The Power of Brand Selfies in Consumer-Generated Brand Images

March 2019

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Funding:

This work was funded by the German Research Foundation (DFG) research unit 1452, "How Social Media is Changing Marketing", HE 6703/1-2.

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Abstract

Smartphones have made sharing images of branded experiences on social media nearly effortless. Tracking and understanding how brands appear online is relevant to brands both as an indicator of social media brand interest, and to incentivize consumers to create and share certain brand images. This research investigates consumer-generated brand images. Aside from packshots (i.e., standalone product images), the authors identify two different types of brand-related selfie images: consumer selfies, i.e., images featuring both brand logos and consumers' faces, and brand selfies, i.e., invisible consumers holding a branded product. Classifying nearly half a million Twitter brand images across 185 different brands and 6,926 Instagram images prompted by a Starbucks campaign using deep convolutional neural networks and text mining tools to measure consumers' engagement with brands, the authors demonstrate that the three brand image types generate different engagement levels among receivers. Specifically, the authors find that an emerging phenomenon, which they term *brand selfies*, leads to high levels of brand engagement from consumers. A controlled lab experiment replicates these findings and provides indications on the psychological mechanism.

Keywords: User-Generated Content; Social Media; Deep Learning; Natural Language Processing.

Every day more than 5 billion images are shared on social media networks such as Facebook, Twitter, or Instagram.[1] Of particular interest to marketers are images that feature brands and consumption experiences. Both interviews with industry experts and the assessment of a sample of images from social media suggest that brand-related images contribute approximately 1% of all social media images.[2] That is, 50 million social media images feature brand logos daily. This magnitude of brand image content is likely to exceed any other advertising channel by an order of magnitude, generating an immense level of reach.

One of the biggest trends introduced by smartphone cameras and social media are selfies. Selfies have quickly become so popular that Oxford Dictionaries named selfie the word of the year in 2013. According to estimates, individual millennial users will take more than 25,000 selfies in their lifetime (Glum 2015). Today, more than 383 million images with the hashtag #selfie exist on a single photo-sharing platform such as Instagram (www.instagram.com).

The emergence of selfies merits the question of how brands appear in selfie images and how observers respond to this type of social media brand images. As a matter of fact, recent marketing practice attempts to capitalize on the selfie phenomenon. For example, companies such as Unilever (Axe deodorant), Dunkin' Donuts, or Coca-Cola actively encouraged consumers to post selfies of their product encounters (see Appendix A). Coca-Cola even constructed a "Selfie Bottle" to assist consumers in taking pictures of themselves while drinking (Coca-Cola 2016). Brand images are also of interest to firms when passively listening in to social media posts. Among other things, companies track brand logo presence on social media to understand social media popularity, rank consumer-generated images on their social media brand page, or use such images as part of their own marketing campaigns. However, not all brand logo appearances are created equal. Some may generate more valuable consumer-brand engagement than others.

Accordingly, the objective of this research is to investigate how brands appear in consumer-

[1]Estimate based on Meeker (2016) and social media growth (Statista 2019).

[2]Based on a random sample of one image each day on Twitter in 2018.

generated images and to examine the effectiveness of different types of social media brand images on generating engagement among consumers. Specifically, we investigate both sender engagement objectives in terms of how brand images may generate image engagement (i.e., likes or comments) and brand engagement objectives in terms of how brand images may generate brand engagement (i.e., brand-related comments). Academic research provides ample evidence for the effectiveness of images in advertising (e.g., Hanssens and Weitz 1980; Xiao and Ding 2014). Recent studies have also explored the motivations to share content and take photos and how this impacts subsequent sender behavior (e.g., Barasch, Zauberman and Diehl 2018; Grewal, Stephen and Coleman 2019). However, little is known about how observers respond to brand images in social media.

Using both manual annotations of a sample of images and convolutional neural networks (CNN) for automated image classification of nearly half a million brand images related to 185 different brands that were posted on Twitter over two years, we identify three types of user-generated brand images that differ in terms of human and facial presence. Consumers post either images of products in isolation or holding products themselves (i.e., selfies). We find that these brand-related selfies exist in two forms with consumers either visible (their face) or invisible to the viewer (e.g., first-person point of view of the product). We name the former consumer selfie and the latter brand selfie to indicate the focus in brand selfies is exclusively on the product and differentiate it from consumer selfies where the face of the sender is visible. This results in the following typology of brand images (see Figure 1):[3]

1. *Brand Selfies:* branded products held by an invisible consumer,

2. *Consumer Selfies:* visible consumer faces together with a branded product,

3. *Packshots:* standalone images of branded products.

[3]Note, we distinguish brand and consumer selfies based on the visibility of consumer faces. Conceptually, the term selfie suggests the person on the image took the photo herself. Yet, in some cases, a third person may have photographed the sender ($< 3\%$ of brand selfies and $< 39\%$ of consumer selfies in our Twitter data). As Figure 1 illustrates, this can be difficult to distinguish empirically for both the human eye and an automated image classifier.

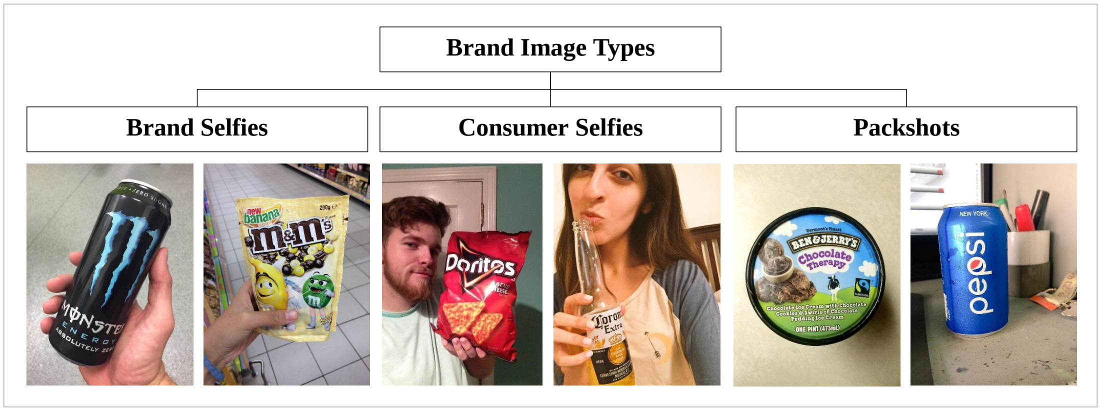


Figure 1: Illustrative Examples of Three Brand Image Types

In the set of 492,860 Twitter brand images we analyzed, we identified 22.42% brand selfies, 72.44% packshots, and only 5.14% consumer selfies. The CNN algorithm accurately classified images into these three categories with a hold-out accuracy level of $> 80\%$. The low fraction of consumer selfies on Twitter suggests that consumers are reluctant to post photos of themselves with the brand on their own accord. At the same time, consumer selfies are the image type most often encouraged by corporate communication campaigns, and face images, akin to consumer selfies, are ubiquitous in print advertising (Xiao and Ding 2014). Whether consumer selfies are well suited as a user-generated media content is an open question, which we attempt to answer in this research.

Analyzing consumers' response to the different types of brand images in terms of likes and comments, we find that consumer selfies, in which a person appears with the brand, generate the highest level of engagement towards the image or the sender in terms of the number of likes and comments on the image. However, these simple engagement measures, while encouraging for brands in terms of user potential, may be misleading. Examining the content of the user comments, using both dictionary-based and machine learning text mining tools, we find that consumer selfies generate fewer self-brand mentions and stated purchase intentions of receivers in response to the original image post. These results are consistent with research from traditional advertising and information systems, which indicate that, on the one hand, images with faces catch more attention than those without faces (Bakhshi, Shamma and Gilbert 2014; Xiao and Ding 2014), but, on the other hand, may detract attention away from the brand itself (Erfgen, Zenker and Sattler 2015).

In a second empirical application, we validate and extend these findings by investigating a company-initiated campaign. Specifically, we analyze images posted as part of a Starbucks campaign that incentivized consumers to post images of Starbucks cups on Instagram. The results largely corroborate the analysis of the Twitter data. We find that brand selfies are consistently the top performing user-generated brand images in terms of brand engagement. However, unlike the more general social media image analysis on Twitter, brand selfies dominate consumer selfies even in generating image- or sender-related engagement (likes and comments), which is plausible given the brand-centric campaign context.

We complement these results with a lab experiment, which allows us to control for the prominence of the brand in the image and collect brand attitude and purchase intent ratings, as well as to test potential psychological mechanisms that may trigger consumers' varying reaction to different brand image types. The results of the experiment further suggest that brand selfies have a superior impact on brand attitude and purchase intent compared to consumer selfies. In addition, it suggests the differential impact of brand selfies is related to easier and more accessible self-reference and mental simulation offered by these image types.

The remainder of the paper is organized as follows: In the next section, we discuss the literature related to the role of user-generated brand content and consumer response to branded images. We then describe the analysis of the extensive Twitter image dataset and the deep learning algorithms we deployed to identify the three types of brand images (brand selfies, consumer selfies, and packshots). The subsequent section analyzes the impact of the different types of images in the context of a company-initiated (Starbucks) campaign, followed by a controlled lab experiment, which allows us to dig in deeper into the possible underlying mechanisms that lead to consumer reactions to the image types. We conclude with a discussion and suggestions for future research.

BRAND IMAGES IN SOCIAL MEDIA

The Role of User-Generated Brand Content in Social Media

Numerous studies demonstrate the importance of user-generated content (UGC) as a platform for social listening and understanding of customer needs, as well as in terms of affecting consumer behavior (Moe, Netzer and Schweidel 2017). The majority of this research has relied either on summaries of text content such as volume and valance (e.g., Chevalier and Mayzlin 2006; Godes and Mayzlin 2004; Liu 2006) or on analyzing user-generated texts to automatically capture consumer perception (Netzer et al. 2012; Tirunillai and Tellis 2014). UGC has been shown to predict demand (e.g., Chevalier and Mayzlin 2006; Liu 2006), customer-based brand equity (e.g., Schweidel and Moe 2014), and stock returns (e.g., Colicev et al. 2018). In addition, individual elements of text content (e.g., valence and arousal) differ in viral potential, perceived usefulness to receivers, and impact on corporate communication effectiveness (e.g., Berger and Milkman 2012; Yin, Bond and Zhang 2017). Taken together, this research demonstrates that communication content on social media carries important information to consumers, linking social media response to brand performance.

However, despite the increasing role of images in social media, academic research on UGC has mainly focused on textual analysis and summaries of text content. Only very few recent papers have made use of advances in image classification and deep learning to study images in UGC (e.g., Liu, Dzyabura and Mizik 2018; Zhang and Luo 2018; Zhang et al. 2018). Most important to this research, Liu, Dzyabura and Mizik (2018) investigate how social media images can reflect perceptual brand attributes. This research provides valuable insights into the impact of user-generated images on receivers. Relatedly, Klostermann et al. (2018) uses and tags social media images related to the McDonald's brand to create an associative network. From the sender perspective, Grewal, Stephen and Coleman (2019) finds that sharing images serves important social objective in terms of identity signaling.

We build on both of these streams of research to study how different types of brand images on social media relate to both sender-related engagement in terms of the number of likes and comments as well as brand engagement in terms of the content of brand-related communication while controlling for the text content of the image post.

Consumer Responses to Different Brand Image Perspectives

The three types of consumer-generated brand images we identified (brand selfies, consumer selfies, and packshots) differ in terms of human presence (both types of selfies with human presence vs. packshots without) and facial presence (consumer selfies with facial presence vs. brand selfies and packshots without). While research on the role of selfies in marketing is scarce, we can draw on findings from traditional advertising and image research on the role of both human and facial presence in images.

