere presence of an image in a social media post helps the post stand out from the majority of text-only posts and, as a result, attracts more attention. Beyond attention, image content may also affect engagement directly by enhancing the perceived quality of a post in a microblogging social media platform such as Twitter. Because most of the tweets consist of text content only, readers may appreciate tweets with pictures more because of the extra effort put in by the posters when composing such tweets. As a result, readers may be more likely to engage with these posts.

Second, extant literature has shown that images affect attention, attitude, affect, or purchase intention through various image characteristics beyond the mere presence effect. Research has found that colorfulness consistently enhances a viewer's attention for ads (Finn 1988) and helps a viewer understand the meaning of an ad during brief and blurred exposures (Wedel and Pieters 2015). Human images contained in print ads also increase the effectiveness of ads and website design (Cyr et al. 2009; Xiao and Ding 2014). High-level image content and style, such as image quality and the presence of visual art, has also been shown to affect viewers' evaluation of products and product sales (Hagtvedt and Patrick 2008; Zhang et al. 2017). Following these studies, we consider picture colorfulness, the presence of human face and facial expressions, and picture quality as image characteristics that may affect social media engagement in our analysis. In addition, unlike in print ads, where the images are mainly taken and processed by professionals, the images featured in a social media post are more likely to come from other sources, such as a photo shot by the poster herself (who is most likely an amateur photographer) or a screenshot.[2] In the current study, we differentiate these three sources of image content in a social media post and consider their relative impacts on user engagement with the post.

Finally, because advertisements are usually composed of both visual and text elements, research has found that the relationship between these two components has an impact on advertising effectiveness (e.g., Heckler and Childers 1992; Houston, Childers, and Heckler 1987; Lee and Mason 1999). Following Heckler and Childers (1992), we focus on image–text fit (or relevancy), which reflects whether the information contained in the picture contributes to or detracts from the clear identification of the verbal information. Heckler and Childers show that irrelevant visual stimulus creates difficulty for the reader to make sense of the ad information and therefore may lead to frustration rather than resolution. Lee and Mason (1999) also find that ads with irrelevant information yielded less favorable attitudes than did ads with relevant information. In the current article, we are interested in determining whether and how the fit between the image content and the text content in a social media post affects user engagement.

Modeling Framework

In addition to the text and image content, user engagement with a social media post is also influenced by account characteristics and posting time. We consider all these factors in our model. We present our modeling framework for the determinants of social media post engagement in Figure 1.

[2] A screenshot is operationalized as an image whose top-three color pixel percentage is greater than 50%, and at least one of the following labels is detected using Google Cloud Vision API: text, font, document, web page, banner, and advertising.

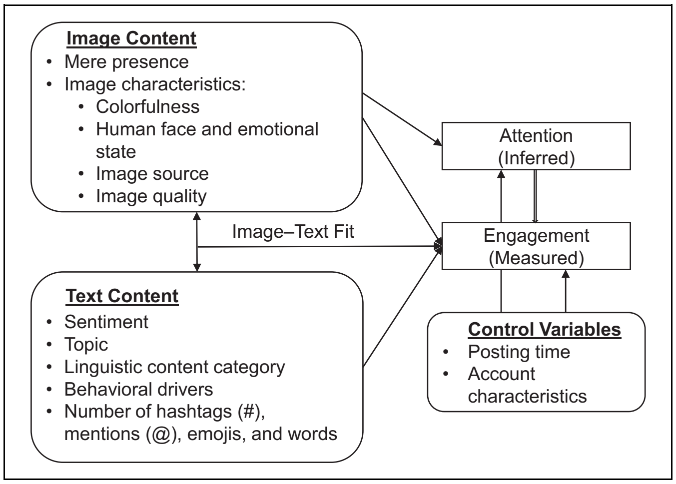

Figure 1. Modeling framework.

Data Description

For our empirical investigation, we first obtain a data set of brand-related Twitter posts in the airline category from a social media consultancy. This data set includes all original tweets (not retweeted tweets) posted in September 2015 if at least one keyword related to the following nine airlines is mentioned in the tweet: American Airlines, JetBlue Airways, Frontier Airlines, Southwest Airlines, Virgin America, Delta Airlines, United Airlines, Alaska Airlines, and Spirit Airlines.[3] As one of the largest sectors in the service industry, the airline industry is an ideal setting for this study because many customers use social networking websites as their primary channel to share experiences, seek information, and complain about air travel directly (Gans, Goldfarb, and Lederman 2017). All nine airlines in our analysis have official Twitter accounts that post content regularly.

We eliminated 59,755 tweets that include hyperlinks to other web pages (except for hyperlinks to photos) because the engagement received by these tweets is likely to be affected by the content quality of the original web pages. Our final sample contains 18,790 original airline-related tweets. We then collected the number of likes and retweets received by each tweet in our sample in September 2017 (i.e., two years after the tweets were posted) to ensure that we captured any potential engagement with these tweets (Rey 2014).

We present summary statistics of our airline tweets sample in the "Before Matching" column of Table 1, Panels A and B. The average number of likes and retweets per tweet is 2.51 (SD = 45.65) and 1.36 (SD = 19.99), respectively. The distributions of both likes and retweets are left-skewed with 70.09% of the tweets in our sample receiving zero likes or retweets. The tweets in our data are of an average length of 15 words due to the 140-character limit imposed by Twitter for compatibility with SMS. On average, an account in our airline tweets sample has 344 followers, and 6.02% of tweets in our sample are posted by verified accounts (i.e., accounts with a blue verified badge on Twitter to ensure the account authenticity).

Because the text and image content contained in a tweet post is unstructured information, we first need to transform it into meaningful numerical measures that can be readily used in quantitative analysis. To process such a large amount of unstructured information efficiently, we use supervised learning algorithms to label text content and deep learning–based image processing application to classify image content. Before data coding, we develop the operational definition for all content-related variables used in the analysis based on previous literature and industry characteristics of our data. Table 2 summarizes the definitions for these variables.

Image Content Coding

In our airline sample, 4,537 tweets (24.15%) contain image content. We combine Google Cloud Vision API (available at https://cloud.google.com/vision/) with manual coding to categorize the image content. Google Cloud Vision API is an easy-to-use API that enables developers to understand the content and features of an image. Its image recognition function is based on the latest deep convolutional neural network model called Inception-v3. This model's performance has been verified in the 2012 ImageNet Large Visual Recognition Challenge (Szegedy et al. 2016): it beat the then-state-of-the-art models including AlexNet, Inception (GoogLeNet), and BN-Inception-v2 by achieving the lowest failure rate of 3.46% in predicting the correct label for an image as one of top five guesses. Google Cloud Vision API's high accuracy rate and fast response speed have also been verified by several industry reviews (e.g., Casalboni 2016; Loeb 2016).

We use three functions offered by Google Cloud Vision API. First, the "image attributes" function provided by the API helps us detect the dominant colors in the image as RGB values and percentage of the total pixel count. We calculate the sum of the top three colors' pixel percentage as our measure of the amount of color variation in an image. A low pixel percentage of the top three colors indicates that the image is colorful, whereas a high color pixel percentage suggests that the image is monotonic. Second, the "label detection" service returns up to ten objects detected in an image along with confidence scores. We then utilize the detected labels together with the pixel percentage of the top three colors to determine whether the image is a screenshot. Finally, we use the "face detection" service to determine whether at least one human face is present in the image as well as the emotional state if a human face is present.[4]

[3] Our data include only tweets that mention the full brand names to avoid generic or general uses of certain words contained in some brand names, such as "United" or "American." As a result, we might have excluded some posts that are also related to these airline companies. We acknowledge this exclusion as a limitation of our data.

[4] We evaluate the performance of Google Cloud Vision API's face detection function by comparing its result with human judgment. Using a random sample of 500 images, Google Cloud Vision API achieves an accuracy rate of 95% and a precision of 92.7% in detecting a human face.

