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Measurement of Visual Cues and Their Effects on Online Users: An Image Mining Approach

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MEASUREMENT OF VISUAL CUES AND THEIR EFFECTS ON ONLINE USERS: AN IMAGE MINING APPROACH

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To my family, who always support me to pursue my dreams.

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ABSTRACT

Textual marketing communication is effective in various contexts such as print advertising, user-generated content, and social media (Diamond 1968; Ludwig et al. 2013; Nam and Kannan 2014). However, visual marketing communication studies are limited in the context of print advertising (e.g., Hagtvedt and Brasel 2017). This dissertation includes two essays to examine the visual communication effectiveness online.

Essay 1 develops a conceptual framework to examine the visual-based brand perception (VBBP) and related concepts on social media. We propose that the VBBP is a co-creational process between a company and its consumers and exhibits three characteristics: i) a two-way communication that both a company and its consumers are pivotal authors of brand stories, ii) a dynamic process that the brand meaning keeps evolving, and iii) a dyadic process between a company and its consumers. In the conceptual model development, we identify six visual attributes as measures of VBBP and adopt a machine learning-based image mining technique to quantify the measures on a large scale. We empirically validate the conceptual model and find that during the co-creational process, both the company and consumer visual-based brand perception information richness (VBBP_R) increase over time. Moreover, in examining the difference between a company and its consumers, we find that there is a visual-based brand perception gap (VBBP_G) between a company and its consumers. From these findings, we advise three marketing communication strategies to help companies manage their VBBP_G.

Essay 2 examines a related research question: the joint effects of visual and textual communication on crowdfunding success. Essay 2 extends Essay 1 in three ways: i) we consider both textual and visual marketing communication on another online platform, ii) beyond the concept of perception, we emphasize examining how marketing communication influences a marketing outcome: duration of crowdfunding success, iii) we investigate not only how visual and textual communication influence crowdfunding success individually but also how they influence the outcome jointly. We empirically validate visual communication is more effective than textual communication on a crowdfunding platform. Our findings support an integrated marketing communication strategy that marketers should implement using multiple communication tools in a harmonic way. We demonstrate that the synergistic effect of visual and textual communication has a positive effect on crowdfunding outcome.

OVERVIEW

Textual marketing communication is effective in various contexts, such as print advertising, user-generated content, and social media (Diamond 1968; Ludwig et al. 2013; Nam and Kannan 2014). However, visual marketing communication studies are limited in the context of print advertising (e.g., Hagtvedt and Brasel 2017). With the proliferation of image-based communication online (e.g., social media, online reviews, online forums, etc.), an important question is how do we understand visual communication effectiveness online?

The challenge is that online visual messages are ill-structured and large in volume, which makes it difficult to filter important and related information from the massive data. Moreover, it's hard to apply traditional experiment or survey methods because the visual content changes rapidly online, so prior research results may not apply to the current situation. The complexity to find important information from visual messages and a large amount of data motivates the dissertation to seek a machine learning-based image mining technique to automatically quantify images on a large scale. This dissertation includes two essays to examine visual marketing communication effectiveness online.

In Essay 1, we study both company and consumer-generated visual messages on social media. We seek to understand how the company and consumers perceive the same brand using visual messages on social media. The conceptualization of VBBP is different from traditional marketing communication. First, both a company and its consumers are pivotal authors of brand stories on social media while the company is the only contributor to the brand story. Second, a company and its consumers can influence each other on social media, whereas traditional marketing communication is a one-way approach from the company to its consumers. Thus, we develop a conceptual framework and propose that visual marketing communication on social media between a company and its consumer is a co-creational process. We empirically validate the conceptual model and find that during the co-creational process, both the company and consumer visual-based information richness (VBBP_R) increase over time. Moreover, in examining the difference between company and consumer VBBPs, we find that there is a visual-based brand perception gap (VBBP_G) between a company and its consumers. From these findings, we advise three marketing communication strategies to help companies manage their VBBP_G.

In Essay 2, we focus on the project creator generated content on the crowdfunding platform. We dive deep to study one side of the communication party (i.e., company side). Extending from Essay 1, Essay 2 focuses on: i) a different online platform to check the robustness of visual communication effectiveness, ii) a marketing outcome as dependent measures to expand beyond the effect of visual cues on brand perception, iii) investigating not only how visual and textual communication influence crowdfunding success individually but also how they jointly influence the outcome. We empirically validate visual communication is more effective than textual communication on a crowdfunding platform. Consistent with integrated marketing communication that marketers should use multiple communication tools in a harmonic way, our findings support that the synergistic effect of visual and textual communication has a positive effect on a crowdfunding outcome.

ESSAY 1. VISUAL-BASED BRAND PERCEPTION ON SOCIAL MEDIA

INTRODUCTION

Social media has entered the mainstream media in the past decade. The percentage of the U.S. population with a social media profile increased from 10% to 77% from 2008 to 2018 (Statista 2018). Companies have shifted from traditional advertising to social media to invest in their brands. Digital media will exceed the traditional advertisement spending and account for 55.0% of total media ad spending by 2019 (eMarketer 2018a). Digital media is digitized content that can be transmitted over the internet or computer networks. Social media is a popular form of digital media. American companies now spend on average 13.8% of their marketing budget on social media (CMO Survey 2018).

Content Placement on Social Media

A recently emerged marketing communication strategy on social media is content placement (Kumar et al. 2016; Nam and Kannan 2014; Schweidel and Moe 2014). In the context of social media, content placement refers to placing ads (e.g., textual ads, visual ads, etc.) on social media. The content placement on social media differs from traditional marketing communication in three ways. First, companies have lost their pivotal role of sole authors of brand stories (Kuksov, Shachar, and Wang 2013). In traditional marketing communication, brand meaning is under the control of brand managers (Keller 1993). There is only one collective brand meaning held by companies. On social media, consumers can contribute to brand meaning and stories through content placement as well (Lee and Bradlow 2011; Tirunillai and Tellis 2014). Consumers can use a hashtag from the company to share their view of the brand, or they can like, share, and comment on company postings. Consumers may also be influenced by other consumers' opinions. Brand managers often incorporate consumers' opinions to reconstruct brand meaning.

Second, the brand co-creational process between a company and its consumers is dyadic on social media. We can divide social media messages into two categories: owned social media (OSM) and earned social media (ESM) based on who creates social media messages. OSM refers to a brand’s communication created and shared through its own online social network assets, for example, a Facebook fan page (Colicev et al. 2018). In contrast, ESM refers to the brand-related content that entities other than a company – typically the consumers – create, consume, and disseminate through online social networks (Colicev et al. 2018). For example, we consider the brand-related content such as likes, shares, comments, etc., placed by a consumer as ESM. OSM messages lead to substantially more ESM messages, which, in turn, affect company sales (Kumar et al. 2016). ESM messages can add to existing brand meaning authored by a company, and they can also add new meaning to a brand that contests to the brand's aspired identity (Gensler et al. 2013). Thus, the company and its consumers can influence each other’s brand building on social media over time.

Third, consumer messages have equal weight, if not more, to companies’ messages on the same social media platform. OSM and ESM messages are possible from the same social media platform (e.g., Instagram). User-generated content can influence other consumers just like messages generated by companies (Awad and Ragowsky 2008; Dubois, Bonezzi, and De Angelis 2016; Kozinets et al. 2010). Messages from a company and its consumers are omnipresent and affect consumers simultaneously. Furthermore, using the same social media platform prevents the influence of confounding factors from separate platforms.

Visual Content on Social Media

Although there are different forms of digital messages such as text, audio, visual, etc., we focus on visual content specifically in this study. Visual content such as images provide companies with two important opportunities to communicate with target consumers and manage their brands. First, visual content on social media is impactful. Visual content increases user engagement and purchase likelihood of online shoppers. Social media posts with visuals receive 94% more page visits and engagements than those without, and they elicit twice as many comments on average (Kane and Pear 2016). 60% of U.S. digital shoppers said they needed to see an average of three or four images before making a purchase when shopping online (eMarketer 2018b). Furthermore, visual search improves the online shopping experience. Visual search with Pinterest, Amazon, Google, eBay, and Bing has taken off since 2016. Similar to keyword search, consumers can enter use a picture or a part of the picture to search for related content. For example, consumers can click on a picture of a garment to search for similar clothes on Pinterest. Over 60% of U.S. and U.K. millennial internet users believe visual search should be part of their digital shopping experience (eMarketer 2018c).

Second, visual content on social media enables us to measure brand perception empirically. Brand perception is the total impression that consumers have of a brand, based on their exposure to that brand. Empirical evidence has suggested that visual content on social media is impactful on brand perception (Culotta and Cutler 2016; Tirunillai and Tellis 2014). Previous studies use a survey approach to measure brand constructs, such as brand personality (Aaker 1997; Grohmann 2009; Lovett, Peres, and Shachar 2014; Malär et al. 2011), customer-based brand equity (Park and Srinivasan 1994; Rego, Billett, and Morgan 2009), brand association (Roth 1995; Sonnier and Ainslie 2011), etc. Mining information from unstructured data to understand brand perception are increasingly important (LaVelle et al. 2010; Tirunillai and Tellis 2014). In these studies, results are generated by using a small sample in a limited period, which may be biased over time. The survey method is limited to measure brand meaning on social media because visual content on social media is ill-structured in nature and large in volume because of its low cost, which makes the traditional survey method hard to apply. The newly developed machine learning-based image mining technique can analyze visual content in a large volume automatically without asking companies and consumers directly. This approach overcomes the disadvantages of the survey approach. Thus, mining visual content on social media enables companies to measure their VBBP by analyzing the visual OSM and ESM empirically. In this study, VBBP is the total impression that companies intend to let consumers have, or consumers have of a brand, based on their exposure to the visual content of that brand. Marketers can quantify VBBP automatically. Two other important concepts are extended from VBBP: VBBP_R and VBBP_G. VBBP_R measures the amount of visual information contained in a brand on social media. For example, a large-sized image from a brand is more likely to contain more visual information than a small-sized image. VBBP_G describes the inconsistency between a company VBBP and its consumer VBBP. For example, a company may intend consumers to perceive the brand as a colorful brand while the consumers perceive the brand as a colorless brand. The VBBP_G is large in this case. Thus, we focus on the three main visual based concepts in this study.