Human presence. In print advertising, human presence is common practice in over 50% of ads (Xiao and Ding 2014). Marketing scholars extensively studied this from the perspective of brand endorsement (Knoll and Matthes 2017). Similarly, consumers holding a branded product as in both selfie types is likely to be a stronger personal endorsement than a packshot. At the same time, image endorsements are non-trivial and can backfire (Knoll and Matthes 2017). For example, celebrities in advertising can overshadow brands and inhibit brand recall (Erfgen, Zenker and Sattler 2015). Outside the selfie and branding context, social media users often seek popularity within their personal network (Ansari et al. 2018) and self-advertise themselves when posting images (Toubia and Stephen 2013). The fact that even paid brand ambassadors on professional images can be detrimental to brand recall suggests similar effects are conceivable when self-interested consumers post self-generated images. This can result in brand engagement falling short of image engagement and result in increasing discrepancies as the visibility of the sender increases in brand and consumer selfies.

Facial presence. While brand selfies and consumer selfies differ from packshots in endorsement and consumer presence, consumer selfies also differ from both packshots and brand selfies in terms of facial sender presence. In addition, unlike consumer selfies where the receiver looks directly at the sender, brand selfies but also packshots typically involve a shared point of view between senders and receivers.

As the amount of available information proliferates, facial images can play a pivotal role in attracting selective attention (Tomalski, Csibra and Johnson 2009). Indeed, social media research reports the "faces engage us" effect, suggesting that the most liked and commented images on social media are those containing faces (Bakhshi, Shamma and Gilbert 2014). This is consistent with findings that faces capture more attention than competing visual stimuli and are processed at higher speed and in greater detail (e.g., Devue, Belopolsky and Theeuwes 2012). This attentional bias has also been demonstrated in print advertising (Guido, Pichierri and Pino 2018). From a brand perspective, facial consumer images in UGC can be a double-edged sword. On the one hand, faces increase attention to the image itself, but on the other hand, the brand has to share a physical space with the sender's face, which can result in smaller brand logos on average and lower attention to the brand itself compared to the other two brand image types.

When it comes to brand selfie images, the necessity for a brand selfie photographer to be within arm's length of the camera and the natural position within the center of the image might ensure the featured product is subjectively within intimate space to the receiver. In advertising, this proximity is associated with heightened attention, more intense involvement, salience, and brand-related engagement (Messaris 1997).

The three types of brand images may also trigger different types of psychological processes. Specifically, first-person perspectives result in more vivid mental visualizations compared to third-person perspectives (Bone and Ellen 1992). Consequently, viewers can relate the brand more easily to themselves, which may result in higher levels of elaboration and depth of encoding than information unrelated to the self (e.g., Bower and Gilligan 1979). These benefits of self-reference processing have produced robust effects in terms of elaboration and recall across a wide variety of domains (Symons and Johnson 1997). In contrast, faces of other consumers visibly holding a product are likely to drive other- as opposed to self-related thoughts, suggesting brand selfies, and to some extent packshots, are likely to lead to higher levels of self-reference and consequential engagement than consumer selfies.

Furthermore, brand selfies can result in mental visualizations of connections to the product, which in turn may lead to subjective feelings of psychological ownership, i.e., consumers feeling as if they possessed the presented product (Peck, Barger and Webb 2013; Weiss and Johar 2018). In contrast, consumer selfies emphasize actual ownership of another individual, which can inhibit psychological ownership perceptions (Kirk, Peck and Swain 2017) and inhibit assimilations of product traits towards the self-image of the viewer (Weiss and Johar 2013). This suggests brand engagement is stronger whenever sender and receiver share the same point of view as in brand selfies and packshots (Peck and Shu 2009; Shu and Peck 2011). Additionally, the egocentric perspective of brand selfies may serve as an executional cue that facilitates actions over and above subjective feelings of ownership or self-reference thoughts (Krishnamurthy and Sujan 1999). Previous research has linked such mental simulations of actions to brand-related behavioral outcomes such as purchase intentions (e.g., Elder and Krishna 2012; Zhao, Hoeffler and Zauberman 2011).

In summary, research on endorsement and attention to faces suggest that consumer selfies are likely to attract higher levels of engagement (e.g., impressions and likes) than the other two image types. At the same time, endorsement research indicates that the presence of faces can detract attention away from the brand, in particular, when senders are motivated to promote themselves rather than the brand. Self-reference, psychological ownership, and mental simulation theories suggest that brand selfies, which often involve a consumer touching the brand from the point of view of the viewer, may generate higher levels of brand-related information processing, memory recall, and brand purchase desire. Empirically, both brand selfies and packshots appear very similar to a superficial observer as they share similar image compositions and differ mainly in the presence of the sender hand. We investigate next whether such subtle differences can result in a detectable impact on social media response.

EMPIRICAL APPLICATION: BRAND IMAGES ON TWITTER

To investigate the prevalence of the different brand image types and their impact on brand engagement, we analyze an extensive set of images shared via Twitter, a social network with high reach both in terms of individual (321 million monthly active users as of 2018; Twitter 2019) and corporate users (91% of Fortune 500 companies; Barnes, Kane and Maloney 2018). Moreover, in recent years, the amount of image content on Twitter has increased rapidly and approached as much as 20% of all posts (Vicinitas 2018).

Data

As a first step, we wish to collect a comprehensive dataset of Twitter images that include brands. An intuitive approach to identify brand logos on Twitter is accessing all image posts featuring a brand name as a hashtag. While it is relatively simple to collect such data, such approaches can be potentially misleading because the majority of the posted brand logos (85%) do not feature the respective brand hashtag (Cass 2016).[4] Furthermore, brand images that include brand hashtags (e.g., #brand) or handletags (e.g., @brand) may be inherently different from brand images that do not, as the decision to add a brand mention may involve more conscious brand deliberations by the sender.

Our analysis, therefore, requires more comprehensive access to brand images. For this purpose, we collaborate with a U.S.-based vendor with a Twitter firehose access to a random sample of 10% of all tweets on Twitter. This allowed automatic tracking of logo appearances for 185 brands across 10 categories (including sweet and salty snacks, non-alcoholic and alcoholic beverages, cereals and ice cream) over two years (January 2014 to December 2016). The vendor identifies images that contain brand logos using machine learning. The resulting data comprises 883,304 brand logo images in total and contains the original image, the size,

[4] We found similar figures in our data, which involves only branded images. Only 13.44% of the images mention the brand as a hashtag or handletag in the sender caption.

and location of the detected logo as well as an identification number of the original tweet, allowing us to augment the data.

We assess the quality of the brand logo detection in two ways. First, a research assistant inspected a random sample of 16,949 images to identify potential false positives (4:45 hours of manual work). This revealed a precision (i.e., the share of correct classifications of all identified logos) of 95.9%, suggesting negligible false classifications. These high values of accuracy are plausible given that identifying brand logos is a relatively easier task than common image recognition tasks with much higher levels of heterogeneity across items (see Deng et al. 2009, introducing the large-scale ImageNet dataset). Second, we conducted hashtag searches of individual brands on Twitter to see all available images and inspect recall, i.e., whether all relevant logos on Twitter are systematically captured. A comparison with the subset of our data with brand hashtags suggests high levels of recall. For example, for the brand hashtag #Heineken we find 115 logo appearances in a single month. For the same month, our image data contains 13 brand logo appearances with Heineken hashtag (246 without), which is in line with expectations for a random Twitter sample of 10%.

Using the identification number of the original tweet, we augment this data by accessing the original Twitter post of each image and collecting the number of likes each image has received, the number of comments, the caption of the post (i.e., the text accompanying the image post) and all comments' text content, hashtags and handletags of the post as well as all available information on the senders (their posting activity, number of friends, and number of followers). Note that we collected this information three months after the last image was posted. However, because most comment responses and likes on Twitter happen within the first 24 hours (Hennig-Thurau, Wiertz and Feldhaus 2015), we are confident that our data contains the vast majority of the relevant responses to the posts. Additionally, we control for post age in our econometric models.

Automated Image Classification

Recent advances in computer vision have produced remarkable accuracy levels, which in certain domains exceed (expert) human capability, e.g., in lip reading from videos (Chung et al. 2017). Having obtained a dataset of images with brand logos, we build on these deep learning architectures to automatically classify the types of user-generated brand images. For this purpose, we apply transfer learning. The idea of transfer learning is to obtain an existing CNN pretrained on a large dataset (e.g., the 1.2 million ImageNet images, Deng et al. 2009) and *transfer* the learning from that dataset to our context by adjusting the CNN through modified and added layers. This procedure is common in image analysis as it reduces the human-annotated training data and avoids overfitting to limited datasets (Yosinski et al. 2014; Zhang and Luo 2018).

Our training data comprises 16,949 randomly drawn images from the Twitter data. We asked a research assistant, who was unaware of the purpose of this investigation, to manually classify the brand images into the three brand image categories by visual inspection (brand selfies, consumer selfies, and packshots). Because some of the images contain advertising content such as banner ads, which are not user-generated, we added a fourth category to the classification (advertising).

To speed up this coding process, a program displayed the images sequentially, allowing the human coder to quickly assign each image to one of the four categories by pressing a button (below one second per image, 4:45 hours in total). To assess the validity of the resulting manual classification, we selected a random sample of 400 images (100 images per class) and asked an independent research assistant to verify the classification. The results of this reveal a correct classification of above 95% of the data (2.75% error rate), suggesting the manual classification is a valid representation for training our deep learning algorithm.

We split the classified data into training (60%), validation, and test sets (20% each). The training data is used to train the CNN, the validation set is used to tune the CNN hyperparameters, while the test set provides an unbiased performance estimate on data that was not used to estimate the model. For our application, we employ the VGG-16 CNN architecture, which produced high performance in the ImageNet challenge, especially for classification and localization tasks (Simonyan and Zisserman 2014). In the CNN, the first layers learn to detect low-level features such as contours, textures, and colors that are expected to generalize well across classification tasks. We retain these layers and replace only the last few layers by four new layers to automatically classify brand images (see Web Appendix A for details).

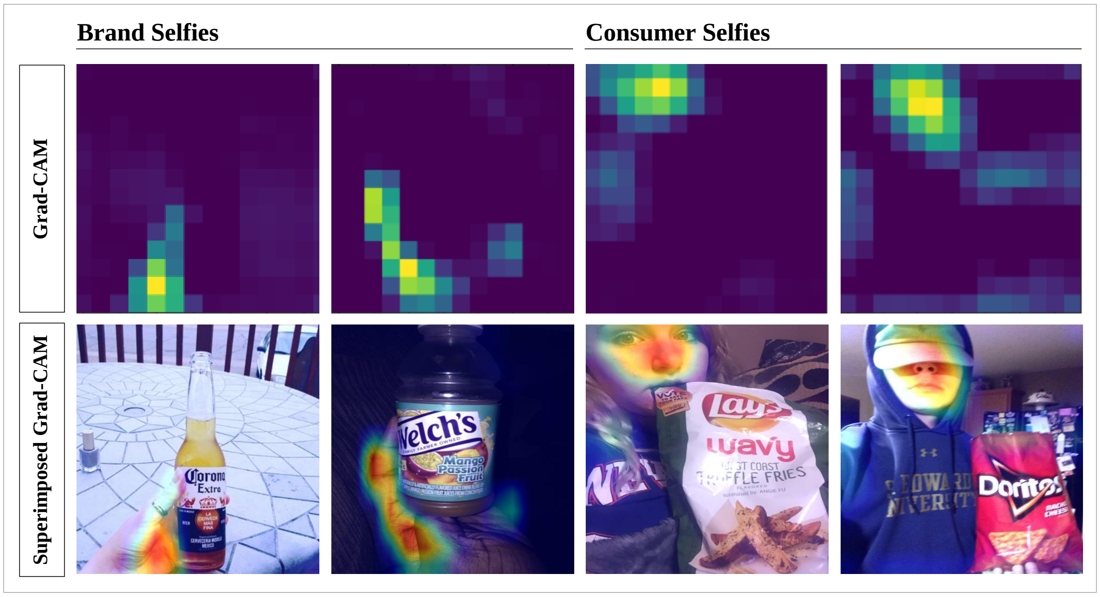
To further increase the learning capacity of the CNN, we also fine-tune the parameters of the last convolutional block, which consists of four convolutional layers. Thus, in addition to the new layers and their approximately 3.2 million parameters, which we added to the existing CNN architecture, we update also parameters of selected layers of the existing network. Precisely, after replacing the last layers, we fine-tune 48.11% of the pretrained parameters (i.e., approximately 7.1 million weights) and hold the remaining 51.89% constant (i.e., approximately 7.6 million weights).