Table 1. Summary Statistics of the Airline Tweets Sample.

A: Discrete Variables

	Levels	Before Matching Count	Before Matching Percentage	After Matching Count	After Matching Percentage
Image	None	14,253	75.85%	3,415	50%
	Direct	3,137	16.70%	2,367	34.66%
	Link	1,400	7.45%	1,048	15.34%
Relevant	Yes	1,820	40.11%[a]	1,421	41.62%[a]
Human image	Face presence	1,046	23.05%[a]	804	23.54%[a]
	Happy face	534	11.77%[a]	408	11.84%[a]
	Other or no expression	512	11.28%[a]	396	11.70%[a]
Picture source	Screenshot	770	16.97%[a]	591	17.30%[a]
	Amateur photo	3,172	69.91%[a]	2,430	71.16%[a]
	Professional photo	595	13.12%[a]	394	11.54%[a]
Picture quality	High	1,334	29.40%[a]	985	28.84%[a]
	Medium or low	3,203	70.60%[a]	2,430	71.16%[a]
Sentiment	Positive	4,760	25.33%	2,241	32.81%
	Negative	5,721	30.45%	1,253	18.35%
	Neutral	8,309	44.22%	3336	48.84%
Behavioral driver	Useful information	5,374	28.60%	1,119	16.38%
	Good image	415	2.21%	161	2.36%
Topic	Ticket sale	1,417	7.54%	272	3.98%
	September 11	952	5.07%	294	4.30%
	Delay/luggage	1,136	6.16%	267	3.91%
	Flight experience	3,183	16.94%	1,071	15.68%
	Other personal	5,668	30.16%	2,220	32.50%
Brands	American	4,841	25.76%	1,693	24.79%
	JetBlue	7,438	39.58%	3,333	48.80%
	Frontier	470	2.5%	123	1.80%
	Southwest	1,347	7.17%	615	9.00%
	Virgin	770	4.1%	366	5.36%
	Delta	1,187	6.32%	223	3.27%
	United	3,069	16.33%	398	5.83%
	Alaska	203	1.08%	36	.53%
	Spirit	284	1.51%	65	.95%
Verified	Yes	1,131	6.02%	539	7.89%

B: Continuous Variables

	Before Matching				After Matching			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Number of retweets	1.36	19.99	0	1,561	2.07	25.65	0	1,561
Number of likes	2.51	45.65	0	3,698	3.55	52.59	0	3,394
Top 3 color	47.8%[a]	21.9%[a]	2.3%	100%	48.7%[a]	22.1%[a]	2.3%	100%
Number of mentions	.58	.90	0	12	.62	.94	0	12
Number of hashtags	.59	1.17	0	15	.79	1.26	0	11
Number of emojis	.16	.77	0	19	.21	.89	0	19
Number of words	14.57	5.83	0	21	12.20	5.34	0	31
Log follower number	5.84	2.59	0	18.17	6.33	2.33	0	18.17

[a]Calculated using the subsample with images.

The remaining three image-related variables—picture quality (the inherent quality of a picture perceived by the viewer in terms of brightness, colorfulness, clarity, visual balance, and focus of the picture), amateur photo (whether a nonscreenshot image is shot by an amateur photographer), and picture relevancy (whether the image is relevant to the text content of the tweet)—are coded manually. We hired workers on Amazon Mechanical Turk to code these three variables for each image in our sample. Each image was coded by at least three expert workers. We provided workers with a detailed explanation of the variables as well as several examples to ensure that they fully understood the coding procedures. We coded each

Table 2. Coding Categories.

Variables	Definition
Image Content	
Top 3 color percentage	Sum of pixel percentage of top-three colors. A smaller sum of percentage indicates a larger color variation.
Human Image	
Face presence	The image content is coded as 1 if at least one human face is detected; otherwise, it is coded as 0.
Happy face	The image content is coded as 1 if at least one happy human face is detected; otherwise, it is coded as 0.
Screenshot	The image content is coded as 1 if the picture is a screenshot of a web page; otherwise, it is coded as 0.
Amateur photo	The image content is coded as 1 if the picture is rated as a photo shot by an amateur photographer; otherwise, it is coded as 0.
High-quality picture	The image content is coded as 1 if the picture is rated as high quality; otherwise, it is coded as 0.
Relevant picture	The image content is coded as 1 if the picture is related to the topic of text component; otherwise, it is coded as 0.
Text Content	
Sentiment	The text content is coded as positive, negative, or neutral based on the overriding sentiment of the post.
Topics	The text content is classified as one of the six topics (different for each product category). The baseline is "Other Public Topic."
Behavioral drivers	Two dummy variables are created to indicate whether the text content of a tweet is shared to "provide useful information" (useful information) and "look good to others" (good image).

variable with the value chosen by the majority of three workers (i.e., at least two workers).

We report the frequency distribution of all categorical variables, including the presence of an image, presence of a human face in the picture, picture quality, picture source, and picture relevancy, for our sample of 18,790 airline tweets in the "Before Matching" column of Table 1, Panel A. We also report the mean and standard deviation of the top-three color pixel percentage in Table 1, Panel B.

Text Content Coding

We create five sets of text content measures following our modeling framework. The linguistic content category variables include affect words (Affect), social words (Social), cognitive words (Cogproc), perceptual words (Percept), biological process words (Bio), and words for drive and need (Drive). These variables are the percentage of words in the text content of a tweet belonging to the corresponding psychological construct categories defined by the 2015 Linguistic Inquiry and Word Count dictionary. The numbers of mentions, hashtags, and emojis are coded using standard keyword search, while the number of words is generated using the Carnegie Mellon University tweet part-of-speech tagger (http://www.cs.cmu.edu/∼ark/TweetNLP/). The remaining three sets of text content measures—sentiment, topic(s), and two behavioral drivers—are coded using supervised machine learning models (e.g., Tirunillai and Tellis 2012; Kumar et al. 2016). We have experimented with four different supervised machine learning models: logistic regression, multinomial naive Bayes, linear support vector machine, and random forest. Using ten-fold cross-validation, we find that the linear support vector machine model yields the best accuracy rate. Therefore, we use it to code the three remaining measures of the text content in our data. We provide a detailed description of our text-mining procedure in Web Appendix A. We report the summary statistics of the resulting text content measures in the "Before Matching" column of Table 1, Panels A and B.

The Model

Our primary interest is to understand how image content affects social media engagement. However, because we only have observational data, the inclusion of image content in a tweet is not randomly assigned across posts. In other words, whether to include a picture in a tweet can be a deliberate decision made by the poster, which may correlate with other factors that also influence user engagement with the post. To alleviate the endogeneity concern, we rely on propensity score matching to create a pseudo "treatment" group and "control" group and use the matched sample for our model estimation. In this section, we first describe how we create the matched sample using propensity score matching and then present our proposed model to be estimated on the matched sample.

Propensity Score Matching

There are several potential sources of endogeneity in our case. First, it might be easier to find a relevant picture for certain topics compared with others. For example, one may post a photo featuring a JetBlue airplane next to the gate with the tweet "Waiting to depart for New York @Jetblue." However, it may be much more difficult to find a matching picture to go with "@Jetblue your call center never picks up the phone." Second, posters may be well aware that image content enhances the popularity of a post. Therefore, they are more likely to attach a picture to a tweet that has the potential to become viral than to other, more mundane tweets. This issue is commonly referred to as the self-selection bias. Finally, the existence of image content may be due to unobservable post or account features that drive both the popularity of the tweets and the propensity to have images in those tweets.

Ideally, we would solve the endogeneity problem through an experiment by randomly assigning the followers of each tweet into one of two groups: followers in the treatment group would be exposed to both text and image content, while those in the control group would be exposed to only the text content of the same tweet. However, with observational data, all followers are either in the treatment group or in the control group. As a result, followers in the treatment group may be systematically different from followers in the control group, thus making the inference about the treatment effect biased.