Research Questions

To our best knowledge, little research has been paid attention to investigate 1) the brand perception on social media from both a company and its consumers and 2) the brand perception on a visual base. To bridge this research gap, we conceptualize and empirically measure the VBBP in this study. Since the VBBP is co-created by a company and its consumers on the social media platform, we extend to demonstrate the VBBP using both visual OSM from a company and ESM from its consumers. Since the co-creational process allows a company and its consumers to influence each other over time, we seek to understand how a company and consumer VBBP_R influence each other and change over time. In addition, do a company and its consumers perceive their brand the same way? To understand the interaction between a company and its consumers in depth, we also investigate whether there is a VBBP_G between a company and its consumers and the marketing strategies to manage the VBBP_G. Specifically, we seek to address the following research questions. (1) How is VBBP dynamically formed and measured on social media? (2) How do a company and its consumers interact, and how do the company and consumer VBBP_R change over time? (3) Is there a VBBP_G between a company and consumers, and how do we use marketing communication strategies to manage the VBBP_G over time?

Contributions

We make three contributions to the extant literature. First, we conceptualize and empirically measure VBBP on a social media platform in a co-creation process. The conceptualization of brand perception in this study is unique in three ways: (1) brand perception in this study is visual-based, (2) both a company and its consumers are active co-creators of brand perception, (3) since OSM and ESM messages can influence each other over time, brand perceptions from both parties are not always consistent. To our best knowledge, this is the first study that empirically measures the VBBP on social media. The machine learning-based image mining method is particularly effective to quantify visual content on social media where visual data from both a company and its consumers are readily available and in sheer volume.

Second, we contribute to the literature that during the brand co-creational process, the VBBP_R of both a company and its consumers keeps evolving, and the brand meaning becomes increasingly rich. For the company and consumer VBBP_R, our results indicate that VBBP_R not only keeps increasing for both parties over time but also positively influences each other's VBBP_R over time.

Third, there is a discrepancy between the company VBBP and consumer VBBP. We find that the discrepancy can either be on all visual attributes of brand perception or a certain visual attribute of brand perception. We adopt a set of marketing communication strategies to address how to manage the discrepancy of VBBPs on social media. Depending on whether companies need to mitigate or enlarge the VBBP discrepancy, they can choose appropriate marketing communication strategies. We find that the visual communication strategy (i.e., visual content posting frequency on social media) mitigates the VBBP_G, while non-visual communication strategy (i.e., new volume) enlarges the VBBP_G.

The rest of the study is organized as follows. We first develop a conceptual framework and hypotheses of a dynamic co-creational process for VBBP formation on social media. We then develop measurements for the VBBP using machine-learning techniques and the data collected from Instagram to illustrate the interactions and discrepancy of VBBP between a company and its consumers. Finally, we show how companies can undertake a set of marketing communication strategies to manage the interaction of the VBBP of both a company and its consumers using visual content placement on social media.

CONCEPTUAL DEVELOPMENT

VBBP Co-creation

Marketing is evolving toward a service-based model of all exchanges, which is known as service-dominant (S-D) logic highlighting the co-creation of value, process orientation, and relationships (Vargo and Lusch 2004). In it, consumers are endogenous to value creation and constitute as operant resources (Vargo and Lusch 2008). In the era of S-D logic, not only individual consumers but also brand communities and other stakeholders constitute as operant resources. Brand value co-creation process is a continuous, social, highly dynamic, and interactive process between a company, a brand, and all stakeholders (Merz, He, and Vargo 2009). Rather than thinking of brands as controllable knowledge structures and consumers as passive absorbers of brand knowledge, all stakeholders, including consumers, are active co-creators of these brand meanings (Gensler et al. 2013). Empirical evidence has suggested user-generated content are influential in the context of electronic word of mouth (eWOM) (Ghose, Ipeirotis, and Li 2012; Goes, Lin, and Au Yeung 2014; Ransbotham, Kane, and Lurie 2012).

Social media marketing communication is a two-way interaction while traditional marketing communication is one-way. On social media, consumers have equal chances to contribute to brand stories just as companies do. Social media enables interaction between a company and its consumers. Social media also provides a unique channel that OSM and ESM messages are told through a dynamic and evolving process. The construction of brands on social media can be interpreted as a collective, co-creational process that allows both brand authors to contribute to their stories. A company and its consumers generate content on social media simultaneously to form their brand stories. Our study focuses on the direct interplay between a company and its consumers within one self-contained platform (i.e. Instagram).

The brand value co-creation is more than dyadic communication on social media. Co-creation brings a company and its consumers together to produce a mutually valued brand meaning. Dyadic communication describes the interrelationship between two parties (Barry and Crant 2000). Both co-creation and dyadic communication capture the interrelationship between the two parties. For example, consumers interact with a company by liking, sharing, or commenting on a company's brand page. However, in the co-creational process, a company or its consumers can independently communicate with each party. For example, a company may revise the brand meaning by creating new content on its page over time. Consumers may generate content or read other consumers' content by searching hashtags. The self-interactivity is also a part of the co-creational process.

The VBBP co-creational process is dynamic on social media. On social media, a company and its consumers create brand stories jointly. Both a company and consumer VBBP keeps evolving due to the interactivity within and across the two parties. The left side of Figure 1 illustrates how the company and consumer VBBP evolves from time t-1 to time t. The formation of a company VBBP at time t comes from two sources: a company VBBP at time t-1, and its consumer VBBP at time t-1. Thus, at time t, a company considers its pursued VBBP as well as consumer VBBP to update its VBBP. Similarly, a company VBBP keeps evolving at time t+1 and is influenced by a company and consumer VBBP at time t. Following the same logic, the consumer VBBP keeps evolving as well.

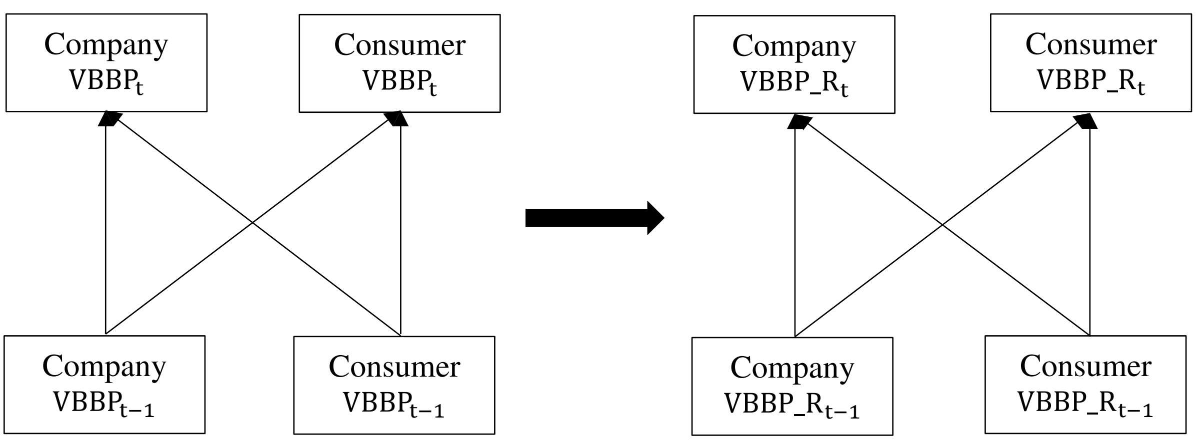

Figure 1 The Dyadic and Dynamic Process of VBBP and VBBP_R
Note: VBBP refers to visual-based brand perception. VBBP_R refers to visual-based brand information richness. Figure 1 describes the dynamic process of VBBP and VBBP_R.

VBBP_R

In this study, we focus on a related element of VBBP – VBBP_R, which is defined as the social media's ability to reproduce the brand-related information sent over it. We aim to understand how information richness of VBBP changes during the co-creational process over time. We adopt from media richness theory (MRT) and social information processing (SIP) theory to explain the process of VBBP_R change.

MRT, also known as information richness theory, is a framework to describe a communication medium's ability to reproduce the information sent to it. Under the MRT framework, Daft and Lengel (1986) first proposed ranking and evaluating certain communication mediums within an organization. When facing different levels of equivocality and uncertainty, Daft and Lengel (Daft and Lengel 1986) suggest using proper communication media, such as face-to-face, phone calls, and email. Low equivocality and low uncertainty represent a clear, well-defined situation, resulting in using a leaner medium. High equivocality and high uncertainty indicate ambiguous events that need clarification by managers, resulting in using a richer medium. Thus, richer communication media are more effective for communicating with equivocal and uncertain issues than leaner media. The MRT has been adapted to new media communication, such as video and online conferencing (Dennis and Kinney 1998). The communication on social media is asynchronous that a company and its consumers do not receive the message at the same time. Therefore, compared to face-to-face communication, social media is a leaner medium. However, to better understand the ambiguous and complex meaning of a brand, a richer medium is needed for a company and its consumers.