Overall, this procedure allows the CNN to better adjust to the particularities of our classification task, while at the same time leveraging existing classification experience. For example, the features that the CNN learned to detect cats and dogs during training on the ImageNet dataset might also be useful to detect facial features on consumer selfies. In addition, we artificially augment the available data. Specifically, we rotate, flip, and shift images by random factors (see Web Appendix B). For example, most brand selfie images (about 80%) feature the left hand holding the product (right hand holding the smartphone), making it challenging for the algorithm to classify the remaining 20% of the images with right hands holding a product. Mirroring the images provides more balanced training data and better classification performance.

After calibrating the CNN on the training and validation data, we compute the accuracy of the image classification algorithm on the 20% of images in the test data, which were not used for training. For this purpose, we compute the harmonic mean (i.e., F1 score) between the proportion of all images the network identifies correctly (recall) and the proportion of the identified instances that are correct brand representations (precision). This results in an F1 score of 81% overall, with the highest performance for packshots (83%) and the lowest performance for consumer selfies (70%), suggesting that the brand image types can be classified automatically with sufficient accuracy to warrant further analysis (see Web Appendix C for further details).

While CNNs are commonly considered *black boxes* when it comes to understanding how the algorithms decide to classify certain images to certain classes, we create gradient-weighted class activation maps (Grad-CAM; Selvaraju et al. 2017) to provide post-hoc interpretation for the aspects of the image that play an important role in the classification task. The Grad-CAM algorithm allows us to explore which image features the network is receptive to and to localize objects that the network deems informative for predicting a specific class. Figure 2 presents two Grad-CAM examples for each selfie type and lends insights into how our CNN arrives at its predictions. As expected, we can see from the Grad-CAM heat maps that the main features for the CNN to distinguish between brand selfies and consumer selfies are the presence of a hand and a face, respectively. Both are highlighted in dark red on their superimposed heat maps, showing that, contingent on these two classes, the network is highly activated by these regions. As can be seen, the network provides robust classifications also for challenging examples, e.g., low contrast images and covered eyes, which are a distinctive feature of faces (rightmost image in Figure 2). For packshots, the CNN appears to act as a general product classifier, detecting packaging edges, while at the same time recognizing the absence of faces and hands (see Web Appendix D for four packshot Grad-CAM examples).

Given the high accuracy level of our fine-tuned classifier, we proceed and apply the re-trained CNN to the full set of 883,304 images to classify all images into the four image type categories. For the subsequent analysis, we exclude the fourth category of corporate-generated advertising content (492,860 images remaining). Analyzing such a large number



Notes: During image pre-processing, images are rescaled to standard size of 224 by 224 pixels.

Figure 2: Grad-CAM Examples for Both Selfie Types

of images is pertinent since images are disparate across product categories and brands. Also, selfies and brand-related comments occur less frequently than standard image engagement metrics (i.e., few combined observations, see Table 1 below). Thus, automated image classification allows us to analyze sufficient data also on rarely occurring events. Having said this, an econometric analysis of the manually classified data is possible for the number of likes and comments. The results from analyzing only the human-coded data are directionally and substantively similar compared to the results reported next, which further reaffirms the analysis of automatically classified data.

Automated Text Classification

In terms of outcome measures, we are interested in both image (or sender) as well as brand engagement. To measure image engagement, we count the number of likes and comments that the image posted by the sender received. However, we cannot disentangle whether the likes or comments that a brand image received occur in response to the brand-related content or brand-unrelated (e.g., sender-related) elements of the image. To investigate whether the comments relate to the brand and consumers' intentions about the brand, we employ text mining tools.

Specifically, we text mine both the caption (text written by the sender accompanying the image post) and the comments (public responses by receivers of the post). In terms of captions, we use LIWC (Pennebaker et al. 2015) to obtain the share of first-person (senders referencing themselves) and second-person (senders referencing receivers) words, the share of words indicating a question, and the share of netspeak (e.g., thx, lol) out of all words to control for differences in accompanying caption text between the image types. Explicit mentions of the brand in the image caption and brand tags can also drive brand-related response. We therefore also control for the number of brand tags (both hashtags and handletags) as well as occurrences of the full brand name in the caption based on a custom brand dictionary for the 185 brands in our analysis.[5] Additionally, we code the sentiment of the caption by calculating the positive and negative word share in the caption using VADER sentiment dictionary (Hutto and Gilbert 2014).[6]

To analyze the impact of user-generated images on brand engagement, we investigate the comments receivers of the image made. Specifically, we look at consumers mentioning the brand visible in the image with references to themselves (e.g., "I also love Pepsi"), as well as receivers mentioning purchase intentions of the product (e.g., "omg, now I also want one!!"). To capture self-brand mentions, we count co-occurrence of a first-person receiver statement based on the LIWC dictionary and a brand mention similar to the approach used for the captions.[7] Capturing purchase intent is more difficult as it involves a sequence of words with a specific semantic relationship. Accordingly, we train a machine learning algorithm

[5]A set of ten brands (e.g., Crush, Extra, Surge) also occur as part of natural language. Eliminating these brands results in stable findings. We therefore kept all data on all brands for subsequent analyses.

[6]We use VADER because it provided better results on sentiment analysis than other sentiment dictionaries such as LIWC (Hartmann et al. 2018). Additionally, a model controlling for sentiment based on LIWC resulted in similar conclusions.

[7]A model based on all brand mentions (without requiring co-occurrence with self-related speech) results in directionally and substantively similar findings. Since such brand mention extraction is less clearly related to brand engagement of the receiver, the following is based on self-related brand speech.

to capture these expressions. Creating training data for purchase intent using a random sample of comments can be inefficient due to the low frequency of purchase intent statements across all comments. To address this issue, we use selective sampling (Donkers, Franses and Verhoef 2003) by employing a two-step sampling approach. First, to increase the likelihood of purchase intent expressions, a research assistant labeled a random sample of 1,000 comments that mention a brand on whether the comment included a purchase intent. Second, we train a random forest (RF) based on these annotated data to learn what words are most predictive of expressed purchase intentions (i.e., “want”, “buy”, and “bring”) to identify another set of 1,000 comments with an above-average probability of purchase intent statements. We collected three independent judgments for each of the additional 1,000 comments through MTurk with the majority vote as the final annotation (inter-coder agreement: 80.6%). This procedure resulted in an oversampled number of purchase intentions of 553 (27.65% of all instances used for training).

We then use ten-fold cross-validation with 80% training and 20% hold-out data to train an RF model for this binary classification task (Hartmann et al. 2018). We obtain a hold-out classification accuracy of 81.95% (average cross-validation accuracy of 81.07%, suggesting overfitting is not an issue).[8]

To summarize, we obtained the number of likes and comments the image received to capture image engagement directly from the data. To capture brand engagement, we use a dictionary-based text mining approach to capture self-mentions of the brand, and an RF machine learning approach to capture expressed purchase intents. We also control for the textual information in the image caption.

[8] We compare the performance of the RF classifier to that of a support vector machine (SVM), commonly used in marketing (e.g., Ordenes et al. 2019). The SVM resulted in a lower accuracy level (80.95%) relative to the RF model.

Descriptive Characteristics of Brand Selfies, Consumer Selfies, and Packshots

Before analyzing the level of engagement that different types of brand images generate, it is useful to examine some model-free evidence on differences between the three types of images. As can be seen in Table 1, we find that most brand images are packshots (72.44%), followed by brand selfies (22.42%), and consumer selfies (5.14%). Interestingly, consumer selfies, in which consumers take a selfie with the brand, are not common among social media images, suggesting that users are not self-motivated to take and post pictures of themselves with branded products. This is also in contrast to the prevalence of faces in 50% of all images in traditional advertising (Xiao and Ding 2014), and inconsistent with many brand campaigns on social media, which encourage consumers to take consumer selfie images with brands (see Appendix A).

— Insert Table 1 about here —

In terms of image and brand engagement, consumer selfies generate most likes (7.45 on average vs. 5.09 and 4.34 for brand selfies and packshots, $p < .01$) and most comments (.52 vs. .44 on average for both brand selfies and packshots, respectively $p < .05$). Conversely, relative to consumer selfies, brand selfies result in higher levels of self-brand mentions (.03 vs. .02, $p < .01$) and expressed purchase intents (.08 vs. .05, $p < .01$). We do note that these differences between the engagement that different brand images generate may be the result of other factors, such as image prominence or the text in the caption that accompanies the image, which we control for in the subsequent analysis.

As expected, brand selfies on average feature the largest brand logo, which is almost twice the size compared to consumer selfies (logo share of 3.11% vs. 1.60%, $p < .01$). In addition, brand selfies seem to induce natural gravitation of the brand logo towards the image center, reflected in the lowest distance of the logo midpoint from the image center at 178.05 pixels. In contrast, brand logos on consumer selfies are on average 270.33 pixels away from the image center. Packshots are at an intermediate position in terms of both logo share and distance. In terms of objective image quality measures such as visual complexity (JPEG file size divided by the image area; Pieters, Wedel and Batra 2010), image brightness (average pixel illumination; Matz et al. 2019), and contrast of image brightness (SD of illumination across all image pixels; Zhang et al. 2018), we see comparable values across image types, suggesting image type reflects image content rather than photographic technicalities.

Table 1 also reveals that brand selfies tend to come with shorter captions as well as fewer hashtags and handletags than both other types of brand images. Interestingly, brand selfies have the highest share of first-person pronouns of caption words, suggesting senders who post images without showing their face talk more about themselves (5.41% vs. 4.58% and 4.35% for consumer selfies and packshots, respectively). At the same time, brand selfies refer equally often to the receiver, as we see a similar share of second-person captions across all three brand image types. In line with the spontaneous snapshot characteristics and social media connotation of selfie-type images, both brand and consumer selfies feature a higher share of netspeak than packshots (2.29% and 2.22%, respectively vs. 1.93%). In terms of text valence, we find that fewer positive and more negative words accompany brand selfies. This would suggest a less favorable brand response to brand selfies relative to consumer selfies based on the text alone. Interestingly, despite and possibly because of the visual prominence of the brand in brand selfies relative to consumer selfies, we see that only 6.27% of brand selfies are accompanied with a brand caption, relative to 7.09% of the consumer selfies.

To investigate whether brand images with brand tags differ from those without, we also look exclusively at brand images that are accompanied by brand hashtags or handletags (see 'Brand Tags' columns in Table 1). We find some notable differences. Specifically, posts with brand tags are more likely to feature brand selfies (24.33% vs. 22.42%), and are less likely to contain packshots (70.98% vs. 72.44%; $\chi^2(2) = 133.86$, $p < .01$). As expected, brand images accompanied by a brand tag feature significantly larger brand logos across all three image types and are more central on the image. Also, the caption text differs and contains less brand mentions and first-person text content when brand tags are present. These observations suggest that senders who employ brand tags intend to send messages systematically different from the majority of brand images that do not contain hashtags, which highlight the risk of relying on hashtags in analyzing social media brand images.

Impact of Brand Image Type on Image and Brand Engagement

To analyze the impact of brand image type on engagement, we explore four behaviors. To capture image (or sender) engagement, we examine the number of likes and comments the brand image received. To capture brand engagement, we examine whether the comments to the image include self-related mentions of the brand and expressions of purchase intent. As all these behaviors are collected as count data and their distributions indicate overdispersion, we estimate negative binomial regressions (e.g., Akpinar and Berger 2017; Ordenes et al. 2019). The four receiver reactions serve as dependent variables and the brand image type as an independent variable, while controlling for the aforementioned text and image characteristics, sender characteristics (post age, number of posts, followers, and friends of the sender), and brand-level fixed effects to take brand-level heterogeneity into account (e.g., brand equity, differences in logos, or overall product desirability).[9]

The analysis of the number of self-brand mentions and expressed purchase intentions is by definition limited to those brand images that receive at least one comment (16.49% of all posts). Within this group, the probability of self-brand mentions and purchase intent expressions increases with the number of comments. To interpret the impact of brand image type over and above the impact on the absolute number of comments, we control for the number of comments in these two models. We inspect variance inflation values to investigate whether this high level of control results in multicollinearity and find that all values for all models are well below 3. Table 2 summarizes the results of the regressions.