Propensity score matching is an effective way to adjust for the differences in the treatment and control group, which may bias the inferences about the treatment effect (Rosenbaum and Rubin 1983). In our study, the propensity score is the predicted probability that an observational unit (a tweet) receives a treatment (the inclusion of image content) conditional on the value of covariates. When the propensity scores for two observations are close enough to each other, the treatment is considered random. Thus, the biases in the comparisons between treated and control units are eliminated.

As discussed previously, both observable and unobservable factors may lead to endogeneity. Therefore, we include all text content features of a tweet (i.e., sentiment, topics, two behavioral drivers, number of mentions, hashtags, emojis, and six linguistic features), account characteristics, and posting time in our matching model. To account for the unobservable factors, we use two instrumental variables: (1) whether the account holder (i.e., the poster) is self-stated to be a photography lover in her Twitter bio, and (2) the percentage of tweets that contain images in the account history. We argue that these instruments are related to the account holder's propensity to post images in general but are uncorrelated to the popularity of a specific tweet. We use a logistic regression to estimate the probability of the inclusion of image content in a tweet as a function of these covariates. Table B-1 of Web Appendix B reports the estimation result of the logit model.

We then calculate the propensity score for each tweet in our sample based on the covariates and parameter estimates. We adopt a 1:1 nearest-neighbor matching algorithm without replacement and a caliper of .01 to match a tweet posted with image content with a tweet posted without image content but with the closest propensity score (Stuart 2010). The resulting matched sample contains 6,830 tweets, half with image content and half without. We have validated that after matching, the control group and treatment group are not significantly different in any of the covariates. We present the summary statistics of the matched sample in the "After Matching" column of Table 1, Panels A and B.

Bivariate Zero-Inflated Negative Binomial Model (BVZINB)

We are interested in two types of user engagement with tweets: (1) liking, which is measured by the number of likes, and (2) sharing, which is measured by the number of retweets. Because these measures are discrete and nonnegative, a count model (e.g., Poisson regression, negative binomial regression) is more appropriate than a linear regression model. However, we have to extend the standard univariate count regression model to account for two patterns that are present in our data: (1) the presence of excess zeros in our data and (2) the significant positive correlation between the two engagement measures.

Zero responses to a tweet may be due to the lack of views from followers or to the lack of interest in responding after followers see the post. The former case is often termed structural zero in count data analysis. However, due to the data limitation, we do not have the information on the number of views each tweet receives. As a compromise, we rely on post and account characteristics that may affect the amount of attention received by each tweet to predict the success of a tweet in getting at least one view. First, the attention that a tweet attracts is affected by the obtrusiveness of the post. We argue that the presence of pictures and emojis, as well as the length of the tweet, contribute to the obtrusiveness of a tweet. Second, the amount of attention received by a tweet also depends on the specific audience it targets, which can be captured by the number of mentions (@) and hashtags (#) used. Finally, the timing of the post and the account characteristics may also affect the amount of attention a tweet can attract.

More formally, we model the latent attention level received by tweet i, Att_i, as follows:

$$\begin{aligned} Att_i = {} & \gamma_0 + \gamma_1 Img\_direct_i + \gamma_2 Img\_link_i + \gamma_3 Emoji_i \\ & + \gamma_4 Length_i + \gamma_5 At_i + \gamma_6 Hashtag_i + \gamma_7 Time_i \\ & + \gamma_8 Weekend_i + \gamma_9 Follower_i + \gamma_{10} Verified + \varepsilon_i, \end{aligned} \tag{1}$$

where γ_0 is the intercept, Img_direct_i is a dummy variable indicating that tweet i has image content that is directly viewable on the Twitter home timeline, while Img_link_i is a dummy variable indicating that tweet i has image content which requires clicking on a link to be viewed. $Emoji_i$, At_i, and $Hashtag_i$ are the number of emojis, mentions (@), and hashtags (#) used in tweet i, respectively. $Length_i$ is the number of words in the text content. $Time_i$ and $Weekend_i$ are dummy variables indicating whether tweet i is posted during one of the six four-hour time periods of a day (baseline is 12 A.M. to 4 A.M. PDT), and whether it is posted during a weekend, separately. $Follower_i$ is the natural logarithm of the number of followers of the poster. $Verified_i$ is a dummy variable indicating whether tweet i is posted by a verified account, which is used to establish authenticity of identities of key individuals and brands on Twitter. The error term ε_i follows i.i.d. Gumbel distribution.

The minimal level of attention that needs to be obtained to warrant at least one view on the tweet is represented by $Att_{i0} = \alpha_0 + \varepsilon_{i0}$, where α_0 is the deterministic level of attention which is normalized to zero, and ε_{i0} is the i.i.d. stochastic error term that follows a Gumbel distribution. Therefore, the probability that tweet i receives a positive number of views can be expressed as follows:

$$\Pr(\text{view}_i>0) = \Pr(\text{Att}_i - \text{Att}_0>0) = \frac{\exp\left(\overline{\text{Att}_i}\right)}{1+\exp\left(\overline{\text{Att}_i}\right)}. \quad (2)$$

After a tweet attracts at least one view, we model the number of likes and the number of retweets received by the tweet using a bivariate negative binomial (BVNB) model, which can accommodate the correlation between the two dependent variables and overdispersion at the same time. There are several ways to introduce correlation among count variables (for two alternative methods, see Winkelmann [2008]). For computational convenience, we adopt the multivariate Poisson gamma mixture model proposed by Hausman, Hall and Griliches (1984). Let y_{ij} follow a Poisson distribution with $E(y_{ij}) = \lambda_{ij}u_i$, where u_i follows a gamma distribution with $E(u_i) = 1$ and $\text{Var}(u_i) = \alpha$. It can be shown that the joint distribution function of $y_i = y_{i1} + y_{i2}$, which denotes the sum of the numbers of likes and retweets for tweet i, is of a negative binomial form with the following distribution function

$$f(y_i|x_i) = \frac{\Gamma(y_{i1}+y_{i2}+\alpha^{-1})}{y_{i1}!y_{i2}!\Gamma(\alpha^{-1})}\left(\frac{\lambda_{i1}}{\lambda_{i1}+\lambda_{i2}+\alpha^{-1}}\right)^{y_{i1}} \left(\frac{\lambda_{i2}}{\lambda_{i1}+\lambda_{i2}+\alpha^{-1}}\right)^{y_{i2}}\left(\frac{\alpha^{-1}}{\lambda_{i1}+\lambda_{i2}+\alpha^{-1}}\right)^{\alpha^{-1}}. \quad (3)$$

The marginal distributions of the bivariate Poisson gamma model are univariate negative binomial with $E(y_{ij}) = \lambda_{ij}$ and $\text{Var}(y_{ij}) = \lambda_{ij} + \alpha\lambda_{ij}2$, where λ_{ij}, ($j = 1, 2$) is specified as follows:

$$\begin{aligned}\log\left(\lambda_{ij}\right) = {} & \beta_0{}^j + \beta_{i1}{}^j\text{Img\_direct}_i + \beta_{i2}{}^j\text{Img\_link}_i + \beta_{i3}{}^j\text{Color}_i \\ & + \beta_{i4}{}^j\text{Face}_i + \beta_{i5}{}^j\text{Happy}_i + \beta_{i6}{}^j\text{Screen}_i \\ & + \beta_{i7}{}^j\text{Amateur}_i + \beta_{i8}{}^j\text{Quality}_i + \beta_{i9}{}^j\text{Relation}_i \\ & + \beta_{i10}{}^j\text{Sentiment}_i + \beta_{i11}{}^j\text{Topic}_i + \beta_{i12}{}^j\text{Driver}_i \\ & + \beta_{i13}{}^j\text{Brand}_i + \beta_{i14}{}^j\text{At}_i + \beta_{i15}{}^j\text{Hashtag}_i \\ & + \beta_{i16}{}^j\text{Emoji}_i + \beta_{i17}{}^j\text{Length}_i + \beta_{i18}{}^j\text{Follower}_i \\ & + \beta_{i19}{}^j\text{Verified}_i. \end{aligned} \quad (4)$$