Building upon SIP theory, we argue that communication on social media becomes richer over time. SIP theory explains online interpersonal communication without nonverbal cues and how people develop and manage relationships in a computer-mediated environment (Walther 1992). SIP proposes that online interpersonal relationships may demonstrate the same relational dimensions and qualities as face-to-face relationships (Walther 1992). We use SIP theory to explain the VBBP co-creational process. In the beginning, social media was a lean medium for communication between a company and its consumers. However, the medium became richer due to the interactivity between the company and consumer VBBP. A company exchanges visual content with its consumers over time to enrich brand stories. The interpersonal communication of social media may demonstrate the same information richness compared to face-to-face communication. Thus, social media communication between a company and its consumers may grow from lean to rich over time.

In the VBBP co-creational process, VBBP_R increases if social media communication moves from a lean to a rich medium due to the interactivity of a company and its consumers. The right side of Figure 1 illustrates that from time t-1 to time t, both a company and consumer VBBP_R increase. Taking the company VBBP_R as an example, at time t, VBBP_R increases due to the interactivity between the company and consumer VBBP at time t-1. The formation of VBBP at time t is influenced by the company and consumer VBBP at time t-1. Therefore, both the company and consumer VBBP_R at time t-1 are likely to increase the company VBBP_R at time t. Therefore, we hypothesize:

H1: Company VBBP_R has a positive effect on a) itself and b) consumer VBBP_R over time.

H2: Consumer VBBP_R has a positive effect on a) company VBBP_R and b) itself over time.

VBBP_G

During the VBBP co-creational process, a company and its consumers may form different VBBPs toward the same brand. Brand perception discrepancy occurs when a company's pursued brand perception is not consistent with consumers' perceived brand perception (Akdeniz and Calantone 2017). Consumers from different segments may form different brand perceptions of the same company. The following factors may explain brand perception discrepancy.

First, brand perceptions between a company and its consumers may be different due to individual characteristics such as gender, age, education, income, culture, etc. (Cyr, Head, and Larios 2010; Gefen and Straub 1997; Munn 1960). The individual has his or her schemas, attitudes, and expectations. Individual's prior experiences influence brand perceptions.

Second, the difference in brand perceptions may come from the way consumers process information. Elaboration likelihood model (ELM) states that at one end of the continuum, termed the "peripheral route," persuasions occur because of a simple cue in the context; at the other end of the continuum, termed the "central route," persuasions form from a consumer's careful and thoughtful deliberation of the true merits of the information presented in the communication (Herr, Kardes, and Kim 1991; Petty and Brinol 2012). Whether a consumer processes information using the central route, the peripheral route, or a combination of the two depends partly on the consumer's motivation. Consumers with low motivation are likely to be operated by a company and form a brand perception consistent with the company's pursued brand perception. Consumers with high motivation use the central route to evaluate a company's brand information carefully and are able to form their own brand perception, which deviates from a company's pursued brand perception.

We conceptualize the VBBP discrepancy between a company VBBP and consumer VBBP as VBBP_G. Specifically, when the company and consumer VBBP are consistent, the VBBP_ G is small. When the VBBPs are not consistent, the VBBP_G is big. In this study, the

VBBP_G has no valence. A big VBBP_G does not necessarily negatively affect the brand. For example, if a company would like to expand to a new market, the company pursued VBBP may be very different from its historical VBBP. The VBBP_G could be large because the company intends to attract more consumers from other segments. When a company and its consumers communicate through visual content on social media, we propose three marketing communication drivers that will influence VBBP_G.

The first driver of VBBP_G is the overall marketing communication strategy, represented by advertising spending per ad in this study. Advertising spending per ad is a signal for information credibility. A signal is an action that the company can take to convey information credibility about the brand to the consumers (Rao, Qu, and Ruekert 1999). A high adverting spend per ad signals high information credibility (Cheung, Sia, and Kuan 2012). Thus, companies can selectively use high advertising spending per ad to move consumer perceptions toward companies' brand perception. Therefore, we have:

H3a: Advertising spending per ad has a negative effect on VBBP_G.

The second driver is the visual communication strategy, operationalized as communication frequency. Selective perception involves screening out the information that is less relevant to the customers (Celsi and Olson 1988). On a social media platform, companies can choose the type of visual content that they expect consumers to see, and they can also encourage consumers to post brand-related images using hashtags. Thus, companies can change the consumer VBBP by increasing communication frequency to feed relevant information to consumers routinely. In addition, companies can also motivate consumers to consistently post relevant information about the brand to influence subsequent consumers. The same applies to consumers. Therefore, we have:

H3b: Company communication frequency has a negative effect on VBBP_G.

H3c: Consumer communication frequency has a negative effect on VBBP_G.

The third driver is the non-visual communication strategy, represented by news volume. Usually, companies have no control over the news media. The information provided by news media is likely to be more objective and comprehensive. It is more likely that consumers' brand perception deviates from a company's brand perception. In addition, larger assortments can increase choice deferral and switch (Diehl and Poynor 2010). Large news volume also causes the selective perception that customers screen out the irrelevant information (Celsi and Olson 1988). Consumers' brand perception will deviate from companies' brand perception. Thus, we have:

H3d: News volume has a positive effect on VBBP_G.

Figure 2 summarizes the VBBP co-creational process between a company and its consumers into a conceptual model. VBBP co-creation is a dyadic and dynamic process as both a company and its consumers contribute to brand building significantly on social media. During this process, two crucial concepts emerge: VBBP_R and VBBP_G. From time t-1 to time t, both the company and consumer VBBP_R increase because visual content from OSM and ESM keep adding new meaning to the brand that moves the visual communication on social media toward a richer medium. There is a VBBP_G between company and consumer over time. In such a process, the VBBP_R is likely to increase because the company and its consumers will update the current VBBP according to each other's feedback. In turn, this adds more brand meaning to the VBBP_R over time. A set of marketing communication strategies can help companies to manage their VBBP_G. Advertising spending per ad, company communication frequency, and consumer communication frequency mitigate VBBP_G while News Volume enlarges VBBP_G over time.

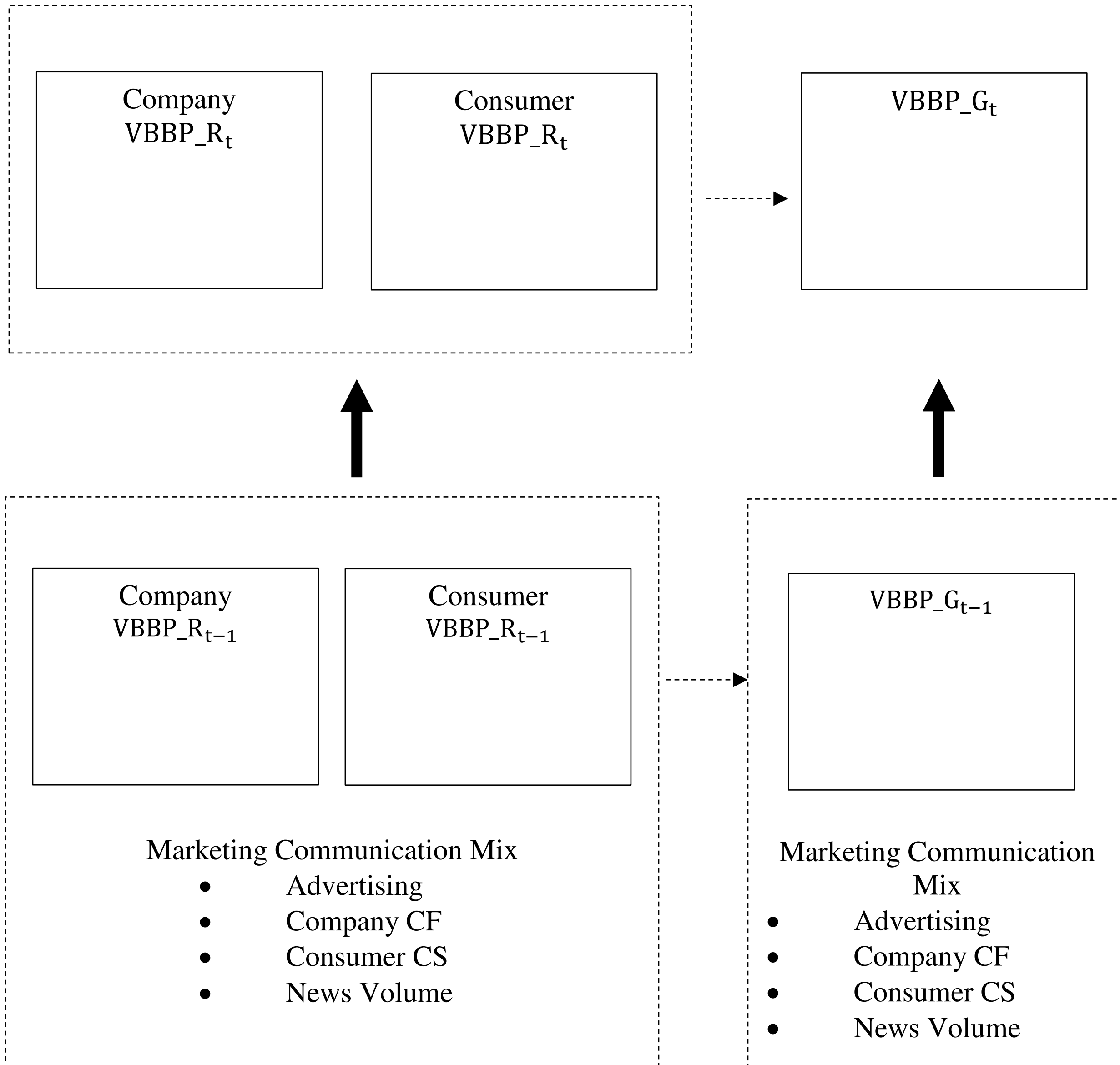

Figure 2. VBBP Co-Creational Process on Social Media
Note: VBBP_R refers to visual-based brand perception information richness. Advertising refers to advertising spending per ad. CF refers to communication frequency. VBBP_G refers to visual-based brand perception gap. From time t-1 to time t, both company and consumer VBBP_R increase. The marketing communication strategies Advertising, Company CF, and Consumer CF mitigate VBBP_G while News Volume enlarges VBBP_G.