[9]We also estimated Poisson regressions which resulted in qualitatively similar results, but had lower model fit. Because these controls may not capture all differences in post texts potentially associated with the three image types, we run another text classification model based on RF and predict each image class based on the caption text (predictive accuracy of 73.43%). Controlling for these predicted values leads to consistent results.

— Insert Table 2 about here —

The impact of control variables with clear theoretical expectations are all in the expected direction. Specifically, having more followers results in more likes and comments (.72 and .52, both $p < .01$). If the sender posts more content, individual posts compete for attention and receive fewer likes and comments (-.24 and -.02, both $p < .01$). Larger logo share receives more self-brand mentions (2.51, $p < .05$). More central logo positions (i.e., with lower logo distance from image midpoint) also benefit self-brand mentions (-.16, $p < .01$) and purchase intentions (-.05, $p < .10$). Interestingly, these effects reverse for likes and comments, suggesting that viewers are less interested in brands and brand logos compete for attention with other aspects of the image such as consumer faces. Thus, the objective of the sender to garner popularity and virality may be misaligned with the objective of the brand to achieve brand-specific engagement.

In line with these image content observations, brand tags are undesirable in terms of likes and comments, but, as expected, result in more self-brand mentions. Conversely, questions result in more likes and comments while at the same time being associated with fewer self-brand mentions. Also, prior research reports neither too high nor too low levels of visual complexity are desirable (e.g., Pieters, Wedel and Batra 2010), which is what we find as evidenced by a positive linear (.17 and .25, both $p < .01$) and a negative quadratic impact (-.02, and -.03, both $p < .01$) for likes and comments, respectively. Longer captions result in fewer likes (-.08, $p < .01$), but appear to contain more topics for discussion and result in more comments (.07, $p < .01$). Interestingly, negative sentiment generates more likes and comments than positive sentiment.

More important to this investigation is the effect of the three image types on the four behaviors. Consistent with social media research (Bakhshi, Shamma and Gilbert 2014), the appearance of faces drives image engagement. Specifically, we observe the highest number of likes for consumer selfies compared to brand selfies (-.37, $p < .01$) and packshots (-.54, $p < .01$), with brand selfies generating more likes than packshots ($p < .01$). While a like requires no more than the click of a mouse and needs little consideration, comments require more processing of the posted information content and require higher effort in terms of phrasing and typing. Faces attract immediate attention (Tomalski, Csibra and Johnson 2009), but may not necessarily result in more thorough information processing. For comments, we indeed observe that consumer selfies and brand selfies generate similar levels of comments (-.003, $p > .10$). Similarly, the difference between consumer selfies and packshots is also smaller for comments than for likes (-.12 vs. -.54, both $p < .01$).

From a brand perspective, the fact that consumer selfies achieve more likes does not necessarily translate into higher levels of brand engagement. Interestingly, brand selfies attract a significantly higher number of self-brand mentions relative to consumer selfies (.64, $p < .01$). This effect of brand selfies is also higher than that of packshots (.64 vs. .42, $p < .05$), which also outperform consumer selfies ($p < .05$), suggesting that faces can divert attention away from the brand. Brand selfies and packshots also receive more purchase intents (.44 for brand selfies and .41 for packshots, both $p < .01$) relative to consumer selfies. The difference between packshots and brand selfies is not statistically different ($p > .10$).

Taken together, these results suggest that consumer selfies and consumer faces can be a double-edged sword for marketers. While consumer selfies can represent a stronger level of endorsement, they also risk diverting attention away from the brand (see Knoll and Matthes (2017) for similar findings in advertising). Our results also suggest reconsidering the marketing value of likes of consumer-generated brand images. Both brand selfies and packshots receive fewer likes, but more self-brand mentions and purchase intents, implying that likes often refer to brand-unrelated content (e.g., the sender) as opposed to how the brand is perceived on the images. When comparing both forms of selfies in terms of commenting, brand selfies dominate consumer selfies as they produce a highly similar number of comments, but brand selfies provide more brand-related comments and higher purchase intent expressions. Next, we test whether these findings replicate in a campaign setting where a brand (Starbucks) encourages consumers to join a brand image contest on social media (Instagram).

COMPANY-INITIATED BRAND IMAGE CONTEST

The objective of the second empirical application is to replicate and extend the results of the first empirical application to a different platform (Instagram, as opposed to Twitter in the first application). Moreover, we now explore a context in which the firm is encouraging consumers to share photos as part of a marketing campaign. Hence, all images are expected to have a branded product in them. Also, by analyzing a specific brand campaign, we can hold the brand constant across images, providing a more controlled setting for the analysis of brand images and social media engagement.

In November 2015, Starbucks launched a brand image contest on Instagram. With 17.3 million followers, Starbucks is the brand with the largest followership in the food and beverages category on Instagram (Paul 2018). Starbucks encouraged its followers to create and share Starbucks images and tag them with a dedicated campaign hashtag, which has become a common marketing strategy. All participants had the chance to win a Starbucks gift card, incentivizing them to share appealing image content with a spotlight on the Starbucks brand.

With more than 1 billion monthly active users, Instagram is considered the most popular image-sharing platform (Statista 2019). In contrast to Twitter as a micro-blogging platform, Instagram provides significantly higher entertainment and less information value, providing a native visual environment for the creation and curation of creative content (Voorveld et al. 2018). For the Starbucks campaign, user comments such as "this literally looks like a screenshot of a Starbucks commercial" or "I thought this was one of those advertisements until looked at the screen name" indicate that the level of image quality produced by consumers is likely to be higher than the average social media image.

Data

We identified 6,926 public Instagram posts that appeared as part of Starbucks' contest, featured the campaign hashtag, included the Starbucks logo, and appeared after the campaign launch. Hashtag identification is meaningful in this context because only those tagged images could participate in the contest. Given the relatively smaller size of available campaign images for Instagram (compared to almost 900,000 Twitter images) and the efficiency of image coding, we manually coded all available Starbucks images (approximately 2 hours of a human coder).

Additionally, we compare the manual classification of images to those based on an automated CNN classification. We compare three classification approaches. The first simply takes the model trained on the Twitter data and applies the classification to the Starbucks data. This is a difficult task because the Twitter dataset is in many ways quite different from the Starbucks dataset (more than twice as many labeled images, multiple brands, and product categories, and many advertising images, which do not exist in the Starbucks data). Even this simple approach, which fully transfers the training from the Twitter data to the Starbucks application with no additional training leads to reasonable accuracy levels of F1 = 73%. A second approach is to mimic the approach we used in the Twitter application and to retrain a CNN trained on ImageNet specifically for the Starbucks application using 80% of the data for calibrating the model (training and validation sets) and retain 20% as a hold-out test set. As expected, we find that training the CNN using data from the specific application leads to a substantial increase in accuracy (F1 = 84%; see Web Appendix E).

A limitation of the second approach is that it does not transfer the learning from the Twitter application to the Starbucks application. Accordingly, in the third approach, we leverage the CNN that we trained to classify Twitter images in the previous analysis (see Web Appendixes A and B), and retrain only the last couple of layers in the CNN to the new application. This approach is similar in spirit to the Twitter application, in which we took a CNN trained on millions of ImageNet images and retrained it to the Twitter application by fine-tuning only a subset of the layers and parameters. As this approach leverages both the ImageNet data and the Twitter data it is expected to lead to higher accuracy levels. Indeed, we find that this approach yields the highest average F1 score for the test data of 88%.

These findings suggest it is useful to transfer the knowledge of classifying brand image types across domains and improve classification accuracy by using transfer learning. Specifically, in our application previous training of a related task in another environment (different social network, brands, and product categories) benefits classification of a more narrow problem on a smaller dataset.

The high levels of classification accuracy are encouraging. As in the Twitter analysis, results of the analyses comparing the three image types are directionally consistent between manual and the different automated classification. For the following analysis, we make use of the best level of data quality available to us and study the human image classification. For the Twitter analysis we studied many more images (N = 492,860). This allowed us to run meaningful analysis on rarely occurring events such as purchase intent statements. The lower number of campaign observations does not permit such analysis for the Starbucks campaign. However, we can replicate the analysis on likes and comments to study differences between solicited and unsolicited brand images.

Web Appendix F contains exemplary Instagram images for all three brand image types. Most user-generated campaign images are packshots, contributing a share of 56.27%. 31.11% are brand selfies, and 12.62% are consumer selfies. Compared to the organic Twitter content, this distribution is shifted from packshots to consumer selfies, suggesting either the campaign context or the Instagram platform prompted more users to reveal their face. At the same time, consumer selfies continue to be the least commonly used category, supporting our previous observation that consumers themselves do not appear inclined to take the types of consumer selfie images that marketing campaigns encourage them to do (see Appendix A).

Similar to the Twitter analysis, we collect information on the number of likes, comments, and self-related brand mentions. However, on Instagram, and particularly in the image contest under investigation, conversations are few and brief. As a consequence, we are not able to replicate the purchase intent analysis due to a limited set of observations. Instead, we observe many more compliments towards the posted images (27.26% of all comments, e.g., "I like your pictures, keep it up" or "Aww love this shot!! Amazing!!"), which is much more common than in the organic Twitter data. We follow the same machine learning approach used to classify expressed purchase intents in the Twitter analysis to classifying response comments in terms of compliments (inter-coder agreement of two judges: 91.94%, disagreements were resolved through discussion). The RF trained for compliments achieves a predictive accuracy on a hold-out test set of 81.07%.[10]

We control for the same set of variables as in the Twitter application excluding the brand hashtag as we exclusively focus on posts with Starbucks-related hashtags. As in the previous analysis, we also include the number of comments in the compliments and self-brand mentions regressions because the probability of each increases with the number of comments.

Results

Similar to the previous analysis, we run negative binomial models for all four dependent variables to take overdispersion in the count variables into account. In terms of control variables, the results replicate those of the Twitter analysis (see Table 2). Specifically, visual complexity has an inverted U-shaped impact on image engagement. The posts compete for attention with more posts, resulting in fewer likes and comments, while conversely a larger followership results in more likes and comments. Also, branded captions are detrimental to achieving likes, but have a positive impact on self-brand mentions. Similarly, larger logo size leads to fewer likes, comments, and compliments, suggesting that also in the campaign context users react adversely to images dominated by brand logos. However, there are also some noteworthy differences between the two empirical applications. For example, more central logo positions have a positive effect on likes and comments (-.24 and -.16, both $p < .01$), presumably because the contest objective was to produce Starbucks-related images making a reasonable compromise between logo centrality and the desirable size. Variance inflation

[10] As a robustness check, we again train five SVM varying the cost parameter c, all producing inferior results (highest of 79.13% accuracy) compared to the RF. Thus, we use the RF predictions for our econometric model.

values are again all well below 3.

— Insert Table 3 about here —

Turning to brand image type, the Starbucks data from Instagram results in more consistent evidence in favor of brand selfies. In particular, brand selfies generate significantly more likes (.23, $p < .01$), comments (.13, $p < .05$), and compliments (.13, $p < .10$) than consumer selfies. This consistent evidence suggests that the brand image type plays a different role in a social media image-centric campaign. Specifically, faces appear less needed to catch attention, as the images themselves are of higher quality and more inspirational. Brand selfies also result in significantly more self-brand mentions than packshots (.44, $p < .05$), more compliments (.15, $p < .01$), more comments (.14, $p < .01$), and more likes (.19, $p < .01$) while the coefficients for consumer selfies and packshots do not differ significantly for any of the four dependent variables ($p > .10$). However, unlike the Twitter results, we find only directional but no statistically significant evidence in favor of brand selfies relative to consumer selfies in terms of self-brand mentions (.06, $p > .10$), presumably due to lack of statistical power (only 471 consumer selfie posts with comments). In terms of image contest success, three of the five winning and most engaging customer-submitted Starbucks images of the 2015 campaign were in fact brand selfies (Starbucks 2015). While this is merely anecdotal evidence, it is in line with our findings.