In Equation 4, Img_direct_i, Img_link_i, Emoji_i, Length_i, At_i, Hashtag_i, Follower_i, and Verified_i are defined as in Equation 2. Color_i, Face_i, Happy_i, Screen_i, Amateur_i, Quality_i, and Relation_i are image characteristics defined in Table 2. Sentiment_i is a vector of two dummy variables indicating whether the sentiment of the text content is positive, negative, or neutral (with neutral set as the baseline). Topic_i is a vector of dummy variables indicating whether the topic of the text content is “ticket sale,” “9-11,” “delay and luggage,” “flight experience,” or “other personal topics” (with “other public topics” set as the baseline topic). Driver_i is a vector of two dummy variables indicating whether the text content of a tweet is shared to “provide useful information” (useful information) and “look good to others” (good image). Brand_i is a vector of dummy variables indicating whether a particular airline’s name was mentioned in tweet i (with “American Airlines” set as the baseline brand).

Combining the logistic model and the BVNB model, we obtain the BVZINB as follows:

$$p(y_i|x_i) = \begin{cases} \Pr(\text{view}_i=0) + \Pr(\text{view}_i>0)\times \Pr_{NB}(y_{i1}=0, y_{i2}=0) & \text{if } y_{i1}=y_{i2}=0 \\ \Pr(\text{view}_i>0)\times \Pr_{NB}(y_{i1}=k_{i1}, y_{i2}=k_{i2}) & \text{otherwise} \end{cases}$$

$$= \begin{cases} \dfrac{1}{1+\exp\left(\overline{\text{Att}_i}\right)} + \dfrac{\exp\left(\overline{\text{Att}_i}\right)}{1+\exp\left(\overline{\text{Att}_i}\right)}\left(\dfrac{\alpha^{-1}}{\lambda_{i1}+\lambda_{i2}+\alpha^{-1}}\right)^{\alpha^{-1}} & \text{if } y_{i1}=y_{i2}=0 \\ \dfrac{\exp\left(\overline{\text{Att}_i}\right)}{1+\exp\left(\overline{\text{Att}_i}\right)}\dfrac{\Gamma(k_{i1}+k_{i2}+\alpha^{-1})}{k_{i1}!k_{i2}!\Gamma(\alpha^{-1})}\left(\dfrac{\alpha^{-1}}{\lambda_{i1}+\lambda_{i2}+\alpha^{-1}}\right)^{\alpha^{-1}}\prod_{j=1,2}\left(\dfrac{\lambda_{ij}}{\lambda_{i1}+\lambda_{i2}+\alpha^{-1}}\right)^{k_{ij}} & \text{otherwise.} \end{cases} \quad (5)$$

We estimate the model described in Equations 1–5 using a maximum likelihood estimator. The resulting set of parameters $\theta = \{\gamma, \beta, \alpha\}$ maximizes the following log-likelihood function:

$$\begin{aligned}\ell = {} & \sum_{\{i:y_{i1}=y_{i2}=0\}} \ln\left[1+\exp(z_i'\gamma)\left(1+\alpha\sum_{j=1,2}\exp\left(x_i'\beta_j\right)\right)^{-\alpha^{-1}}\right] \\ & + \sum_{\{i:y_{i1}+y_{i2}>0\}}\left[z_i'\gamma + \sum_{s_0=0}^{y_{i1}+y_{i2}-1}\ln\left(s_0+\alpha^{-1}\right) - \sum_{s_1=1}^{y_{i1}}\ln s_1 - \sum_{s_2=1}^{y_{i2}}\ln s_2\right] \\ & + \sum_{\{i:y_{i1}+y_{i2}>0\}}\left[-\left(y_{i1}+y_{i2}+\alpha^{-1}\right)\ln\left(1+\alpha\sum_{j=1,2}\exp\left(x_i'\beta_j\right)\right)\right. \\ & \left. + (y_{i1}+y_{i2})\ln\alpha + \sum_{j=1,2}y_{ij}x_i'\beta_j\right] \\ & - \sum_{i=1}^{N}\ln[1+\exp(z_i'\gamma)]. \end{aligned} \quad (6)$$

Results

In this section, we first present the model estimates on the matched sample for our airline related tweets. We then present and discuss the model estimation results from two other data sets we collect: the SUV Twitter data set and the airline Instagram data set. Finally, we quantify the net effect of image content on user engagement using our parameter estimates for each of the three data sets and summarize similarities and differences in the three proposed imagery effects across product categories and platforms.

Airline Tweets

Before discussing the details of parameter estimates, we first compare the in-sample fit statistics of three successively restricted BVZINB models and one BVNB model to demonstrate the importance of accounting for the image content and structural zeros when predicting the number of likes and retweets. All three BVZINB models incorporate the effects of text content variables and all other control variables, but they differ in the extent to which they take into account the effect(s) of image content. Model 1 is our proposed model, which accounts for all three proposed effects of image content. Model 2 considers the mere presence effect but does not account for the other two image content effects. Model 3 does not consider any effects related to the image content. Model 4 is a BVNB model that incorporates all three proposed effects of image

Table 3. Model Comparison Based on Marginal Likelihood and In-Sample Goodness-of-Fit Measures Across Models with Different Components.

	N				MAE	
	Parameters	LL	AIC	BIC	Retweets	Likes
Model 1: Proposed model	94	−13,215.91	26,431.83	27,261.76	2.763	4.715
Model 2: Proposed model without image characteristics and image–text fit variables	80	−13,555.91	27,271.82	27,818.15	2.935	4.858
Model 3: Proposed model without any image-related variables	74	−13,775.91	27,699.81	28,205.16	2.854	5.114
Model 4: BVNB model with all three proposed effects of image content	79	−13,262.08	26,524.17	26,682.17	2.831	4.697

Notes: LL = log-likelihood; AIC = Akaike information criterion; BIC = Bayesian information criterion; MAE = root mean absolute error.

content but does not include the zero-inflation component. Table 3 reports the log-likelihood, Akaike information criterion, Bayesian information criterion, and in-sample root mean absolute error of these four models. Our proposed model (Model 1) outperforms Model 2 through Model 4 on almost all five statistics. In addition, because Model 2 and Model 4 are nested within Model 1, and Model 3 is nested within Model 2, we have conducted three likelihood ratio tests comparing Model 1 with Model 2 (chi-square = 679.99, $p < .001$), Model 1 with Model 4 (chi-square = 92.34, $p < .001$), and Model 2 with Model 3 (chi-square = 439.99, $p < .001$). These test results suggest the inclusion of all three proposed effects of image content and the zero-inflation component significantly improves the model fit.

Image content. We report the parameter estimates of the proposed BVZINB model in Table 4. In this subsection, we discuss our estimation results regarding three aspects of image content: the mere presence effect, the image characteristics effect, and the image–text fit effect. With regard to the mere presence effect, we find that the mere presence of directly viewable image content significantly increases both types of engagement. However, a hyperlinked image backfires, as indicated by the significantly negative coefficients of linked image for both engagement measures. We suspect this is because readers do not have the patience to go through additional steps to open the hyperlinked images.

Regarding the image characteristics effect, we find that pictures with more color variation lead to a higher number of retweets, consistent with findings in the visual marketing literature (Finn 1988; Wedel and Pieters 2015). Also consistent with prior work (Xiao and Ding 2014), we find that the presence of human face in the image content increases both types of engagement. Curiously, we find that pictures with happy faces tend to induce significantly fewer retweets than pictures containing other facial expressions, but they do not affect liking significantly. This finding may seem counterintuitive at first; however, after a closer examination, we discover that images with facial expressions classified as "happy" are mostly selfies and contain only personal information that is not useful or relevant to readers beyond the poster's own follower base. Therefore, such tweets are less likely to be shared.