Visual Attributes

Visual cues are impactful on brand perception, brand attention, brand image, brand attitude, brand evaluation, and brand choice (Chan, Boksem, and Smidts 2018; Littel and Orth 2013; Pieters and Warlop 1999; Rothman, Lanes, and Robins 1993; Tokioka et al. 1985). For example, the location of the brand logo influences consumer attention toward a brand. The centrally located branding strategy can counteract the negative effects of digital video recorders to capture consumer attention (Tokioka et al. 1985). Compared to text brand information, consumers use more visual information to make a brand choice (Pieters and Warlop 1999). It is important to know the individual visual characteristics that are influential on branding in the marketing literature.

To have the broadest lens on the visual characteristics, we conducted a literature review on visual characteristics relevant to marketing to derive key visual attributes in the four leading marketing journals. Marketing researchers often use visual cues in the context of print advertising. Emerging literature adopts image mining/processing techniques to study human faces and facial expressions. We consider both literature streams when selecting the search keywords. Thus, we adopted seven related keywords: “image,” “visual,” “picture,” “print advertising,” “color,” “face,” and “facial expression.” Second, we went through abstracts to eliminate irrelevant articles (i.e., does not include any visual characteristics). For example, we excluded the articles with keywords on “brand image” and “corporate image.”

The search resulted in 39 related articles. We further searched business magazines and newspapers from 2010 to 2017 to cross-validate whether these visual attributes are relevant to marketers and are up to date. We focus on four sources: *Harvard Business Review, MIT Sloan*

Management Review, Wall Street Journal, and *Forbes*. Different from the keywords used in journal search, we used “image,” “picture,” “online image,” and “image processing” as keywords because we would like to know how online images (e.g., social media) and image processing techniques influence marketers and customers. We followed the same procedure to eliminate irrelevant articles. This search resulted in nine articles.

We summarized visual characteristics from the marketing literature into seven general visual attributes: camera angle, color, domain-specific object, facial features, size, object location, and sharpness. With a limited search on four business magazines and newspapers, we found four overlapping categories (i.e., camera angle, color, domain-specific object, and facial features) with academic research. It provides us with confidence that the visual attributes studied in the literature are relevant and up to date.

We provide definitions of visual characteristics in Table 1. For example, camera angle refers to whether an image is shot at an upward, downward, or eye-level angle (Meyers-Levy and Peracchio 1992; Laura A. Peracchio and Meyers-Levy 2005). Appendix A includes detailed information about each visual attribute and the visual characteristics that measure them. We also incorporated findings from business magazines and newspapers at the end of each visual attribute section. Table 14 lists visual characteristics, measures used in the literature, results, and authors in the rows.

Table 1. Visual Characteristics Definitions and Computer Measurement Capability

Visual Attribute	Visual Characteristic	Definition
Camera Angle	Camera Angle	Whether an image is shot at an upward, downward, or eye-level angle.
Color	The Number of Colors	The number of colors used in an image.
	Dominant Foreground Color	The most attention-grabbing color at the front of an image.
	Dominant Background Color	The most attention-grabbing color in the back of an image.
	Color Association	The degree to which a color is associated with brands, senses, language, objects (or forms), personality characteristics, etc.
	Hue	The degree to which a stimulus can be described as similar to or different from stimuli that are described as red, green, blue, and yellow.
	Saturation	The degree of intensity or purity of a color.
	Value	The degree of blackness and whiteness in a given color.
	Lightness	The degree of darkness in a given color.
Domain-Specific Object	Image-text Integration	Whether the text is integrated into an image.
	Image-text Consistency	The degree to which the text and image convey a consistent message.
	Image-text Interactivity	The degree to which the text is interactive with an image.
	Brand logo	Whether a brand logo appears in an image.
	Warning Sign Icons	Whether a warning sign icon appears in an image.
Face	Babyface Feature	The degree to which a person has a child-like face in an image.
	Celebrity Face Feature	The degree to which a stranger's face was blended with a celebrity's facial features in an image.
	Emotion	The degree to which an emotion is expressed from the face(s) in an image. The emotions include happiness, sadness, fear, disgust, surprise, anger.

Note: The definition of each visual characteristic is provided.

(Table cont'd)

Visual Attribute	Visual Characteristic	Definition
Size	Image/Ad Size	The amount of space that an image/a print ad takes.
	Brand Logo Size	The amount of space that a brand logo takes in an image.
	Size Ratio	The relative space proportion of a focal object in an image.
Object Location	Product Location	The placement of a product in an image.
	Brand Logo Location	The placement of a brand logo in an image.
Sharpness	Sharpness	The amount of details an image contains.

Data

We chose Instagram as the social media platform because it is a smartphone app with a social community built for sharing images. We collected static images from different brands' company official accounts and consumer hashtags between 2011 and March 2018. Each image is collected with a timestamp. The data represents a relatively broad category, including the following eight digital camera brands: Canon, Fujifilm, Kodak, Leica, Nikon, Olympus, Samsung, and Sony. If a brand has multiple company accounts for different regions and countries, we collected images from North America or USA account. We collected consumer images with fan-based hashtags, for example, #canonfanclub. The fan-based hashtags mainly come from existing and potential consumers of the companies. Samsung exited the digital camera market in 2016. Therefore, we excluded the images after Samsung exited the market. After the collection process, we had 10,765 company images and 6,689 consumer images.

Figure 3 describes how the VBBP measures are derived from Instagram images. First, we employ machine-learning techniques to process company images into numerical visual characteristics. Second, we extract visual attributes from the characteristics using an exploratory factor analysis (EFA). Third, we validate the attribute dimensions by i) recruiting experts to test content and face validity, ii) comparing human and computer measures to ensure convergent validity, iii) testing external validity by using consumer images to extract visual attributes following the same procedure. Finally, we combine the company and consumer VBBP measures to form the measure of VBBP_G.

Image Processing Source

Computer vision, or image processing, refers to a computer's ability to see the way humans do. Computer vision studies how to reconstruct, interpret, and understand a three-dimensional (3D) scene from its two-dimensional (2D) images (Ballard and Brown 1982). It is a process through which visual sensation is transformed into visual perception. During this process, a computer acquires visual data, processes, analyzes, and makes decisions about the image or video (Szeliski 2011). In this study, we adopt Microsoft and Google's cloud-based computer vision APIs and Python libraries to process images. Computer vision API allows customers to build their image processing programs locally to send images to the companies' cloud. The cloud-based, computer vision APIs receive images, process them, and send the results back to the customers' local computers.

We adopt leading technology companies' vision APIs for three reasons. First, the machine learning-based image recognition model requires a significant number of images initially to ensure classification accuracy. Leading technology companies can continuously update their machine learning algorithms to improve classification accuracy. Thus, using trained models from them not only saves training cost and time but also has a low classification error rate. Second, computer vision APIs have provided a wide range of features needed for this study, such as object detection, emotion detection, brand logo detection, text detection, etc. Third, the cost-effective APIs are suitable to process the images on a large scale in a short time duration[1]. Additionally, we adopt Python libraries to measure the visual characteristics that are not provided by APIs, such as hue.

This study focuses on static, general, and context-free visual characteristics. Computer vision APIs and Python libraries cannot measure all the visual characteristics because some are (1) unique or (2) context dependent. We believe that with the development of machine learning models, more visual characteristics can be directly measured in the future. The unique visual characteristics are the warning sign icon, babyface feature, and celebrity face feature. These visual characteristics require customized model training, which current computer vision APIs do not offer. The data is not representable to capture these visual characteristics either. In other words, only the computer might capture these visual characteristics in only two or three images. Thus, we excluded specific visual characteristics in this study.

Furthermore, some visual characteristics are context dependent, which requires additional information. First, the camera angle depends on the distance between the viewer/camera and the height of the focal object in an image. Without knowing the distance, height, and focal object, computers have difficulties in calculating camera angles. Second, color can be associated with multiple brands, objects, personalities, the representation of concepts, etc., which is not generalizable to every image. Third, image-text consistency and interactivity require a comprehensive understanding of messages conveyed by the image and text at an abstract level.

[1] The features and pricing of Microsoft Computer Vision APIs are available at https://azure.microsoft.com/en-us/services/cognitive-services/computer-vision/?v=18.05 and https://azure.microsoft.com/en-us/services/cognitive-services/face/?v=18.05. The features and pricing of Google Cloud Vision API are available at https://cloud.google.com/vision/.