Overall, we find that brand selfies are superior to packshots as well as to consumer selfies when we take into account the full range of objectives. Interestingly, across all objectives, and consistent with the Twitter analysis, the type of image, which is posted most frequently (i.e., packshots), is inferior. Also, the image type promoted by social media campaigns and common advertising practice (consumer selfies with consumer faces) do not produce consistently better results. In the context of a company-initiated campaign, we find that brand selfies can produce an alignment between user and firm objectives to generate higher levels of engagement. Consequently, firms could benefit in terms of brand engagement by encouraging users to post brand selfies. The superiority of brand selfies raises the question which underlying psychological mechanism drives the superiority of this image type. It is possible that brand selfies reflect the sender perspective that may in turn generate stronger feelings of ownership and mental simulation (Weiss and Johar 2018). Accordingly, in the next section, we conducted a lab experiment that allows us to investigate such psychological mechanisms.

EXPERIMENTAL EVIDENCE ON CONSUMER RESPONSE TO USER-GENERATED BRAND IMAGES

While the field data and analysis so far is useful because of its external validity presenting a large number of brand images in two actual social media platforms, as with any secondary data, it comes with some limitations. First, Table 1 demonstrates that the three brand image types differ significantly in terms of size and centrality of logos. While we statistically control for these in all analyses, it is not clear whether the statistical control is sufficient, e.g., due to measurement error or functional form assumptions, and whether the subjective or perceived prominence brand logo is controlled for. Second, in our previous analysis, we have taken sender-level heterogeneity into account by controlling for the size of their followership and their past activity, i.e., number of posts. However, senders may vary with respect to other relevant dimensions. For instance, ego-networks of senders might differ in terms of connectedness and virality potential, such that likes of certain followers may produce likes of additional followers. Third, in the previous analysis, we statistically control for the captions that accompany the text, however, because textual information is often rich, it is difficult to control for all aspects of the text. Fourth, our measures of purchase intent and brand engagement rest on indirect incidental commenting behavior, which may only imperfectly reflect true brand attitude or purchase intentions. As we could not ask social media users about their preferences and underlying deliberations, we are unable to investigate these measures directly nor the theoretical mechanisms that may lead to varying engagement levels.

To address these limitations, we complement the secondary data analysis with an experimental design with the objective of replicating the brand engagement effects of the prior field studies in a controlled experimental setting, holding constant the sender information, and removing any effect of the caption text that accompanies the image. We also use conventional Likert-scale questions to directly elicit brand attitudes and purchase intentions, testing whether our comment-based inferences on brand engagement are consistent with established measures. Finally, we use the experimental design to explore potential theoretical mechanisms underlying the observed effects.

Method

Experimental design. We recruited N = 412 MTurkers who were randomly assigned to 1 out of 90 images from our three experimental conditions (brand selfie, consumer selfie, packshot). We selected actual social media images from the Starbucks campaign discussed in the previous section to make the simulated social media setting as authentic as possible. The selection of the 90 images followed the following criteria: Each image featured exactly one Starbucks logo, exhibited a similar logo share (on average 5.54% for brand selfies, 5.55% for packshots, and 5.54% for consumer selfies, $p > .10$ across the three conditions), and featured no objects likely to divert receivers' attention, e.g., animals or babies, to make subjective logo prominence as comparable as possible.

To further investigate the subjective prominence of the logo, we asked experimental subjects to rate how prominent they perceived each logo on a 7-point scale. Comparing these values across conditions does not result in significant differences ($M_{Brand\ Selfie} = 5.72$, $M_{Consumer\ Selfie} = 5.45$, $M_{Packshot} = 5.67$, $p > .10$). To explore this further, we applied an image visual attention software (VAS) by 3M — a machine-learning based eye-tracking application (see Mormann, Towal and Koch (2016) measuring visual saliency with a similar neuroscience-based algorithm). For all 90 images across the three conditions, we collect the rank of the brand logo in eye fixations as well as the probability that individuals focus on the region of the brand logo in their first fixation. Web Appendix F displays representative images per condition as well as their respective areas of visual attention. For both measures, we find no differences across the three brand image types selected for the experiment (F(2,87) = .14, p = .87 for the rank; F(2,87) = 1.46, p = .23 for the probability measure). Although faces received attention as well, this suggests the particular images we have selected are comparable in terms of the actual size of the logo and their visual attention allowing us to test whether effects above and beyond simple attention and logo prominence exist.

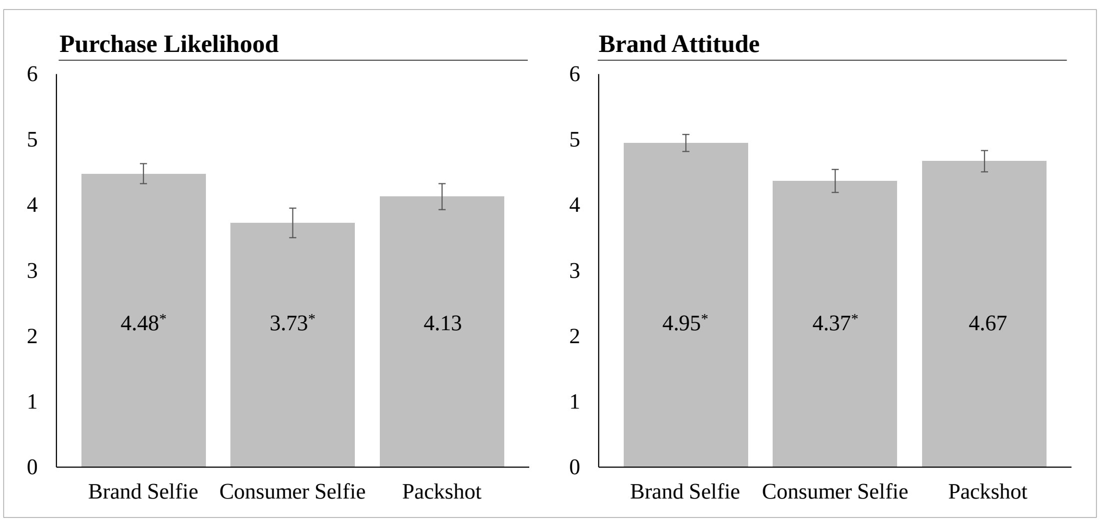
Procedure. Respondents first indicated their level of social media usage for Twitter, Instagram, and Facebook, as well as pre-attitudes for a list of several brands including Starbucks. To mimic actual behavior on social media, we created an Instagram online environment and asked subjects to decide whether to comment and to like two hypothetical posts. These did not feature any brands and were unrelated to our investigation. As a third task, subjects were randomly assigned to one of the 90 Starbucks images followed by questions on purchase likelihood and attitude towards Starbucks, both on 7-point Likert-scales. Subjects then listed all associations that came to their mind based on the image they saw in an open-ended format before responding to multi-item scales taken from prior research on psychological ownership, self-reference, endorsement, and mental simulation (see Web Appendix G for an overview). Finally, the respondents answered several questions on brand familiarity, the perceived prominence of the brand logo, the perceived sender attractiveness, and demographics including the dominant hand of the respondent.

Results

Influence of image type on purchase likelihood. In line with our previous findings, purchase likelihood is significantly lower for consumer selfies compared to brand selfies ($M_{Brand\ Selfie} = 4.48$, $M_{Consumer\ Selfie} = 3.73$, $p < .05$; see Figure 3). This main effect is also robust when controlling for the perceived attractiveness of the sender, brand familiarity, pre-attitudes towards Starbucks, and perceived logo prominence, as well as the respondents' dominant hand, and their social media usage in a regression analysis ($\beta_{Brand\ Selfie} = .41$, $p < .05$; see Table

4). Also packshots result in directionally higher levels of purchase intents than consumer selfies, although this difference is not statistically significant according to conventional alpha levels ($M_{Packshot} = 4.13$, $M_{Consumer\ Selfie} = 3.73$, p = .19). This effect is statically significant at the .10 level in the more controlled regression model ($\beta_{Packshot} = .38$, $p < .10$), confirming our previous findings that consumer selfies are the least impactful type of user-generated brand image.

As a robustness check for this finding, we evaluate if perceived sender attractiveness might asymmetrically influence our results (e.g., because subjective attractiveness differs systematically whenever a face is present). We focus on both types of selfies for this analysis. As expected, the main effect of attractiveness is positive, but the interaction with the experimental condition is not ($\beta_{Brand\ Selfie\ \times\ Attractiveness} = .04$, $p = .75$), suggesting differences in attractiveness are not the primary driver behind the effect of brand image type.



Notes: N = 412, *$p < .05$ between the indicated groups.

Figure 3: Purchase Likelihood and Brand Attitude Across Brand Image Types

Influence of image type on attitude towards the brand. The results for attitude towards the brand mirror those of purchase likelihood. Specifically, attitudes towards Starbucks are highest after being exposed to a brand selfie, resulting in significant differences across the conditions ($M_{Brand\ Selfie} = 4.95$, $M_{Consumer\ Selfie} = 4.37$, $M_{Packshot} = 4.67$, $F(2, 409) = 3.44$,

$p < .05$; see Figure 3). Brand attitude in the brand selfie condition is significantly higher than that of the consumer selfie condition ($p < .05$). However, while the brand attitude in the brand selfie condition is directionally higher than that of the packshot, the difference is not statistically significant ($p = .18$). The regression analysis controlling for all confounds mentioned above further reveals that the consumer selfie performs significantly worse than both the brand selfie and the packshot condition ($\beta_{Brand\ Selfie} = .27$, $p < .05$; $\beta_{Packshot} = .30$, $p < .05$; see Table 4).

Impact of brand familiarity. Theoretically, higher levels of brand familiarity and memory accessibility should increase the probability of self-reference thoughts and mental simulation concerning the brand. This suggests a potential interaction between brand familiarity and image type. When adding such interaction effects to the purchase likelihood regression, we indeed find positive interactions with both the brand selfie ($\beta_{Brand\ Selfie \times BF} = .38$, $p < .05$) and the packshot ($\beta_{Packshot \times BF} = .36$ $p < .05$) compared to the consumer selfie as the reference category. For brand attitude, we find a positive interaction with the brand selfie ($\beta_{Brand\ Selfie \times BF} = .29$, $p < .01$) but not with the packshot ($\beta_{Packshot \times BF} = .12$, $p = .24$). Taken together, this suggests the negative impact of faces on brand engagement is amplified when brand memory is more accessible, presumably because brand familiarity makes self-reference thoughts and mental simulations more likely.

Mediation. To explore the potential psychological drivers behind the relative performance of the different brand image types more directly, we run a simultaneous mediation analysis for the four potential mediators psychological ownership, self-reference, mental simulation, and brand endorsement. As all multi-item scales produce acceptable levels of Cronbach's alpha larger than .78, we averaged the items in each scale (see Web Appendix G). We performed mediation analyses on both brand image dummy variables with consumer selfies as the reference category employing 1,000 bootstrapping iterations to obtain standard errors for the conditional indirect effects (Preacher and Hayes 2008).

For purchase likelihood, we find that the impact of brand image type on purchase likelihood is fully mediated by both mental simulation and self-reference and the indirect effects are significant ($p < .05$), whereas psychological ownership and brand endorsement do not have significant effects on purchase intent. Compared to brand selfies and packshots, consumer selfies appear less effective in helping consumers picture drinking a Starbucks coffee and fostering self-brand connections. For brand attitudes, we find that the effects of brand image type are fully mediated by self-reference ($p < .05$ for indirect effect), with no effect of mental simulation, psychological ownership, or brand endorsement. Our results suggest the behavioral intent measures are more directly related to actions on brand images and mental simulation of coffee consumption.

To further explore the mental simulation and self-reference account, we manually coded relevant keywords and the sentiment (as positive, negative, or neutral) of the associations that the respondents provided after seeing the respective brand image. Both the number of associations ($M_{Brand\ Selfie} = 8.81$, $M_{Consumer\ Selfie} = 8.92$, $M_{Packshot} = 9.42$, $F(2, 409) = .17$, $p = .85$), and the sentiment ($\chi^2(2) = 4.97$, $p = .29$) do not differ across the three brand image conditions. However, respondents in the brand selfie condition revealed significantly more associations referring to the warm sensation of holding a Starbucks coffee (e.g., "This picture describes coffee perfectly on a cold winter day where the warm coffee will keep you going and keep you warm") than for consumer selfies, which appear to inhibit mentally simulating consumption ($\chi^2(2) = 8.37$, $p < .01$).