Regarding the effect of picture source, we find that professionally taken pictures tend to boost the number of retweets relative to pictures taken by amateur photographers. This result can be explained by the personal nature of the amateur pictures in our airline tweets sample. These pictures contain many details of the poster's private life and therefore are inappropriate to be retweeted by followers to their friends. We also find that tweets containing screenshots receive a significantly lower number of retweets than the ones with professionally taken pictures, probably because screenshots are less interesting and informative than other pictures. Finally, consistent with extant research (Hagtvedt and Patrick 2008; Zhang et al. 2017), we find that high-quality images can improve user engagement on social media posts, as reflected by their significant and positive effect on the number of retweets.

Regarding image–text fit, we find that relevant image content has a statistically positive effect on the number of likes for the post. This result is consistent with previous findings that relevant pictures in print ads lead to more favorable attitude toward the ad (Heckler and Childers 1992; Lee and Mason 1999).

Text content. Although not the focus of this research, we also examine how text content of a social media post affects user engagement. We find that positive content increases both types of engagement, and negative content has a significant positive effect on sharing but a significant negative impact on liking. These findings are consistent with Berger's (2014) perspective that both positive and negative WOM can induce sharing because both types of valence can facilitate desired impressions in certain circumstances. The significant negative effect of negative content on liking, in contrast, is likely to be triggered by different motivation for liking versus sharing on social media (Buechel and Berger 2018). While sharing negative content such as critiques on airline quality deterioration due to one's unpleasant travel experience may provide useful and unique information to others, liking such negative content seems to be unsympathetic and insensitive because it implies an affirmation to the unfortunate experience encountered by the poster.

Table 4. Estimation Results for User Engagement: Airline Tweets.

		Attention	Retweets	Likes
	Intercept	1.23 (.75)	−4.76 (.14)	−3.45 (14)
Image Content				
Mere presence	Direct image	.08 (.22)	**1.19 (.20)**	**.64 (.20)**
	Linked image	1.71 (1.19)	**−2.37 (.15)**	**−1.78 (.13)**
Image Characteristics				
Colorfulness	Top 3 color	—	**−.85 (.21)**	−.05 (.21)
Human image	Face presence	—	**.59 (.12)**	**.33 (.11)**
	Happy face	—	**−.72 (.15)**	.23 (.14)
Picture source	Screenshot	—	**−.37 (.11)**	.00 (.10)
	Amateur photo	—	**−.29 (.09)**	−.07 (.09)
Picture quality	High quality	—	**.19 (.09)**	−.16 .09)
Image–text fit	Relevancy	—	.07 (.14)	**.35 (.14)**
Text Content				
Sentiment	Positive sentiment	—	**.71 (.07)**	**.39 (.07)**
	Negative sentiment	—	**.42 (.42)**	**−.22 (.08)**
Topics	Ticket sale	—	**.38 (.18)**	.21 (.19)
	September 11	—	**.59 (.11)**	−.04 (.11)
	Delay and luggage	—	**−1.92 (.20)**	−.16 (.17)
	Flight experience	—	**−.98 (.10)**	.07 (.09)
	Other personal topics	—	**−.57 (.07)**	.10 (.07)
Behavioral drivers	Useful information	—	**−.20 (.09)**	**−.87 (.09)**
	Good image	—	**1.05 (.17)**	**.93 (.17)**
Other text features	Number of mentions (@)	1.83 (.60)	**.09 (.03)**	.14 (.03)
	Number of hashtags	−.19 (.08)	**.22 (.03)**	.08 (.03)
	Number of emojis	2.10 (2.08)	**−.20 (.04)**	.04 (.04)
	Number of words	.01 (.02)	.01 (.01)	.01 (.01)
Brand mentioned	JetBlue	—	**−.23 (.07)**	**−.41 (.08)**
	Frontier	—	**−.97 (.29)**	−.25 (.31)
	Southwest	—	**−.84 (.10)**	−.18 (.10)
	Virgin	—	**−.54 (.19)**	−.18 (.16)
	Delta	—	**−.62 (.16)**	**−.71 (.17)**
	United	—	**−.50 (.12)**	**−1.07 (.12)**
	Alaska	—	−.54 (.48)	−.81 (.44)
	Spirit	—	**−.70 (.31)**	**−.84 (.41)**
Account Characteristics and Other Controls				
Account characteristics	Log number of followers	−.04 (.54)	**.55 (.14)**	**.44 (.01)**
	Verified account	4.67 (14.46)	.14 (.12)	**.72 (.12)**
Linguistic features	Linguistic content category	—	✓	✓
Time fixed effects	Time-of-day fixed effects	✓	—	—
	Weekend fixed effects	✓	—	—
Correlation Between Sharing and Liking				
	Alpha	**3.10 (.15)**		

Notes: Standard errors in parentheses. Boldfaced estimates are statistically significant at $p < .05$.

Among the various topics discussed, we find that all three types of personal topics (i.e., delay and luggage, flight experience, and other personal topics) tend to reduce the number of retweets because they are less informative than public topics (i.e., ticket sales and September 11). Both behavioral drivers have significant effects on user engagements, but the effects work in opposite directions: while a tweet with text that is intended to provide useful information tends to receive fewer retweets and likes, a tweet with text that is perceived to generate good image for the poster tends to receive more retweets and likes. Consistent with Tan, Lee, and Pang (2014), we find that the inclusion of user mentions (@) and hashtagged topics (#) has a significant effect on user engagement. The length of a tweet does not affect user engagement, but the inclusion of emojis tends to reduce the number of retweets received. Regarding brand-specific effects, our results show that tweets about American Airlines are liked and shared most, suggesting that AA enjoys a higher level of user engagement than other major airlines on Twitter.

Account characteristics. We find that tweets posted by an account with a more extensive follower base tend to receive more likes and retweets, simply because the potential audience size is larger.[5] We also find that the account verification status is associated with a higher number of likes received for the post; however, it does not affect the number of retweets.

SUV Tweets

To assess the applicability of our findings from the airline related tweets to other product categories, we collected original tweets posted in September 2015 that were related to major compact SUV models using Twitter search. We chose this category because, as highly visible utilitarian consumption, SUVs are one of the most active product categories on social media. We compile a list of top-selling compact SUV models as the keywords for scraping, including Honda CRV, Ford Explorer, Ford Escape, Toyota RAV4, Nissan Rogue, Jeep Cherokee, Jeep Wrangler, Chevrolet Equinox, Subaru Forester, and Jeep Grand Cherokee. We found 12,817 tweets mentioning at least one of these ten SUV models, among which 2,204 (17.2%) contain image content. We then use the same 1:1 propensity score matching approach to create a treatment group of SUV tweets posted with image content matched with a "pseudo" control group of SUV tweets without image content. The parameter estimates of the propensity score model appear in Table B-2 of Web Appendix B. The resulting matched SUV sample contains 1,660 SUV tweets with image content and 1,660 SUV tweets without image content. We present the summary statistics of our unmatched SUV tweets sample and matched SUV sample in Table 5, Panels A and B. Like the airline tweets sample, our SUV sample exhibits a similar pattern of excess zeros, with 73.19% of the tweets receiving zero like or retweet. We also note that in the matched SUV sample, no tweets contain any hyperlinked images, and 96.62% of the images are relevant to text content and 94.82% of the images are original photos shot by amateur photographers. Therefore, we drop these three variables in the main model due to their high correlation with the mere presence of image content.