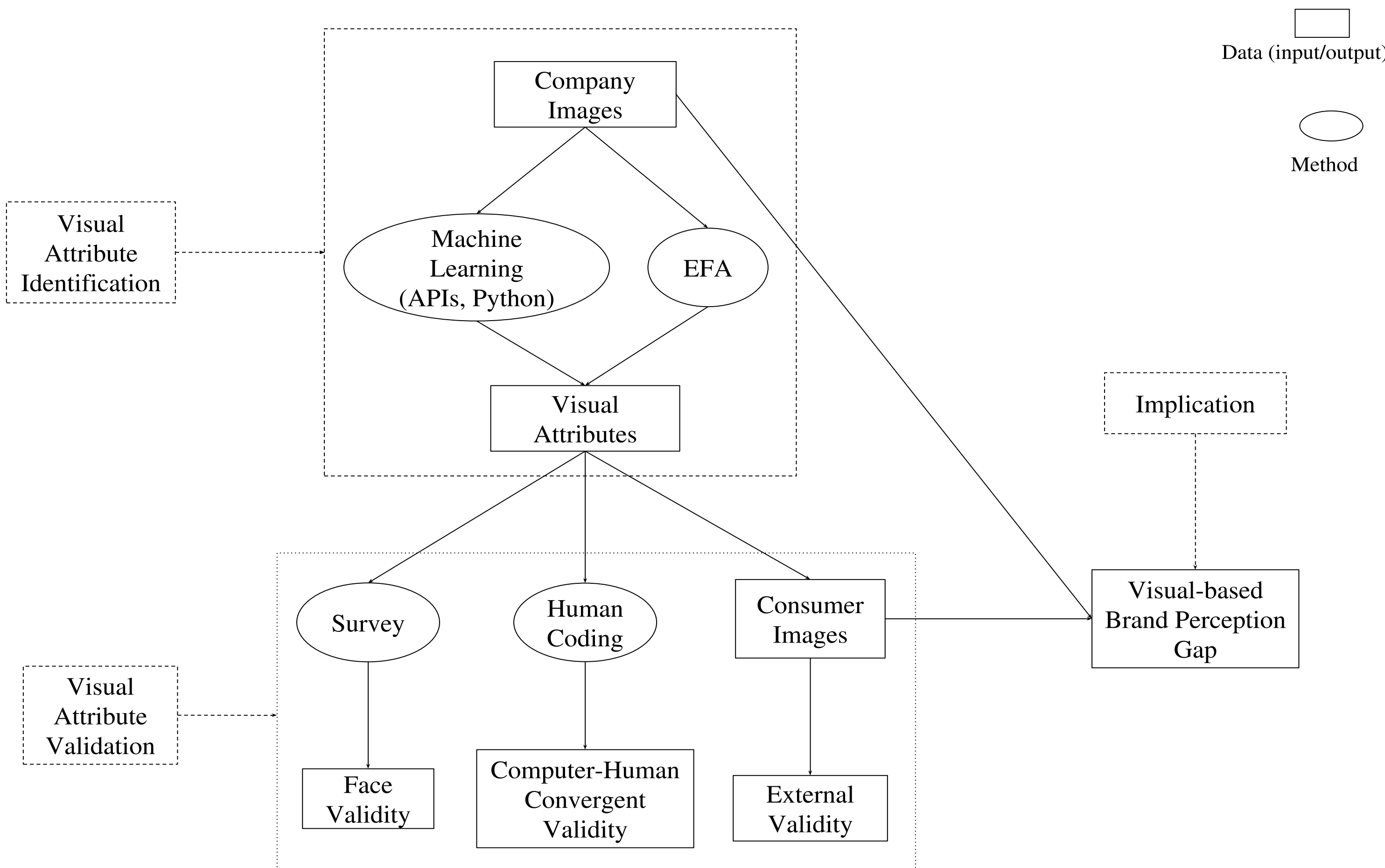

Figure 3. A Process to Extract Visual Attributes to Form VBBP Measures
Note: First, we employ machine-learning techniques to process company images into numerical visual characteristics. Second, we extract visual attributes from the characteristics using exploratory factor analysis. Third, we validate the attribute dimensions by i) recruiting experts to test content and face validity, ii) comparing human and computer measures to ensure convergent validity, iii) testing external validity by using consumer images to extract visual attributes following the same procedure. Finally, we combine the company and consumer VBBP measures to form the measure of VBBP_G.

The primary task of current computational algorithms is to recognize specific objects in an image. The API has limited ability in interpreting the relationship between text and image at an abstract level. Fourth, product location, brand logo location, image/ad area, brand logo area, and size ratio depend on the focal product, brand, or object in an image, which cannot be measured directly by computer vision APIs. The primary goal of the study is to find out the general and context-free visual characteristics. Thus, it is reasonable to exclude context dependent visual characteristics.

In Table 2, we summarize the computer measurement capability in the last column. Computer measurement capability illustrates whether a visual characteristic is measurable by the computer vision APIs or python libraries. We denote “Yes” to measurable visual characteristics, and “No” to unmeasurable visual characteristics. We will utilize the visual characteristics that are relevant and measurable in this study.

Computer Measures

We use Microsoft and Google’s cloud-based computer vision APIs and Python libraries to process images. Microsoft has two computer vision APIs called Microsoft Azure Vision API and Microsoft Azure Face API. The Face API has two main functions: face detection and face recognition. The Vision API mines information about visual content found in an image other than human faces. Google Cloud Vision API has the combining functions of two Microsoft APIs. Python libraries are used to process visual measures not provided by the APIs. Table 2 summarizes image processing sources and computer measures of the visual characteristics.

Table 2. Visual Characteristics Computer Measurement Capability and Measures

Visual Attribute	Visual Characteristic	Computer Measurement Capability	Image Processing Source	Computer Measure
Camera Angle	Camera Angle	No		
Color	The Number of Colors	Yes	Microsoft Azure Vision API	binary: black and white:0, color:1
	Dominant Foreground Color	Yes	Microsoft Azure Vision API	red (1), orange (2), yellow (3), green (4), teal (5), blue (6), purple (7), pink (8), white (9), gray (9), brown (9), black (9)
	Dominant Background Color	Yes	Microsoft Azure Vision API	red (1), orange (2), yellow (3), green (4), teal (5), blue (6), purple (7), pink (8), white (9), gray (9), brown (9), black (9)
	Color Association	No		
	Hue	Yes	Python Library	0 to 360 degrees
	Saturation	Yes	Python Library	from 0% to 100%
	Lightness	Yes	Python Library	from 0% to 100%
	Value	Yes	Python Library	from 0% to 100%
Domain-Specific Object	Image-text Integration	Yes	Microsoft Azure Vision API	binary: 1: present, 0: absent
	Image-text Consistency	No		
	Image-text Consistency	No		

Note: Computer measurement capability illustrates whether a visual characteristic is measurable by computer vision APIs or python libraries. “Yes” means measurable; “No” means not measurable. The image processing source and computer measures are provided for each visual characteristic.

(Table cont’d)

Visual Attribute	Visual Characteristic	Computer Measurement Capability	Image Processing Source	Computer Measure
Domain-Specific Object	Brand Logo	Yes	Google Cloud Vision API	binary: 1: present, 0: absent
	Warning Sign Icons	No		
Face	Babyface Feature	No		
	Celebrity Face Feature	No		
	Happiness Emotion	Yes	Microsoft Azure Face API	likelihood from 0 to 1
	Sadness Emotion	Yes	Microsoft Azure Face API	likelihood from 0 to 1
	Fear Emotion	Yes	Microsoft Azure Face API	likelihood from 0 to 1
	Disgust Emotion	Yes	Microsoft Azure Face API	likelihood from 0 to 1
	Surprise Emotion	Yes	Microsoft Azure Face API	likelihood from 0 to 1
	Anger Emotion	Yes	Microsoft Azure Face API	likelihood from 0 to 1
Size	Image Width	Yes	Microsoft Azure Vision API	the number of pixels
	Image Height	Yes	Microsoft Azure Vision API	the number of pixels
	Image Area	Yes	Microsoft Azure Vision API	the dimension of an image calculated by multiplying width and height
	Brand Logo Size	No		
	Brand Logo Size	No		
Object Location	Product Location	No		
	Brand Logo Location	No		
Sharpness	Sharpness	Yes	Python Library	the average gradient magnitude

The Number of Colors, Dominant Foreground and Background Color

We used Microsoft Azure Vision API to measure the number of colors, dominant foreground color, and dominant background color. The API can distinguish black and white vs. color images. We measure the number of colors as a binary variable where a black and white image is coded as 0 and a color image is coded as 1. The API processes the image color in three different contexts: foreground, background, and whole. The API detects 12 dominant accent colors: black, blue, brown, grey, green, orange, pink, purple, red, teal, white, and yellow. Consistent with the literature, we measure colors as warm, cool, and neutral. Thus, we coded dominant foreground and background colors as follows: red (1), orange (2), yellow (3), green (4), teal (5), blue (6), purple (7), pink (8), white (9), grey (9), brown (9), black (9). We coded all natural colors as 9.

Hue, Saturation, Lightness, and Value

We used Python libraries to measure hue, saturation, lightness, and value as these measures come directly from image pixels. Consistent with the measures from the literature, hue ranges from 0 degrees to 360 degrees (0 degrees as red, 60 degrees as yellow, 120 degrees as green, and 240 degrees as blue). Saturation, lightness, and value range from 0% to 100%. The larger the number is, the more the image is saturated/lighter/with high value.