Discussion

The results of the controlled lab experiment corroborate the empirical findings of the field data. Specifically, brand selfies clearly outperform consumer selfies. This effect holds when using an experimental design, holding constant the image composition and subjective logo prominence, as well as sender characteristics and captions. Due to the sender's physical touch of the branded product, brand selfies might be most attractive to receivers as they help receivers relate the depicted products to themselves and induce favorable consumer responses, while at the same time avoiding overshadowing the brand with a competing face of another consumer.

The types of associations, the interaction with brand familiarity as well as the mediation analysis suggest self-reference and mental simulation play a role as underlying psychological processes. These results suggest that the previous field results are theoretically consistent and unlikely a function of the peculiarities of the respective dataset.

CONCLUSION

Brand images are ubiquitous on social media. This paper investigates and structures this medium of user-generated social media communication. Employing a combination of deep learning algorithms for visual UGC and natural language processing for textual UGC, we identified three types of user-generated brand images and study their social media impact. We demonstrate that this distinction between different brand image types in UGC is both theoretically meaningful and practically relevant. Specifically, we find that an emerging phenomenon called *brand selfie*, in which consumers take a selfie image of the brand itself as opposed to themselves, leads to the highest brand engagement. Additionally, we find that consumers seldom take an image of the brand together with themselves, despite brands' attempts to encourage consumers to do so. Furthermore, such consumer selfies are not necessarily beneficial to brands either, as they are likely to generate lower brand engagement.

Specifically, we find that in organic social media brand images − in line with previous research about the value of faces in social media and advertising − consumer selfies lead to more likes from other people than other brand image types. Likes can be of interest to brands in terms of lower-funnel engagement metrics such as reach to a receiver potential. However, this engagement is not unlikely to translate into brand engagement. Using natural language processing of user responses make a meaningful analysis of metrics such as self-related brand mentions and expressed purchase intent possible. We find that, possibly due to attention given to the sender in consumer selfies, these images lead to lower self-brand mentions and purchase intent comments than brand selfies. In a brand campaign context, where a single brand is at the center of the campaign, having a face in the image hurts both image engagement (likes and comments) as well as brand engagement.

Our results highlight a potential misalignment between the objectives of UGC creators and brands. UGC creators are often interested in garnering popularity and virality (Toubia and Stephen 2013), whereas brands are often interested in brand-specific engagement. Hence, in organic settings, as in our Twitter application, UGC creators may favor consumer selfies to maximize social media response, whereas brands may prefer brand selfies to maximize brand engagement. In the campaign context, however, the objectives seem more aligned, where brand selfies lead to both higher image and brand engagement (see Figure 4). Brands interested in driving brand engagement will therefore be interested in promoting brand selfies irrespective of the image context, and even better, promote brand selfies in brand campaigns to align the incentives of the UGC creators and the brand.

	Sender Objectives	**Brand Objectives**
Organic Context	***Consumer Selfie***	*Image Engagement:* ***Consumer Selfie*** *Brand Engagement:* ***Brand Selfie***
Campaign Context	***Brand Selfie***	***Brand Selfie***

Figure 4: Recommendations for Desirable Brand Image Types Depending on Objectives

Current user behavior shows that senders lean towards packshots, which account for more than 50% of both organic and campaign images. However, packshots have lower user potential in terms of likes and comments. This is intuitive given the lack of a human touch. As social media users gain experience, they may appreciate this and converge towards consumer selfies in organic settings which can result in conflicts of interest between brands and senders.

Our results suggest that brand selfies are a new and relevant image archetype that may have received less attention than they deserve by marketing research and practice so far. In particular, brands such as Coca-Cola or Dunkin' Donuts, which promoted consumer selfies with social media contests, may not have exploited their campaigns' full potential. Considering the risk that faces can divert attention away from the brand and inhibit favorable brand-related deliberations, we caution the (sole) use of consumer selfies in large-scale communication campaigns but instead suggest considering brand selfie campaigns.

Brands can benefit from brand selfie images in two ways: First, fostering brand selfies can serve as a subtle and organic communication vehicle to induce consumers to place the brand more centrally and prominently in an image (see Table 1). In addition, the mere visible touching of branded products appears to foster self-brand connections of the viewer and helps to stimulate mental simulations of product interactions. Note, our empirical analysis controlled for differences in image composition and found effects of brand selfies over and above differences in size and logo position, i.e., the impact of subjective perspective and logo prominence are additive rather than substitutive. This suggests that selecting brand selfies for display on corporate social media channels can be a powerful vehicle to increase brand engagement. In addition, brand selfies tend to feature the arm or at least the hand of the photographer on the photo, naturally guiding receiver eyes towards the product (Zhang et al. 2018).

We applied a multi-method approach of combining deep learning-based image classification with natural language processing and behavioral experiments. The combination of machine learning approaches can benefit tracking and evaluating a brand's social media presence. Simply counting visibility of brand logos on images or the number of likes and comments these images receive can be misleading. Our data suggest that both image and brand engagement must be assessed to obtain a comprehensive understanding of a brand's standing in social media. Our research highlights that identifying relevant images based on textual information (e.g., hashtags) can result in a biased view of multimedia content. Accordingly, we provide a scalable machine learning approach to classify images into different types, which are meaningfully different from both a theoretical and a practical perspective. We intend to make our classification algorithm publicly available as an online tool to both researchers and practitioners.

From a theoretical point of view, our research provides a first large-scale demonstration, using secondary social media data, of how the point of view from which an image is taken and the existence of other individuals in the image can relate to consumers' engagement with the brand. We identify mental simulation and self-reference as possible drivers behind the success of brand selfies, which help viewers simulate the consumption of the product (Weiss and Johar 2018). We encourage future research to explore more directly the underlying psychological mechanisms induced by different types of social media brand images.

Social media text data has received much attention from marketing research (e.g., Netzer et al. 2012; Timoshenko and Hauser 2019; Tirunillai and Tellis 2014). At the same time, images and videos are likely to proliferate further. Empirical research on these types of data remains scarce. Studying relevant image data with a multi-method approach including deep learning image recognition, machine learning and dictionary-based text mining tools, econometric models, as well as lab experiments has resulted in theoretically plausible findings. This appears a promising approach for related research questions. For example, it is not clear theoretically whether findings on the virality of text content translates to images and how different types of text and image content interact in terms of social media success. Such questions could be investigated with similar approaches as ours.

There are of course limitations to this research, which further studies may address. First, further research might elaborate on the sender perspective, the motivations of sharing product-related content and its impact on sender behavior. For example, Grewal, Stephen and Coleman (2019) suggests conditions under which posting identity-relevant content can inhibit subsequent purchase intentions. Descriptively, we find fewer consumer selfies with visible consumer faces than the other two brand image types, suggesting consumers are reluctant to affiliate with products in this way. It is worth studying how and why consumers choose the brand image type they post. For example, consumers may be more involved and engaged in sharing consumer selfies with their face visible than to post a packshot with the sender invisible. Consequently, it is not clear that our findings on observer response translate to sender behavior. Additionally, if brand images are taken during consumption, they might impact the enjoyment of the sender experience itself (e.g., Barasch, Zauberman and Diehl 2018). As the downstream consequences can be noteworthy, an investigation into sender motivations and behavior appears promising.

Second, future research might also test the applicability of our findings outside of the social media context. In fact, the laboratory experiment we conducted is akin to print advertising with unknown spokespersons promoting a brand. In that respect, the brand selfie with its photographic peculiarities might be worthwhile to explore in other settings. In addition, analyzing the three brand image types with established tools from the field of neuroscience and visual saliency would be a promising avenue for further research (e.g., Mormann, Towal and Koch 2016; Towal, Mormann and Koch 2013). Given the high competition for attention in social media across and within images (e.g., brand vs. sender for consumer selfies), using eye-tracking and fMRI tools could help better understand the different types of brand images and the role of visual attention in distingusihing between the different brand images. Third, in terms of multimedia content, our typology of brand images is conceptually applicable to video content as well. These can also differ in perspectives (first-hand vs. third-hand) and prominence of the sender. In addition, videos allow changing perspectives. Such dynamics are likely to have interesting effects on brand response.

Overall, our study provides a first step to explore the plethora of user-generated brand images posted on social media. Identifying relevant image types as well as their respective role is useful given the diversity of brand images. Selfies are here to stay as a prevalent component of social media, but they are also a matter of perspective. In terms of marketing objectives, faces on selfies are a double-edged sword. They draw engagement to the image but can also draw attention away from the brand, inhibiting self-related brand thoughts and mental simulation. There is still much to learn about how seeing brands through the eyes of other consumers relates to information processing and how this impacts customer-based brand equity and consumer behavior. We hope our work stimulates further research in these and related directions.

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Table 1: Image, Text, and Sender Characteristics Across Brand Image Types for Twitter

	Brand Selfie		Consumer Selfie		Packshot	
	All	Brand Tags	All	Brand Tags	All	Brand Tags
Overall Distribution						
Share of Brand Image Type (in %)	22.42	24.33	5.14	4.70	72.44	70.98
Dependent Variables						
Number of Likes	5.09	1.71	7.45	12.57	4.34	1.75
Number of Comments	.44	.24	.52	.70	.44	.25
Number of Self-Brand Mentions†	.03	.02	.02	.04	.02	.02
Number of Purchase Intents†	.08	.06	.05	.06	.08	.06
Image Characteristics						
Logo Share (in %)	3.11	3.94	1.60	1.94	2.58	3.06
Logo Distance from Image Center	178.05	172.69	270.33	262.26	218.67	204.82
Visual Complexity	.15	.15	.15	.15	.17	.16
Brightness	.48	.49	.52	.53	.53	.52
Brightness Contrast	.25	.26	.27	.27	.25	.25
Caption Characteristics						
Number of Words	9.19	10.23	10.07	10.45	10.17	10.90
Number of Hashtags	.70	2.09	.81	2.02	.84	2.34
Number of Handletags	.24	.49	.34	.65	.26	.55
Branded Caption (in %)	6.27	2.97	7.09	6.75	6.52	4.38
First-Person Singular (in %)	5.41	3.60	4.58	3.65	4.35	2.89
Second-Person Singular (in %)	2.18	1.84	2.10	1.51	2.01	1.65
Question Word Share (in %)	1.35	.93	1.23	.73	1.28	.88
Netspeak Word Share (in %)	2.29	1.85	2.22	1.35	1.93	1.55
Positive Word Share (in %)	16.07	14.61	16.68	14.93	15.77	13.91
Negative Word Share (in %)	4.65	2.87	3.88	1.98	4.04	2.55
Sender Characteristics						
Post Age (in Months)	39.88	38.74	39.02	38.69	39.14	38.99
Number of Posts (in 1,000)	29.50	18.13	27.65	19.48	32.97	21.11
Number of Friends (in 1,000)	1.19	1.09	1.28	1.73	1.52	1.44
Number of Followers (in 1,000)	7.26	3.24	13.82	21.37	11.08	6.69

Notes: N = 492,860 (13.44% with brand tags). All differences between brand image types are significant at $p < .05$.
† Number of self-brand mentions and purchase intents relative to number of posts with at least one comment.