We estimate the same BVZINB model using the matched SUV tweets sample. Table 6 presents the parameter estimates. Consistent with our findings from the airline-related tweets, our results show a robust mere presence effect on both sharing and liking for the SUV-related tweets. As far as image characteristics are concerned, we also have similar findings in the SUV tweets sample: pictures featuring human images lead to an increase in sharing, and moreover, happy faces are less likely to induce sharing compared with faces with other emotional states. In addition, we find a similar effect of picture source and quality on engagement, such that screenshots significantly reduce the number of likes, whereas high-quality pictures significantly increase the number of likes. However, with regard to the effect of picture colorfulness, our two samples yield opposite findings: in our SUV sample, followers seem to engage *more* with monotonic pictures, as SUV tweets with such pictures receive more retweets.

Turning attention to the text content, we find a similar positive effect of positive content on liking and negative content on sharing. However, while negative content decreases liking for airline-related tweets, we find that negative content increases liking for SUV-related tweets. These contrasting findings suggest that it is crucial to consider the category-specific context when evaluating content effectiveness on social media. While a significant proportion of negative content about air travel is complaints about bad experiences, negative content we find in the SUV tweet data is mostly critical assessments of new vehicle models often not owned by the posters. Such negative SUV posts provide useful information for the followers and, therefore, induce more sharing and liking. We also find that both behavioral drivers, as reflected in the text content, have significant effects on user engagement for the SUV-related tweets: tweets perceived to provide useful information tend to receive more retweets, and tweets perceived to generate a good image for the poster tend to receive more likes. Among the various topics discussed, tweets featuring driving experience are associated with more retweets and likes, whereas those featuring car sale and recall information tend to do worse in both sharing and liking. We also find that other text-related characteristics (including number of emoji, the inclusion of hashtags, and number of words) have significant effects on liking or sharing.

Airline Instagram Posts

So far, our empirical inquiry is limited to posts from Twitter, a microblogging platform where text content is more dominant. In this subsection, we extend our analysis to Instagram, a photo-sharing social networking website, to examine how image characteristics and image–text relevancy affect user engagement with Instagram posts. Using a web-scraping program, we collected a sample of over 20,000 Instagram posts published between January 16 and February 15, 2018, concerning the same nine airlines as we have in our airline tweets

[5] We thank an anonymous reviewer for the suggestion to incorporate poster-level fixed effects. We have conducted a robustness check by including poster-specific intercepts. The parameter estimates are qualitatively unchanged. Details of this robustness check can be found in Web Appendix D.

Table 5. Summary Statistics: SUV Tweets.

A: Discrete Variables

		Before Matching		After Matching	
	Levels	**Count**	**Percentage**	**Count**	**Percentage**
Image	No	10,613	82.8%	1,660	50%
	Direct	2,204	17.2%	1,660	50%
Relevant	Yes	2,142	97.19%[a]	1,604	96.62%[a]
	No	62	2.81%[a]	56	3.38%[a]
Human image	Face presence	188	8.53%[a]	159	9.58%[a]
	Happy face	119	5.40%[a]	95	5.72%[a]
	Other or no expression	69	3.13%[a]	64	3.86%[a]
Picture source	Screenshot	49	2.22%[a]	40	2.40%[a]
	Amateur photo	2,104	95.46%[a]	1,574	94.82%[a]
	Professional photo	51	2.32%[a]	46	2.78%[a]
Picture quality	High	545	24.73%[a]	422	25.42%[a]
	Medium or low	1,659	75.27%[a]	1,238	74.58%[a]
Sentiment	Positive	3,921	30.59%	1,524	45.90%
	Negative	404	3.15%	115	3.46%
	Neutral	8,492	66.26%	1,681	50.64%
Behavioral driver	Useful information	4,305	33.59%	626	18.86%
	Good image	462	3.60%	216	6.51%
Topic	Car sale	3,862	30.13%	442	13.31%
	Recall	139	1.08%	36	1.08%
	New purchase	633	4.94%	127	3.38%
	Driving experience	460	3.59%	267	8.04%
	Other personal	1,547	12.07%	485	14.61%
Brands	Toyota	1,390	10.84%	326	9.82%
	Chevy	1,012	7.98%	161	4.85%
	Ford	3,880	30.27%	1,122	33.80%
	Honda	1,243	9.7%	332	10%
	Jeep	2,674	20.86%	708	21.33%
	Nissan	1,057	8.25%	244	7.35%
	Subaru	1,543	12.04%	423	12.74%
Verified	Yes	267	2.08%	146	4.37%

B: Continuous Variables

	Before Matching				After Matching			
	Mean	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**
Number of retweets	.31	8.11	0	839	.87	15.84	0	839
Number of likes	.42	3.05	0	165	.77	3.95	0	79
Top 3 color	42.0%[a]	19.9%[a]	1.3%	100%	42.7%[a]	20.3%[a]	1.3%	100%
Number of mentions	.21	.53	0	8	.35	.66	0	8
Number of hashtags	.80	1.51	0	14	1.29	.89	0	14
Number of emojis	.06	.39	0	9	.06	.39	0	7
Number of words	13.99	5.51	0	30	11.80	4.89	0	29
Log follower number	4.49	2.51	0	14.19	5.47	2.48	0	14.19

[a]Calculated using the subsample with images.

sample. We then draw a random sample of 2,044 (10%) posts as our final estimation sample. Because there is no "sharing" function readily available for Instagram posts, we focus on the number of likes as the sole social engagement measure for this analysis.

We present the summary statistics of our Instagram sample in Web Appendix C. In general, we see that users tend to have a higher level of engagement on Instagram than on Twitter. On average, an airline Instagram post receives 137.6 likes, with a minimum of 11 and a maximum of 11,678. We therefore do not need to employ the zero-inflated model we have used for our two Twitter samples. Instead, we use a log-linear regression to examine how image content in an Instagram post affects the number of likes a post receives. More specifically, we have the following regression model for the number of likes received by an Instagram post:

Table 6. Estimation Results for User Engagement: SUV Tweets.

Variables	Levels	Attention	Retweets	Likes
	Intercept	**−3.63 (.62)**	**−4.27 (.34)**	**−2.36 (.37)**
Image Content				
Mere presence	Direct image	.14 (.26)	**.71 (.21)**	**.65 (.20)**
Image Characteristics				
Colorfulness	Top 3 color	—	**.92 (.39)**	.56 (.34)
Human image	Face presence	—	**1.38 (.45)**	.46 (.46)
	Happy face	—	**−1.98 (.54)**	.14 (.52)
Picture source	Screenshot	—	−1.71 (1.10)	**−1.41 (.53)**
Picture quality	High quality	—	.17 (.17)	**.40 (.16)**
Text Content				
Sentiment	Positive	—	.02 (.14)	**.40 (.14)**
	Negative	—	**.99 (.28)**	**.65 (.34)**
Topics	Car sale	—	**−1.15 (.27)**	**−.60 (.26)**
	Recall	—	**−1.10 (.53)**	**−1.29 (.64)**
	New purchase	—	**−1.09 (.44)**	−.01 (.39)
	Driving experience	—	**.62 (.18)**	**.52 (.17)**
	Other personal topics	—	.27 (.14)	**1.33 (.13)**
Behavioral drivers	Useful information	—	**.58 (.18)**	−.12 (.19)
	Good image	—	−.23 (.17)	**.67 (.15)**
Other text features	Number of mentions (@)	**.45 (.20)**	.09 (.05)	.04 (.05)
	Number of hashtags	**.90 (.22)**	−.06 (.04)	**−.12 (.04)**
	Number of emojis	1.06 (.74)	**−.24 (.10)**	.12 (.09)
	Number of words	**.09 (.03)**	−.02 (.01)	**−.03 (.01)**
Brand mentioned	Chevy	—	.51 (.40)	−.12 (.35)
	Ford	—	.32 (.23)	**.49 (.22)**
	Honda	—	**.84 (.23)**	.13 (.23)
	Jeep	—	.43 (.24)	.37 (.22)
	Nissan	—	**−.95 (.36)**	**−.55 (.27)**
	Subaru	—	.17 (.26)	−.27 (.24)
Account Characteristics and Other Controls				
Account characteristics	Log number of followers	**.38 (.06)**	**.33 (.02)**	**.17 (.03)**
	Verified account	3.79 (23.96)	.28 (.24)	**.80 (.23)**
Linguistic features	Linguistic content category	—	✓	✓
Time fixed effects	Time-of-day fixed effects	✓	—	—
	Weekend fixed effects	✓	—	—
Correlation Between Sharing and Liking				
	Alpha	**2.47 (.23)**		