Image-Text Integration and Brand Logo

Computer Vision API detects objects at top and domain-specific level. Top-level object detection generates a taxonomy-based category with parent/child hereditary hierarchy by using Microsoft Azure Vision API (He et al. 2015; Szegedy 2013)[2]. Domain-specific object detection refers to specific content detection such as text, brand logo, and landmark detections. For

[2] A list of 86 categories is available at https://docs.microsoft.com/en-us/azure/cognitive-services/computer-vision/category-taxonomy.

example, an image of Rockefeller Center would be recognized as a building at the top level, but as Rockefeller Center at the domain-specific level. We measure image-text integration and brand logo using domain-specific object detection method. We measure image-text integration by using Microsoft Azure Vision API's text detection function. It is coded as a binary variable with 0 as the text not integrated into an image and 1 as the text integrated into an image. We measure the presence of brand logo by using Google Cloud Vision API's logo detection feature. In this study, it is coded as a binary variable where 0 means the brand logo is not present, and 1 means the brand logo is present in an image.

Emotion

Microsoft Azure Face API detects faces with high precision face location, the face rectangle (left, top, width, and height) in an image. The Face API takes facial expressions as an input and returns the confidence across a set of emotions for each face in the image. Consistent with the literature, we measure six emotions detected from faces: happiness, sadness, fear, disgust, surprise, and anger. These emotions are understood to be cross-culturally and universally communicated with facial expressions. We measure the likelihood of each emotion from 0 to 1. The higher the number, the more likely the emotion is present in an image.

Image Area

We use Microsoft Azure Vision API to measure the image area. The number of pixels in the dimension measures the area. It is calculated by multiplying the width and height of an image. Image width (height) is the number of pixels contained horizontally (vertically). Thus, we kept width, height, and area for further analysis.

Sharpness

We use the Python library to measure image sharpness. We use the average gradient magnitude to measure image sharpness. An image gradient is a directional change in the intensity or color in an image. It is easy to identify the edges in the image with high gradient magnitude, which makes people see the objects in the image clear. An image with a low average gradient magnitude is blurry. The larger the number, the sharper the image.

The descriptive statistics of visual characteristics are available in Table 3. Image X and Y in Figure 4 serve as an illustrative example to explain how we code the computer measures. The number of colors is coded as 1 because X and Y are colored images. For X, the dominant foreground color is pink (coded as 8), and the dominant background color is grey (coded as 9). For Y, both dominant foreground and background colors are green (coded as 4). The hue of X is 355, which is a color between pink and red. The hue of Y is 89, which is a yellow-green color. The saturation of X is 18% while that of Y is 63% showing that Y is more pigmented than X. For X, lightness and value are 54% and 59%. For Y, those are 42% and 58%, indicating both images are neither too dark nor too bright. For X, the text "SONY" and the brand logo SONY appeared in it, so image-text integration and brand logo are both coded as 1. A face is detected from Image X, so the emotion measures are present. The emotion is happiness with a .998 likelihood while other emotions are close to 0. Neither text or brand logo is detected from Y, so image-text integration and brand logo are coded as 0. Emotion measures are missing because no human faces are detected. The actual image area of X is 612 (width) x 612 (height) = 374,544 while that of Y is 640 x 640 = 409,600. The sharpness of Image X is 7.71 and that of Y is 11.81, indicating that Y is sharper than X.

Table 3. Descriptive Statistics of Visual Characteristic Measures

Visual Attribute	Visual Characteristic	Mean	Standard Deviation	Observations
Color	The Number of Colors	0.892	0.31	10,756
	Dominant Foreground Color	8.453	1.688	10,756
	Dominant Background Color	8.511	1.52	10,756
	Hue	119	67	10,756
	Saturation	0.315	0.199	10,756
	Lightness	0.438	0.171	10,756
	Value	0.508	0.18	10,756
Domain-Specific Object	Image-Text Integration	0.243	0.429	10,756
	Brand Logo	0.02	0.14	10,756
Face	Happiness Emotion	0.331	0.401	1,029
	Sadness Emotion	0.025	0.07	1,029
	Fear Emotion	0.004	0.024	1,029
	Disgust Emotion	0.004	0.016	1,029
	Surprise Emotion	0.028	0.096	1,029
	Anger Emotion	0.008	0.028	1,029
Size	Image Width	873	214	10,756
	Image Height	824	255	10,756
	Image Area	756,048	374,997	10,756
Sharpness	Sharpness	8.328	5.416	10,756

Note: The descriptive statistics of mean, standard deviation, and observations are provided for each visual characteristic.

Visual Attribute Extraction

The descriptive statistics of mean, standard deviation, and observations are provided for each visual characteristic of company images in Table 3. It shows that 1,029 of 10,756 images contain emotion measures because they depend on whether a face is detected in an image. Emotion missing is different from emotion not detected. A natural facial expression in an image may not allow the computer to detect happiness emotion. However, the computer is not able to detect emotion without a human face appearing in the image. Thus, a large number of images contained missing values on emotion measures. Therefore, we kept the missing values of the emotional visual characteristics to distinguish between emotion missing and emotion not detected. We separated the emotional visual characteristics from the rest of the visual characteristics that do not contain missing values.

Image X

Image Y

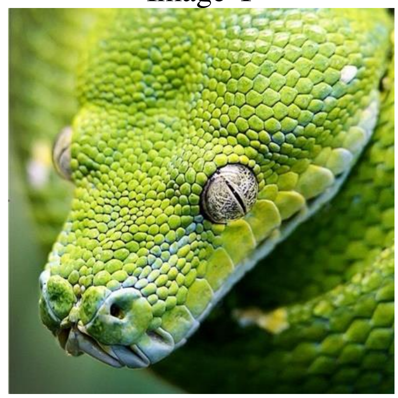

Figure 4. Computer Measure Examples
Note: Image X and Y serve as an illustrative example to explain how we code the computer measures

Next, we examined the 1,029 pictures containing emotions from faces. Except for happiness, the mean and standard deviation of other emotions are low, indicating other emotions are not present in this dataset. Therefore, we kept happiness for further analysis and dropped other emotional visual characteristics from the dataset. We named the dimension as human happiness for further analysis. We only measure happiness for two reasons. First, a human face is unlikely to show multiple facial expressions. In advertising and promotion context, human happiness is the most likely emotion to attract attention, advertising effectiveness, increase purchase intent, etc. (Lewinski, Fransen, and Tan 2014; Teixeira, Picard, and el Kaliouby 2014; Teixeira, Wedel, and Pieters 2012)

We conducted an EFA to extract other visual attributes without happiness measures. This treatment maximizes the usage of data without excluding observations with missing values. Panel A of Table 4 shows that EFA analysis extracted five factors (saturation and sharpness were dropped due to low loading or cross loading). Factor 1 contains three visual characteristics: image area, image height, and image width representing the size of an image. Therefore, we name this factor as size. Lightness and value consist of factor 2. There are two different ways to measure the darkness or lightness of an image in the literature. Therefore, we name the factor as image brightness, which refers to the perception elicited by the luminance of a visual target. Factor 3 includes dominant foreground color and dominant background color. In general, warm and cool colors are more saturated and perceived as more vivid than neutral colors. Thus, we call this factor color vividness, which refers to the degree to which a color in the image is bold, strong, and distinct. Factor 4 includes color hue and the number of colors. This dimension describes the colorfulness of an image because color images contain more hues while the value of the hue is 0 for black and white images. Thus, we call factor 4 colorfulness, which refers to the degree to which an image is perceived to contain more colors. Factor 5 consists of two domain-specific objects: brand logo and image-text integration. 216 images contain brand logos, 179 of which are integrated with text showing that image-text integration serves as an approach to spread the brand name out. Therefore, we name factor 5 as brand focus, which refers to any marketing communication used to inform target audiences of the information of a brand. In summary, we derived six visual attributes**:** human happiness, size, brightness, vividness, colorfulness, and brand focus.

We validate the visual attributes in multiple ways to ascertain the validity of the dimensions of visual attributes. Specifically, we use the following methods to validate the dimensions of visual attributes by conducting (1) face validity check with experts, (2) convergent validity check by comparing across measures generated by computer agents and human coders, and (3) external validity check using customer images from Instagram. Please refer to Appendix

B for detailed results.

Table 4. EFA Results of Visual Attributes

A. Dimensions of Company Image Postings						
Visual Characteristic	Factor1	Factor 2	Factor 3	Factor 4	Factor 5	Variance Explained
The Number of Colors				0.854		11.43%
Hue				0.829		
Dominant Foreground Color			0.845			14.46%
Dominant Background Color			0.841			
Lightness		0.992				17.68%
Value		0.981				
Image-Text Integration					0.742	10.45%
Brand Logo					0.802	
Image Width	0.882					25.02%
Image Height	0.942					
Image Area	0.997					
B. Dimensions of Consumer Image Postings						
Visual Characteristic	Factor1	Factor 2	Factor 3	Factor 4	Factor 5	Variance Explained
The Number of Colors				0.851		11.52%
Hue				0.862		
Dominant Foreground Color			0.865			14.84%
Dominant Background Color			0.854			
Lightness		0.991				17.77%
Value		0.985				
Image-Text Integration					0.773	9.98%
Brand Logo					0.760	
Image Width	0.884					25.06%
Image Height	0.937					
Image Area	0.995					

Note: Variance explained of company image postings: 79.04%. Variance explained of consumer image postings: 79.17%.

Measures of VBBP and VBBP_R

VBBP Measures

The six visual attributes (i.e., human happiness, size, brightness, vividness, colorfulness, and brand focus) represent the measures of VBBP because a company and its consumers can use them to create brand stories. Companies can utilize a set of measures to construct perused brand perception, and consumers respond to the images to form brand perception based on the measures. Table 5 summarizes how these measures represent the company and consumer VBBP.