Table 2: Brand Selfies Exhibit Strongest Brand Engagement (Organic Twitter Data)

	Model 1:		Model 2:		Model 3:		Model 4:	
	Likes		**Comments**		**Self-Brand Mentions**		**Purchase Intents**	
Brand Image Type								
Consumer Selfie (Baseline)								
Brand Selfie	$-.37^{***}$	(.04)	$-.003$	(.02)	$.64^{***}$	(.19)	$.44^{***}$	(.09)
Packshot	$-.54^{***}$	(.03)	$-.12^{***}$	(.02)	$.42^{**}$	(.18)	$.41^{***}$	(.09)
Image Characteristics								
Logo Share (ln)	-1.87^{***}	(.23)	-1.18^{***}	(.15)	2.51^{**}	(1.09)	.66	(.53)
Logo Distance from Image Center (ln)	$.04^{***}$	(.01)	.01	(.01)	$-.16^{***}$	(.05)	$-.05^{*}$	(.02)
Visual Complexity	$.17^{***}$	(.01)	$.25^{***}$	(.01)	$-.05$	(.07)	.03	(.03)
Visual Complexity^2	$-.02^{***}$	(.005)	$-.03^{***}$	(.003)	$-.01$	(.03)	.004	(.01)
Brightness	$-.08$	(.05)	$-.47^{***}$	(.03)	.07	(.27)	.16	(.12)
Brightness Contrast	$-.21$	(.14)	$-.99^{***}$	(.09)	$-.13$	(.75)	$-.58^{*}$	(.35)
Caption Characteristics								
Number of Words (ln)	$-.08^{***}$	(.01)	$.07^{***}$	(.01)	.06	(.07)	$.10^{***}$	(.03)
Number of Hashtags	$-.15^{***}$	(.01)	$-.24^{***}$	(.004)	$-.09^{*}$	(.05)	$-.05^{**}$	(.02)
Number of Handletags	$.21^{***}$	(.01)	$.29^{***}$	(.01)	$-.17^{***}$	(.05)	.01	(.02)
Branded Caption (d)	$-.02$	(.03)	$-.20^{***}$	(.02)	$.72^{***}$	(.12)	.04	(.07)
Brand Tag (d)	$-.40^{***}$	(.02)	$-.23^{***}$	(.02)	$.43^{***}$	(.13)	$-.17^{**}$	(.07)
First-Person Singular	$.14^{***}$	(.01)	$.10^{***}$	(.01)	$.11^{**}$	(.04)	.004	(.02)
Second-Person Singular	$.09^{***}$	(.01)	$.06^{***}$	(.01)	$-.01$	(.06)	$-.01$	(.03)
Question Word Share	$.21^{***}$	(.02)	$.15^{***}$	(.01)	$-.20^{**}$	(.09)	$-.01$	(.04)
Netspeak Word Share	.01	(.01)	$.03^{***}$	(.01)	$-.09$	(.06)	$-.02$	(.03)
Positive Word Share	.04	(.04)	$-.03$	(.02)	$-.11$	(.18)	$-.17^{**}$	(.09)
Negative Word Share	$.15^{**}$	(.06)	$.44^{***}$	(.04)	$-.25$	(.30)	$-.06$	(.14)
Sender Characteristics								
Post Age	$-.02^{***}$	(.001)	$.001^{*}$	(.001)	$-.01$	(.01)	$.01^{***}$	(.002)
Number of Posts (ln)	$-.24^{***}$	(.01)	$-.02^{***}$	(.003)	$.15^{***}$	(.03)	$.14^{***}$	(.01)
Number of Friends (ln)	$-.22^{***}$	(.01)	$-.19^{***}$	(.004)	$.08^{**}$	(.04)	$.06^{***}$	(.02)
Number of Followers (ln)	$.72^{***}$	(.01)	$.52^{***}$	(.004)	$-.16^{***}$	(.03)	$-.14^{***}$	(.01)
Post Characteristics								
Number of Comments (ln)					$.89^{***}$	(.06)	$.77^{***}$	(.03)
Log Likelihood	$-990,581.00$		$-351,257.20$		$-8,956.88$		$-22,545.75$	
Akaike Information Criterion	1,981,578.00		702,930.50		18,331.76		45,509.51	

$^{*}p < .10,^{**} p < .05,^{***} p < .01$.
Notes: Standard errors in parentheses. Intercept and brand-level fixed effects omitted from table. (d) indicates dichotomous variables.
Visual complexity mean-centered.
N = 492,860 (N = 81,252 for Models 3 and 4).

Table 3: Brand Selfies Engage More Than Consumer Selfies and Attract More Self-Brand Mentions Than Packshots (Instagram Campaign Data)

	Model 1:		Model 2:		Model 3:		Model 4:	
	Likes		**Comments**		**Compliments**		**Self-Brand Mentions**	
Brand Image Type								
Consumer Selfie (Baseline)								
Brand Selfie	.23***	(.04)	.13**	(.07)	.13*	(.07)	.06	(.27)
Packshot	.04	(.04)	−.01	(.06)	−.02	(.07)	−.38	(.27)
Image Characteristics								
Logo Share (ln)	−.10***	(.01)	−.11***	(.02)	−.04**	(.02)	.09	(.08)
Logo Distance from Image Center (ln)	−.24***	(.02)	−.16***	(.03)	−.09***	(.03)	.03	(.12)
Number of Logos	.18***	(.01)	.15***	(.02)	.02	(.03)	.03	(.10)
Visual Complexity	.32***	(.03)	.22***	(.04)	.25***	(.05)	.20	(.19)
Visual Complexity^2	−.11***	(.02)	−.10***	(.04)	−.07*	(.04)	−.07	(.15)
Brightness	.34***	(.09)	.57***	(.15)	−.12	(.16)	.27	(.62)
Brightness Contrast	−.50**	(.22)	−.61	(.37)	−1.00**	(.42)	−.81	(1.57)
Caption Characteristics								
Number of Words (ln)	.13***	(.02)	.23***	(.03)	.18***	(.03)	.14	(.12)
Number of Hashtags	.02***	(.002)	.005	(.004)	−.01**	(.003)	−.02	(.01)
Number of Handletags	.02	(.02)	.04	(.03)	−.005	(.02)	.03	(.08)
Branded Caption (d)	−.13***	(.04)	−.10	(.06)	−.02	(.07)	.64***	(.21)
First-Person Singular	−.15***	(.02)	−.01	(.04)	−.03	(.05)	.07	(.19)
Second-Person Singular	.02	(.05)	.05	(.08)	.10	(.07)	−.02	(.28)
Question Word Share	−.07	(.06)	.10	(.10)	−.14	(.11)	.32	(.36)
Netspeak Word Share	.18***	(.05)	.07	(.08)	.02	(.09)	−.98	(.67)
Positive Word Share	−.06	(.07)	.04	(.12)	−.30**	(.15)	−.83	(.56)
Negative Word Share	−.35	(.21)	.40	(.37)	−.44	(.42)	−.60	(1.55)
Sender Characteristics								
Post Age	−.01***	(.002)	−.03***	(.003)	−.01***	(.003)	.01	(.01)
Number of Posts (ln)	−.37***	(.01)	−.25***	(.02)	−.02	(.02)	−.001	(.09)
Number of Friends (ln)	−.08***	(.01)	−.09***	(.02)	.04*	(.02)	.09	(.09)
Number of Followers (ln)	.77***	(.01)	.70***	(.02)	.01	(.02)	−.03	(.07)
Post Characteristics								
Number of Comments (ln)					.86***	(.02)	.81***	(.08)
Log Likelihood	−31,331.54		−12,051.90		−3,623.28		−662.26	
Akaike Information Criterion	62,711.08		24,151.80		7,296.56		1,374.53	

$^{*}p < .10, ^{**}p < .05, ^{***}p < .01$.
Notes: Standard errors in parentheses. Intercept omitted from table. (d) indicates dichotomous variables. Visual complexity mean-centered.
N = 6,926 (N = 3,570 for Models 3 and 4).

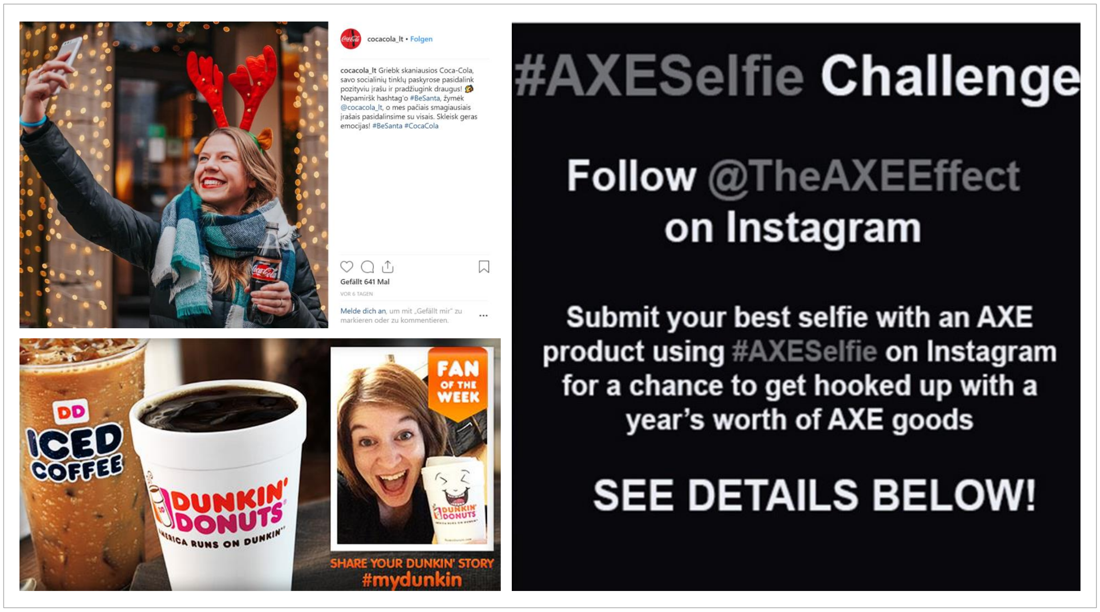
Table 4: Self-Reference and Mental Simulation Mediate the Effects on Purchase Likelihood and Brand Attitude

	Purchase Likelihood						Brand Attitude					
	Base Model		Interaction Model		Mediator Model		Base Model		Interaction Model		Mediator Model	
Brand Image Type												
Consumer Selfie (Baseline)												
Brand Selfie	.41**	(.19)	.44**	(.19)	.12	(.17)	.27**	(.11)	.28***	(.11)	.13	(.10)
Packshot	.38*	(.21)	.42**	(.21)	.08	(.19)	.30**	(.12)	.33***	(.12)	.13	(.11)
Brand Selfie × Brand Familiarity			.38**	(.17)					.29***	(.09)		
Packshot × Brand Familiarity			.36**	(.18)					.12	(.10)		
Controls												
Sender Attractiveness	.17***	(.05)	.17***	(.05)	−.01	(.04)	.12***	(.03)	.12***	(.03)	.02	(.03)
Brand Familiarity	.29***	(.07)	.03	(.13)	.18***	(.07)	.04	(.04)	−.11	(.07)	.01	(.04)
Pre-Attitudes Starbucks	.75***	(.05)	.75***	(.05)	.45***	(.05)	.84***	(.03)	.84***	(.03)	.68***	(.03)
Perceived Logo Prominence	−.06	(.06)	−.06	(.06)	−.05	(.05)	.02	(.03)	.02	(.03)	.03	(.03)
Dominant Right Hand (d)	−.42*	(.22)	−.46**	(.22)	−.46**	(.19)	−.08	(.12)	−.11	(.12)	−.14	(.11)
Intensity of Social Media Usage	.07	(.07)	.08	(.07)	.04	(.07)	.01	(.04)	.01	(.04)	−.02	(.04)
Mediators												
Mental Simulation					.19***	(.04)					.02	(.02)
Self-Reference					.36***	(.06)					.20***	(.04)
Psychological Ownership					.04	(.06)					.07	(.04)
Brand Endorsement					−.03	(.05)					−.01	(.03)
Constant	−1.33	(.71)	.31	(.97)	−.32	(.65)	−.23	(.40)	.74	(.54)	.42	(.37)

$^{*}p < .10, ^{**}p < .05, ^{***}p < .01$.
Notes: Standard errors in parentheses. (d) indicates dichotomous variables. Brand familiarity mean-centered in interaction model.
N = 412.

APPENDIX

Appendix A: Examples of Companies Soliciting Consumer Selfies with Campaigns



Notes: Coca-Cola (top-left), Dunkin' Donuts (bottom-left), Unilever: Axe deodorant (right).