Notes: Standard errors in parentheses. Boldfaced estimates are statistically significant at $p < .05$.

$$\begin{aligned}\log(\text{Likes}_i) = {} & \beta_0 + \beta_1\text{Color}_i + \beta_2\text{Face}_i + \beta_3\text{Happy}_i \\ & + \beta_4\text{Screen}_i + \beta_5\text{Quality}_i + \beta_6\text{Relation}_i \\ & + \beta_7\text{Sentiment}_i + \beta_8\text{Driver}_i + \beta_9\text{Personal}_i \\ & + \beta_{10}\text{Brand}_i + \beta_{11}\text{At}_i + \beta_{12}\text{Hashtag}_i \\ & + \beta_{13}\text{Emoji}_i + \beta_{14}\text{Length}_i + \beta_{15}\text{Follower}_i + \varepsilon_i,\end{aligned} \quad (7)$$

where Color_i, Face_i, Happy_i, Screen_i, Quality_i, Relation_i, Sentiment_i, Driver_i, Brand_i, At_i, Hashtag_i, Emoji_i, Length_i, and Follower_i are all defined as in Equation 4. Personal_i is a dummy variable indicating whether the content of the text is about personal experience/opinion (coded as 1) or public news/information (coded as 0).[6] The error term ε_i is assumed to follow the i.i.d. Normal distribution.

[6] We do not differentiate specific topics for the airline Instagram sample, because after removing hashtags, the text content of an average Instagram post is much shorter than that of an average tweet.

Table 7. Estimation Results for User Engagement: Airline Instagram.

Variables	Levels	Ln_Likes
	Intercept	**.77 (.13)**
Image Characteristics		
Colorfulness	Top 3 color %	**−.22 (.07)**
Human image	Face presence	−.09 (.07)
	Happy face	.10 (.08)
Picture source	Screenshot	**−.50 (.06)**
	Amateur photo	**−.13 (.04)**
Picture quality	High quality	**.09 (.03)**
Image–text fit	Relevancy	.00 (.09)
Text Content		
Sentiment	Positive	.03 (.03)
	Negative	.02 (.05)
Topics	Personal topics	−.06 (.05)
Behavioral drivers	Useful information	−.09 (.08)
	Good image	.02 (.09)
Brand effects	JetBlue	**−.23 (.05)**
	Frontier	−.01 (.14)
	Southwest	−.21 (.04)
	Virgin	.63 (.20)
	Delta	−.08 (.04)
	United	−.06 (.04)
	Alaska	−.02 (.06)
	Spirit	**−.30 (.10)**
Other text features	Number of mentions (@)	**.03 (.01)**
	Number of hashtags	.01 (.00)
	Number of emojis	−.01 (.01)
	Number of words	.00 (.00)
Account Characteristics and Other Controls		
Account characteristics	Log of number of followers	**.51 (.01)**
Linguistic features	Linguistic content category	✓
Time fixed effects	Time-of-day fixed effects	✓
	Weekend fixed effects	✓

Notes: Standard errors in parentheses. Boldfaced estimates are statistically significant at $p < .05$.

Table 7 presents the estimation results. Similar to our finding from the airline tweets sample, colorful pictures are more favorable: the lower the top-three color pixel percentage, the more likes an Instagram post will receive. Our findings on the effect of picture source and picture quality for Twitter posts also hold true for Instagram posts. However, unlike on Twitter, the presence of a human face does not have a significant impact on engagement on Instagram. Finally, we do not find a significant effect of image–text fit on user engagement for Instagram posts.

Regarding the impact of text content, we find that, in general, text content does not affect engagement on Instagram. Most of the text-related characteristics (including sentiment, behavioral drivers, topic, number of hashtags, number of emoji, or number of words) have no significant effects on the number of likes received by an Instagram post. However, mentioning another account still helps increase user engagement. Along with the absence of an image–text fit effect, these results suggest that the text content plays only a secondary role to facilitate content discovery on Instagram. Finally, as expected, the more followers the poster has, the more likes a post will receive.

Quantifying the Imagery Effects

In this subsection, we quantify the net effect of image content on the number of likes and retweets using our model estimates. For the two tweet data sets, to quantify the mere presence effect of a directly viewable image or a linked image, we first compute the expected number of likes and retweets of a typical tweet without an image as the baseline[7] and compare it with the expected number of likes and retweets for a tweet with a typical image to calculate the percentage change. To quantify the effect of image characteristics and image–text fit, we use a typical tweet with a typical image as the baseline and compute the percentage change in the expected number likes and retweets due to a one-unit change in each variable while holding all other variables constant.[8] For the Instagram data set, we use a typical Instagram post as the baseline and compute the percentage change in the expected number of likes of a typical Instagram post due to a one-unit change in each variable. Table 8 reports the results.

Our results provide evidence for a mere presence effect of image content on microblogging social media platforms such as Twitter based on our findings from both the airline and SUV tweet data sets. For the airline related tweets, the inclusion of a directly viewable picture in a tweet increases its expected number of retweets and likes by 119.15% and 87.26%, respectively. For the SUV-related tweets, the lift in user engagement due to the mere presence effect is 213.12% for retweets and 151.56% for likes. However, our analysis using the airline tweets reveals that a hyperlinked picture has an adverse impact by decreasing the expected number of retweets and likes by 78.18% and 66.20%, respectively, compared with tweets without any images. These findings suggest that a user who posts a tweet with directly viewable image content will be rewarded by more retweets and likes for the extra time she spends in uploading a picture.

Regarding the effects of image characteristics, we find that the effect of image source and picture quality are consistent across both product categories and platforms. Compared with posts featuring a picture taken by a professional photographer, posts with an amateur photo led to a 24.78% decrease in

[7] A typical tweet without an image is defined as a post with text content and other control variables set to take the mode value (for categorical variables) or the median value (for continuous variables) in our estimation sample. All image content variables are set to be zero.

[8] A one-unit change for a categorical variable means that the value of the variable changes from 0 to 1. A one-unit change for a continuous variable means the value of the variable increases by one standard deviation.

Table 8. Marginal Impact of Image Content.

	Airline Tweet		SUV Tweet		Airline Instagram
	Retweet	**Like**	**Retweet**	**Like**	**Like**
Direct image	+ (119.15%)	+ (87.26%)	+ (213.12%)	+ (151.56%)	N.A.
Linked image	− (−78.18%)	− (−66.20%)	N.A.	N.A.	N.A.
Top 3 color	− (−21.77%)	n.s.	+ (26.89%)	n.s.	− (−4.50%)
Face presence	+ (80.40%)	+ (38.76%)	+ (291.22%)	n.s.	n.s.
Happy face	− (−12.52%)	n.s.	− (−42.28%)	n.s.	n.s.
Screenshot	− (−31.13%)	n.s.	n.s.	− (−75.47%)	− (−39.41%)
Amateur photo	− (−24.78%)	n.s.	N.A.	N.A.	− (−11.97%)
High quality	+ (20.30%)	n.s.	n.s.	+ (49.14%)	+ (9.89%)
Relevancy	n.s.	+ (42.45%)	N.A.	N.A.	n.s.