Table 5. Measures of VBBP and VBBP_R

Visual Attribute	VBBP	VBBP_R
Human Happiness	Calm, Peaceful vs. Sentimental, Warmhearted, or Affectionate	No Emotion vs. Happy
Size	Cell Phone Friendly vs. Quality Caring	Small vs. Large
Brightness	Masculinity vs. Femininity	Dark vs. Light
Vividness	Competent vs. Excitement	Dull vs. Vivid
Colorfulness	Gentle vs. Colorful	Colorless vs. Colorful
Brand Focus	Quiet vs. Loud	No Brand-Related Information vs. With Brand-Related Information

Note: Table 5 explains how the six visual attributes represent the measures of VBBP and VBBP_R.

The brightness of an image influences perceived brand masculinity/femininity: darker colors enhance perceived brand masculinity and lighter colors enhance perceived brand femininity (Lieven et al. 2015). From the gender dimension of brand personality perspective (Grohmann 2009), a company and its consumers can take advantage of image brightness to shape the brand as masculinity or femininity.

Images with or without human happiness would construct different brand perceptions. Emotion contagion phenomenon shows that a happy-faced image will elicit or enhance happy feelings, and a sad-faced image will elicit or enhance sad feelings (Small and Verrochi 2009).

Images that display a happy face bring warmth to a brand. A brand with smiling faces in images to make consumers feel sentimental, warmhearted, or affectionate, and a brand with neutral human faces in images to make consumers feel calm and peaceful (Keller 2009).

The size of the image signals perceived cost and quality of a social media image (Kirmani 1990). Companies use a large image to signal the high-quality feature of a brand. However, Small images load faster on browsers and cell phones, which signals the fast loading feature of a company account. Therefore, companies can utilize small or large size images to manage different features of their brands.

The vividness and colorfulness of an image reflect different brand personalities. The big five brand personalities are sincerity, excitement, competence, sophisticated, and ruggedness (Aaker 1997). A brand with vivid images is perceived as excited. Red is an example because the colors in vivid images are perceived as bold, distinct, and strong. On the other hand, a brand with less vivid images is perceived as competent (Labrecque and Milne 2012).

Another brand personality categorization is: youthful, colorful, and gentle (Plummer 2000). A brand is perceived as colorful by using colorful images, and gentle by using colorless images (Keller 1993).

Brand-focused images signal whether a brand is loud or quiet. Wealthy consumers in need for status use loud luxury goods to signal to the less affluent that they are not one of them, however, those who are high in need for status but cannot afford true luxury use loud counterfeits to emulate those they recognize to be wealthy. (Han, Nunes, and Drèze 2010). Thus, companies can communicate loud or quiet brand-image leveraging visuals attribute to brand focus.

In summary, the six visual attributes serve as a set of VBBP measures that determines company strategies. Companies choose an assortment of measures to communicate their pursued brand perception to consumers.

VBBP_R Measures

MRT suggests that the information richness differs in different mediums. We argue that within the same communication medium (e.g., visual messages), we can also evaluate information richness, the amount of information contains in an image. VBBP_R is a concept that one image could be richer than another. VBBP_R measures the amount of visual information contains in a brand on social media. A distinction should be made with VBBP vs. VBBP_R. VBBP is simply an assortment of categories since we do not rank VBBP. A company and its consumers perceive the brand in a variety of categories. A brand with rich VBBP_R does not always outperform a brand with lean VBBP_R.

According to social presence theory, images with high human happiness (smiling faces) implies a psychological connection with the user who perceives the website as warm, personal, and sociable, thus creates a feeling of human contact (Yoo and Alavi 2001). The inter-personal connection makes the mediums closer to face-to-face communication. Thus, the images with high human happiness contain richer information for a brand.

Image size, brightness, vividness, and colorfulness signal the amount of information contained in a visual message. Large, bright, vivid, or colorful images are considered to contain richer information as including more information cues and reduce information uncertainty (Mudambi and Schuff 2010).

Brand-focused images contain more brand-related images such as brand logos or text descriptions about a brand. Thus, they are considered richer information.

In summary, the six visual attributes also represent the VBBP_R that happy human, large, bright, vivid, colorful and brand-focused images are considered as richer visual messages.

AN EMPIRICAL STUDY

Data and Sources

We test our hypotheses by combining three data sources (i.e., Instagram, ad$pender, and Orbis) from 2011 to 2018. During this period, the digital camera brands utilized VBBP measures on Instagram through official company accounts and consumer hashtags to promote brands. The company and consumer VBBP measures are from the same social media platform. The same social media platform effectively excludes the confounding effects if measures of the company and consumer VBBPs come from multiple platforms. Our findings are particularly relevant for companies adopting marketing communication strategy to manage their VBBP. We describe the data used to represent each construct. All the measures change over time, and we use monthly data in the following sections for each measure. Table 6 summarizes notations, measures, and descriptive statistics of each construct. There are missing observations for some measures because we merged data from multiple sources. Not all data are available for each month.

Company and Consumer VBBP_R

The six visual attributes are not only a set of VBBP measures but also represent VBBP_R for both the company and its consumers. Therefore, we measure a company’s VBBP_R by averaging the values of all visual attributes of each brand using images generated from the company-official accounts on Instagram. Similarly, we measure the consumer VBBP_R by averaging the values of all visual attributes from each brand using images generated from consumer hashtag postings on Instagram.

Table 6. Construct Measures and Descriptive Statistic

Construct	Notation	Measure	Source	Mean	SD	Observation
Company VBBP_R	ComVBBP_R	The average value of the six company VBBP measures	Instagram	-.05	.29	385
Consumer VBBP_R	ConVBBP_R	The average value of the six consumer VBBP measures	Instagram	-.01	.24	278
VBBP_G	VBBP_G	The additive value of the absolute difference between each measure of company and consumer VBBP	Instagram	3.24	1.43	278
Advertising	AD	Advertising spending/advertising units of a brand	Ad$pender	919	5182	175
Company CF	ComCF	The number of image posts generated by a company's official account of a brand	Instagram	27.94	18.98	385
Consumer CF	ConCF	The number of image posts generated by consumers' hashtags of a brand	Instagram	22.36	27.21	278
News Volume	NV	The number of media news coverage of a brand	Orbis	21.36	106.92	385
Time	t	Month	Instagram	52	19	385

Note: The construct notation, measures, data source, and the descriptive statistics of mean, standard deviation, and observations are provided for each visual characteristic. All the measures are monthly data. There are missing observations for some measures because we merged data from multiple sources. Not all data are available for each month.

VBBP_G

We further demonstrate the VBBP discrepancy between a company and its consumers using a snake chart in Figure 5. We compared the VBBP of a company and its consumers on the six visual attributes. We standardized the values of human happiness to construct the first visual attribute. We obtained the factor scores of the other five visual attribute extracted from the exploratory factor analysis. We summarized the aggregated value of each visual attribute of a brand for the company and its consumers separately. The solid lines (Figure 5) represent the company VBBP; the dashed lines represent the consumer VBBP.

Figure 5 illustrates that VBBP_G exists in two ways. First, the discrepancy is pronounced for most visual attributes. For example, the discrepancy is most pronounced for Sony. The company and consumer VBBP almost do not line up. This may be because Sony has multiple product lines and is not specialized at digital cameras, while other brands concentrate more on their digital camera lines. Both Samsung and Sony have a broad product line, but VBBP_G is much larger for Sony. A possible explanation could be that Sony has a longer history. Thus it is a more well-established brand, so the company and consumer VBBP may have been well formed. Samsung is newer, so the VBBP is more likely to change when expanding to a different product line. Second, the discrepancy lies in certain attributes. The VBBP_G of Fujifilm is mainly on brightness while that of Kodak is mainly on human happiness. The VBBPs of Canon and Nikon are matched well. Therefore, we conclude that the company VBBP does not always adhere to the consumer VBBP.

In this study, we measure the VBBP_G by calculating the additive value of the absolute difference between the company and consumer VBBPs of each visual attribute. In other words, we pooled the six VBBP measures of each brand to construct VBBP_G.