WEB APPENDIXES

Web Appendix A: VGG-16 Architecture After Fine-Tuning

Layer Name	**Output Shape**	**Number of Parameters**	**Fine-Tuned**
Input Layer	244 × 224 × 3	—	—
Convolutional Block 1			
Convolutional Layer 1.1	244 × 224 × 64	1,792	—
Convolutional Layer 1.2	244 × 224 × 64	36,928	—
Max Pooling Layer 1	112 × 112 × 64	—	—
Convolutional Block 2			
Convolutional Layer 2.1	112 × 112 × 128	73,856	—
Convolutional Layer 2.2	112 × 112 × 128	147,584	—
Max Pooling Layer 2	56 × 56 × 128	—	—
Convolutional Block 3			
Convolutional Layer 3.1	56 × 56 × 256	295,168	—
Convolutional Layer 3.2	56 × 56 × 256	590,080	—
Convolutional Layer 3.3	56 × 56 × 256	590,080	—
Max Pooling Layer 3	28 × 28 × 256	—	—
Convolutional Block 4			
Convolutional Layer 4.1	28 × 28 × 512	1,180,160	—
Convolutional Layer 4.2	28 × 28 × 512	2,359,808	—
Convolutional Layer 4.3	28 × 28 × 512	2,359,808	—
Max Pooling Layer 4	14 × 14 × 512	—	—
Convolutional Block 5			
Convolutional Layer 5.1	14 × 14 × 512	2,359,808	Yes
Convolutional Layer 5.2	14 × 14 × 512	2,359,808	Yes
Convolutional Layer 5.3	14 × 14 × 512	2,359,808	Yes
Max Pooling Layer 5	7 × 7 × 512	—	—
Flatten Layer	25,088	—	(new)
Dropout Layer (.5)	25,088	—	(new)
Fully-Connected Layer	128	3,211,392	(new)
Output Layer	4	516	(new)

Notes: The output shape of the last layer corresponds to the number of categories of the classification task, i.e., brand selfie, consumer selfie, packshot, advertising.

Web Appendix B: Hyperparameters for CNN Training

	Hyperparameters
Model Training	
Batch Size	32
Epochs	50
Loss Function	Categorical Cross-Entropy
Learning Rate	1e-4
Optimizer	Stochastic Gradient Descent
Activation Functions	
Convolutional Layers	ReLU
Output Layer	Softmax
Data Augmentation	
Horizontal Flip	True
Width Shift	.1
Height Shift	.1
Rotation (in Degrees)	20

Notes: We implemented our CNNs with Keras (Python).[11] Due to the high computational intensity, we run all training processes on an NVIDIA Tesla P4 GPU.

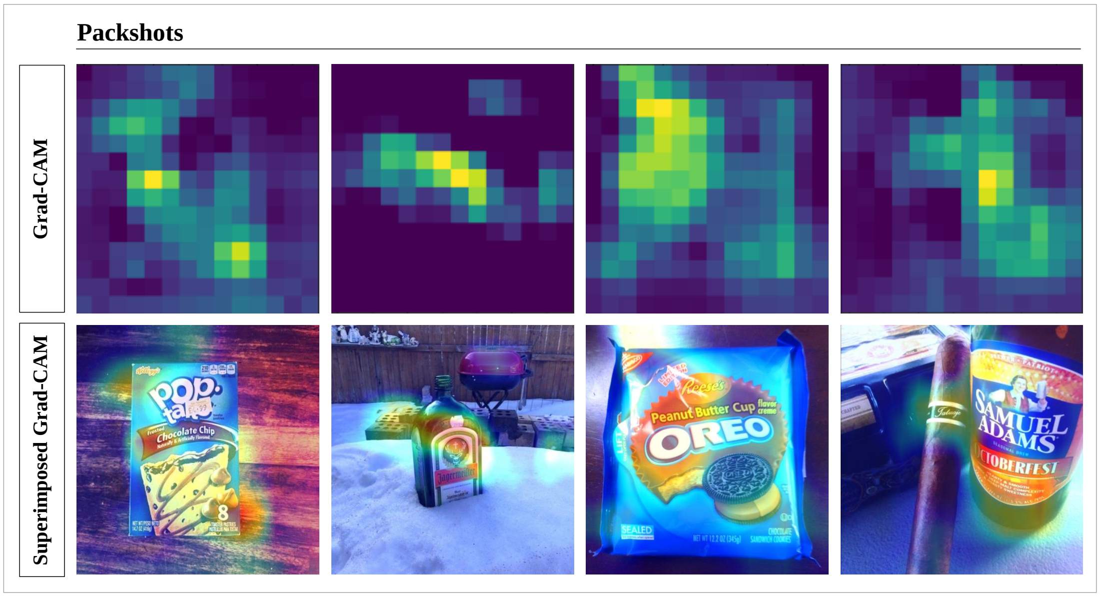
[11] Chollet, François (2017), "Deep Learning with Python", Shelter Island, NY: Manning Publications Co.

Web Appendix C: Performance Evaluation of Fine-Tuned CNN for Twitter

Brand Image Type	**Precision**	**Recall**	**F1 Score**
Brand Selfie	.81	.78	.80
Consumer Selfie	.66	.74	.70
Packshot	.85	.81	.83
Advertising	.77	.84	.80

Notes: Accuracy on hold-out test set: 81.02%.

Web Appendix D: Grad-CAM Examples for Packshots



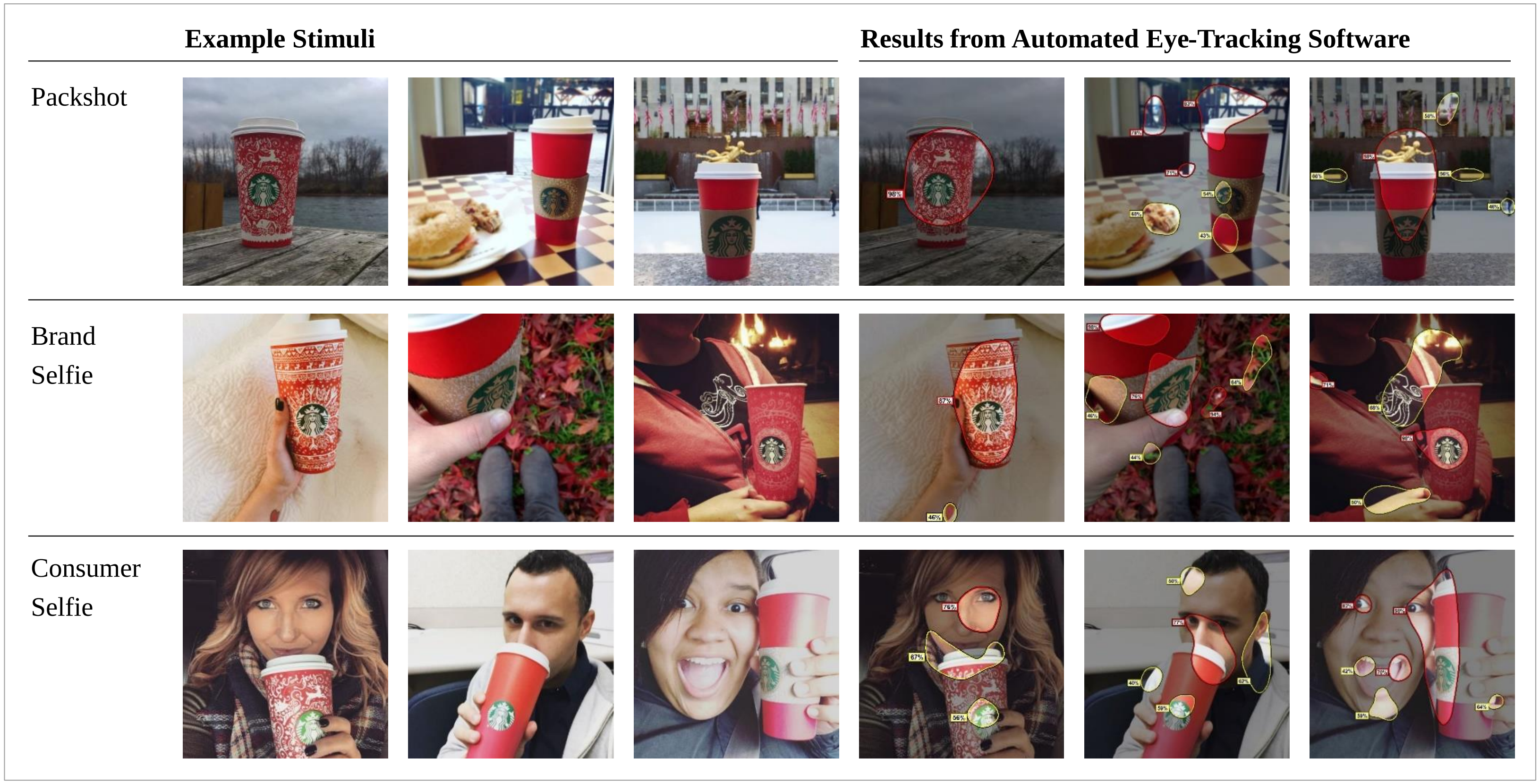
Notes: During image pre-processing, images are rescaled to standard size of 224 by 224 pixels.

Web Appendix E: Performance Evaluation of Fine-Tuned CNN for Instagram

Brand Image Type	**Precision**	**Recall**	**F1 Score**
Brand Selfie	.84 (.81)	.82 (.75)	.83 (.78)
Consumer Selfie	.88 (.87)	.87 (.82)	.88 (.84)
Packshot	.90 (.86)	.91 (90)	.91 (.88)

Notes: Results based on fine-tuned CNN from Twitter analysis.
Results based on pretrained ImageNet model in parantheses.
Accuracy on hold-out test set: 87.88% (84.56%).

Web Appendix F: Controlled Lab Experiment: Example Stimuli



Notes: Circled regions highlight areas that observers are likely view during their first eye fixations according to the probabilities provided next to them.

Web Appendix G: Controlled Lab Experiment: Overview of Operationalizations and Scales

	Measures	Scales	Construct Liability
Dependent Variables			
Brand Attitude	What is your attitude towards Starbucks?	1: very negative, 7: very positive	—
Purchase Intent	If the need arose, how likely would you be to purchase a Starbucks coffee?	1: very unlikely, 7: very likely	—
Associations	Please list all associations you have with the Starbucks brand.	*free text*	—
Mediators			
Pychological Ownership	It feels like this Starbucks coffee is mine.	1: strongly disagree, 7: strongly agree	$\alpha = .89$
	Starbucks feels close to me on that picture.	1: strongly disagree, 7: strongly agree	
Self-Reference	I can personally relate to Starbucks on that picture.	1: strongly disagree, 7: strongly agree	$\alpha = .94$
	I can personally relate to the sender on that picture.	1: strongly disagree, 7: strongly agree	
	When seeing this photo, I can put myself in the shoes of the sender.	1: strongly disagree, 7: strongly agree	
Brand Endorsement	The sender is recommending Starbucks to me.	1: strongly disagree, 7: strongly agree	$\alpha = .78$
	The sender conveys a sincere opinion about Starbucks.	1: strongly disagree, 7: strongly agree	
	The sender is trying to persuade me to buy Starbucks coffee.	1: strongly disagree, 7: strongly agree	
Mental Simulation	When viewing this image, I can imagine drinking a Starbucks coffee myself.	1: not at all, 7: very much	$\alpha = .79$
	I can very vividly remember the last time I had a Starbucks coffee myself.	1: not at all, 7: very much	
Controls			
Social Media Usage	Please indicate how often you use the following social media platforms:	Never, once a month, once a week, once a day,	—
	Twitter, Facebook, Instagram	2-5 times a day, more than 5 times a day	—
Pre-Attitudes	How is your attitude towards the following brands:	1: very negative, 7: very positive	—
	Starbucks, Coca-Cola, Godiva Chocolate		
Sender Attractiveness	How attractive do you find the sender of that photo?	1: very unattractive, 7: very attractive	—
Logo Prominence	How prominent do you perceive the Starbucks logo on this picture?	1: not at all, 7: very prominent	—
Brand Familiarity	Please indicate how familiar you are with Starbucks.	1: never heard before, 7: very familiar	—