Notes: Cells with + or – symbols are significant at $p < .05$; n.s. = not significant; N.A. = not applicable.

sharing for airline tweets and an 11.97% decrease in liking for airline Instagram posts. Meanwhile, including a screenshot leads to a 31.13% decrease in sharing for airline tweets, a 75.47% decrease in liking for SUV tweets, and a 39.41% decrease in liking for airline Instagram posts. Similarly, we find consistent positive effects of high-quality pictures on user engagement. With a high-quality picture, an airline-related tweet receives 20.3% more retweets, and an SUV-related tweet receives 49.14% more likes. A high-quality picture also boosts the number of likes for airline-related Instagram posts by 9.89%.

However, the effects of other image characteristics, such as human image and colorfulness, tend to vary across platforms or product categories. Our analysis reveals that the presence of a human face in an image tends to induce higher user engagement on Twitter but not on Instagram. Specifically, compared with a tweet with a picture that does not contain human face, pictures with human face lead to an increase of 80.40% in sharing and 38.76% in liking for the airline tweets; however, if the face is a happy face, the number of retweets will decrease by 12.52%. These effects are robust across product categories on Twitter: our result shows a 291.4% increase in sharing for pictures with human face for the SUV tweets, and if the face is a happy face, the number of retweets will decrease by 42.28%. However, such an effect is absent on Instagram. This is because selfies or other human images are more common on Instagram than on Twitter and therefore are less likely to stand out. Our analysis also reveals that colorfulness of image content affects user engagement on both platforms, but its influence seems to vary widely across product categories. A one-standard-deviation increase in the top-three color pixel percentage (i.e., a less colorful picture) leads to a 21.77% decrease in the number of retweets on Twitter and a 4.5% decrease in the number of likes on Instagram for air-travel-related social media posts. But the same change leads to a 26.89% increase in the number of retweets for SUV related posts on Twitter.

Finally, our analysis reveals that image–text fit increases liking for airline-related Twitter posts by 42.5%; however, this positive effect is absent in airline-related Instagram posts. Users visit Instagram primarily for high-quality photos rather than breaking news or stories. Text is also shown in smaller fonts and in a less significant position on Instagram. Therefore, users pay less attention to the text content on this photo-centric platform.

General Discussion

Social media has enabled average internet users to share their experiences and opinions online and to let their voice be heard by many others. It also allows marketers to communicate with their customers in a direct yet inexpensive way. Social media users who desire to broaden their reach are interested in learning what factors drive the popularity of social media posts. So far, our knowledge about popularity or virality of UGC is mainly limited to the text content. However, with the tide shift toward visual social media, it is crucial to expand our understanding of how images affect the popularity of UGC on social media.

In the current study, we use observational data to examine the effects of image content on consumer engagement with social media posts. We propose three ways through which image content exerts influence on engagement—mere presence, image characteristics, and image–text fit—and test for the existence of these effects using three data sets containing social media posts about major U.S. airlines and compact SUV models on Twitter and Instagram.

We employ the propensity score matching method to control for the selection bias on the inclusion of image content for the two data sets collected on Twitter and estimate a BVZINB model on the matched sample to quantify all three proposed effects of image content. For the analysis of posts in our Instagram data set, which all included image content and received at least one like, we adopt the log-linear regression to quantify the image characteristics and image–text fit effects. Our findings on the two Twitter samples lend strong support for the mere presence effect and image characteristics effect of image content and some evidence for the image–text fit effect, which we then compare with our findings from the Instagram data set.

Theoretical Implications

Our findings enrich the current knowledge about drivers for user engagement on social media. While conventional wisdom suggests that images help a post become more popular, we offer a more nuanced explanation of how it happens. Our findings confirm that the mere presence of a directly viewable image always helps a tweet post to receive more likes and retweets. However, a linked picture backfires, in that it significantly reduces the number of likes and retweets because readers do not bother to click on external links. Therefore, when posting on social media platforms, the poster should always reupload the pictures to facilitate readers' engagement with the content.

Moreover, the relationship between image content and engagement is more complicated than the mere presence effect alone. Image characteristics also affect user engagement. Among the four image characteristics we examine, image sources and picture quality have consistent effects across the two product categories and social platforms we study. We find that compared with screenshots and photos taken by amateurs, pictures taken by professional photographers are associated with higher engagement. We also find that high-quality pictures always lead to more engagement.

However, the effects of other image characteristics are context dependent. We find that while colorful pictures lead to increased user engagement for airline-related tweets and Instagram posts, they tend to decrease user engagement for SUV-related tweets. We suspect that the different nature of consumption experience in these two categories may play an important role in driving these discrepant effects. We also find that the impact of human image and image–text fit varies by platform. While pictures with a human face and pictures relevant to text content induce more sharing and liking on Twitter, they do not affect engagement on Instagram. We believe this is due to the difference in the focus of these two social media platforms. Because Twitter was created to share breaking news and status updates, text content plays a dominant role. In contrast, Instagram entirely focuses on visual content, and the role of text content is much less prominent. As a result, including a picture with human face or a picture relevant to text content induces more engagement for a tweet but does not help an Instagram post in gaining more likes.

Marketing Implications

Our study offers important managerial implications for social media practitioners. First, our findings can guide social media marketers in identifying critical tweets when conducting brand-related social listening. Many Twitter users utilize the platform to make service complaints. The better identification of potentially influential posts allows these companies to take action before the harmful social buzz becomes viral. Most of the current social listening tools mainly track the total number of brand mentions and the sentiment composition while ignoring image content. Our research suggests that companies should include the presence of an image into their social listening metrics. They may also consider using online image processing tools such as Google Cloud Vision API to analyze the content of the picture further and pay special attention to images with certain characteristics (e.g., colorful pictures, pictures with a human face). Second, our findings also provide insight for social media users on how to create influential posts and, more importantly, how to adjust content characteristics depending on the social media platform they intend to use to maximize content effectiveness. The ubiquity of mobile phone cameras has enabled social media users to take pictures on the go. They should take advantage of this powerful tool and attach a picture to their posts to boost reach and engagement. Meanwhile, they should be more selective when choosing which picture to attach. Our findings give many clues about what types of pictures increase the liking or sharing of a post depending on the social media platform they choose.

Limitations and Further Research

To the best of our knowledge, this research is the first to explore the impact of image content on UGC popularity in the context of social media engagement. This is an important topic that offers plenty of opportunities for future research. First, although we have analyzed social media posts regarding two product categories from two platforms, by no means do we claim that our findings are universally valid. We call for future research to further expand the scope of empirical analysis to other product categories and social media platforms. Second, our analysis examines both user-generated and firm-generated social media posts for an industry. It would be interesting to test whether our findings are generalizable if the analysis is restricted to verified accounts, company-owned accounts, or influencer accounts only. This extension would generate valuable insights especially for industries that heavily rely on influencer marketing, such as apparel and cosmetics. Third, in this study we focus on only two engagement measures: the number of likes and shares. The other engagement measures, such as the number of replies, are also significant social media metrics valued by many companies. It can be challenging to model replying because it is also affected by factors such as the content of previous replies, the poster's propensity to respond, and so on. It is difficult to disentangle the effects of these factors and cleanly measure the impact of the post's image and text content on the number of replies. We acknowledge this as a limitation of our study and leave it to future research. Fourth, an in-depth investigation of what motivates social media users to post pictures online would be an excellent complement to the current study. Finally, a natural extension of this research is to further explore the economic effects of UGC with image content—for example, how does image content affect readers' purchase intentions or purchase behavior?

Acknowledgments

The authors thank Karan Bindra and Charles Ratcliff for their excellent research assistant work. They also thank the seminar and conference participants at University of Texas at Arlington, University of Texas at Dallas, University of Delaware, Syracuse University, Northwestern University Medill School of Journalism, Jinan University, and the 38th ISMS Marketing Science Conference for their feedback.

Associate Editor

Jonah Berger

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no external funding for the research, authorship, and/or publication of this article.

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