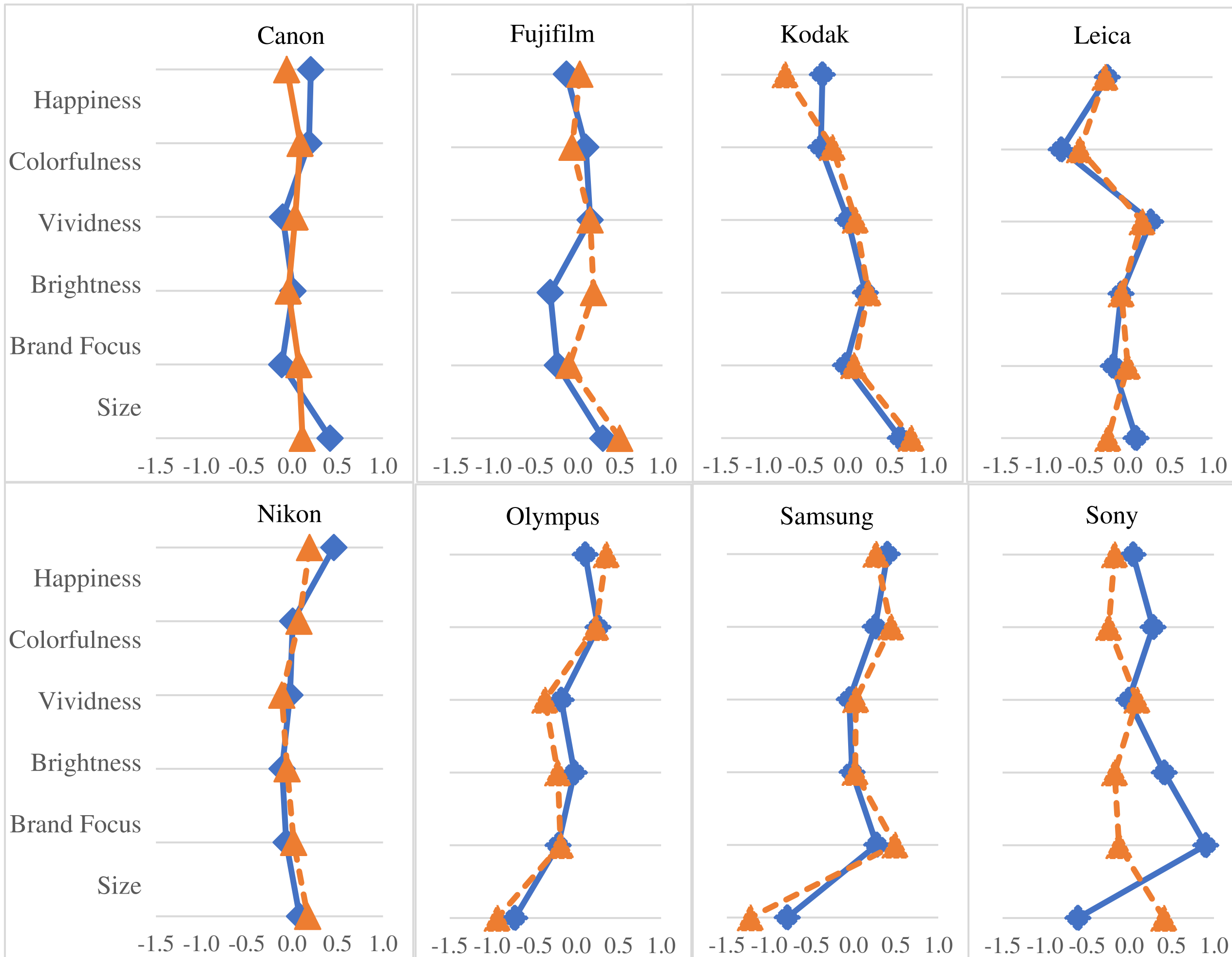

Figure 5. The Discrepancy Between Company and Consumer VBBP
Note: the solid lines represent the company VBBP of each visual attribute, and the dashed lines represent the consumer VBBP of each visual attribute.

Advertising (AD)

We assess advertising spending by using total spending per ad for a brand. Using the ad$pender (Kantar Media) database, we captured advertising expense and advertising units across all media. We constructed advertising spending using the advertising expense divided by the advertising units. Thus, advertising spending per ad = advertising expense/advertising units.

Company CF (ComCF) and Consumer CF (ConCF)

We use image-posting frequency from company accounts and consumer hashtags to measure ComCF and ConCF. We obtain company and customer CFs by counting the number of images posted from the company or consumer of each brand.

News Volume (NV)

Using Orbis database, we capture news articles mentioning any of the eight brands during our study period. The database covers a comprehensive of six news sources: Dow Jones, Thomson Reuters, Bureau van Dijk, Economist Intelligence Unit, Syndicate, Acquire Media. Our analysis covers all six news sources. We classified 8,223 articles in line with the eight digital camera brands.

Time (t)

Since the VBBP co-creational process is dynamic, we used monthly data of all measures to capture the dynamic effects during the co-creational process.

Hypothesis Testing

We use a system of equations to capture the dynamic and interactive process of ComVBBP_R and ConVBBP_R as depicted on the left side of our conceptual model in Figure 2. The conceptual model describes that the current ComVBBP_R and ConVBBP_R are influenced by the ComVBBP_R and ConVBBP_R of the last time period. We control for marketing communication strategies (i.e., AD, ComCF, ConCF, and NV) that will influence VBBP_G on the right side of Figure 2. Thus, the model is specified as below:

$$\mathrm{ComVBBP\_R}_{i,t} = a_0 + a_1\mathrm{ComVBBP\_R}_{i,t-1} + a_2\mathrm{ConVBBP\_R}_{i,t-1} + a_3\mathrm{AD}_{i,t-1} + a_4\mathrm{ComCF}_{i,t-1} + a_5\mathrm{ConCF}_{i,t-1} + a_6\mathrm{NV}_{i,t-1} + \varepsilon_{i,t-1} \quad (1a)$$

$$\mathrm{ConVBBP\_R}_{i,t} = b_0 + b_1\mathrm{ComVBBP\_R}_{i,t-1} + b_2\mathrm{ConVBBP\_R}_{i,t-1} + b_3\mathrm{AD}_{i,t-1} + b_4\mathrm{ComCF}_{i,t-1} + b_5\mathrm{ConCF}_{i,t-1} + b_6\mathrm{NV}_{i,t-1} + \xi_{i,t-1} \quad (1b)$$

Where i is a digital camera brand, t is the month. We used marketing communication strategies as control variables in the model. Table 6 lists the notations and measurements of all the variables we used in Model 1a and 1b.

We use monthly data for all measures, so this is a longitudinal dataset. The data exhibit a panel data structure. Our data have two characteristics. First, the dependent variables ComVBBP_R and ConVBBP_R influenced themselves by the last time period due to the dynamic process of VBBP co-creation. It is likely that the two error terms of VBBP_R are serially correlated. Second, ComVBBP_R and ConVBBP_R are likely to be correlated with each other due to the interactivity between a company and its consumers during the co-creational process. These data characteristics cause the endogeneity issue that the ComVBBP_R and ConVBBP_R on the right-hand side of the equation are correlated with the error terms in both equations. Thus, to test hypotheses 1 and 2, we estimate our Model 1a and 1b by using a panel vector autoregression (PVAR) estimation (Wooldridge 2010). It enable us to treat the company and consumer VBBP_R as endogenous and control for marketing communication strategy variables.

We standardized each variable to ensure each variable has a normal distribution. However, there are missing data for some variables (Table 6) because the dataset was merge from multiple data sources and not all data are available for all the time period in this study. For example, some consumer images are not available in a certain time period due to low posting frequency. The variables are missing at random because the missing data points are random, and we can use other variables to infer the distribution of missing values. The variables contain large missing values at 20% to 50% of a variable. Therefore, we used multiple imputation method to impute missing data to compensate for the large missing values, and the nature of MAR would ensure the data is correctly imputed. Second, we include one lag on the right-hand side of the equations, since we are mainly interested in how the company and consumer VBBP_R at time t-1 can influence themselves at time t. Third, we analyzed data using the PVAR package in STATA following Abrigo and Love (2016)'s approach.

On the right side of Figure 2, the conceptual model describes that VBBP_G is influenced by a set of marketing communication strategies. We control for the feedback loop that the last time period's VBBP_G could influence current time period's VBBP_G. We use equation (2) to test hypothesis 3. Thus, the model is specified as below:

$$\mathrm{VBBP\_G}_{i,t} = C_0 + C_1\mathrm{VBBP\_G}_{i,t-1} + C_2\mathrm{AD}_{i,t-1} + C_3\mathrm{ComCF}_{i,t-1} + C_4\mathrm{ConCF}_{i,t-1} + C_5\mathrm{NV}_{i,t-1} + \varsigma_{i,t-1} \qquad (2)$$

Where i is a digital camera brand, t is the month. We use VBBP_G at time t-1 to control the feedback effect of the VBBP_G. Table 6 lists the notations and measurements of all variables we use in Model 2.

Similar to Model 1a and 1b, our data exhibit a panel data structure for digital camera brands. The VBBP_G at time t-1 is likely to have a carryover effect on the VBBP_G at time period t. To control for the carryover effect, we use a panel data model to compensate for the serial correlation of VBBP_G to test hypothesis 3 (Wooldridge 2010). We test the effects of communication strategy variables on VBBP_G while controlling for the autocorrelation of the VBBP_G. There are missing values on VBBP_G. Following the same logic, we used in Model 1a and Model 1b, we use the imputed data to conduct hypothesis testing.

Data Analysis and Results

Table 7 shows the results of Model (1a) and (1b). On top of the panel of Table 7, ComVBBP_R is the dependent variable of Model 1a, and ConVBBP_R is the dependent variable of Model 1b. The right-hand size of Model 1a and 1b are symmetric. The focal variables of interests are ComVBBP_R and ConVBBP_R at time t -1. AD, ComCF, ConCF, and NV are control variables and not significant. Therefore, the marketing communication strategies used to manage VBBP_G do not affect VBBP_R. In Model 1a, both ComVBBP_R and ConVBBP_R at time t-1 have a positive effect on ComVBBP_R at time t. Thus, ComVBBP_R becomes richer during the dynamic process and is influenced by both the company itself and the consumers. H1a and H1b are supported. In Model 1b, the effect of ComVBBP_R at time t-1 on ConVBBP_R at time t marginally increases, and the effect of ConVBBP_R at time t-1 on ConVBBP_R at time t marginally increases. H2a is marginally supported, and H2b is supported.

Table 7. The Feedback Effect of ComVBBP_R and ConVBBP_R

	Model 1a				**Model 1b**		
	Coef.	Std. Err.	P-value		Coef.	Std. Err.	P-value
ComVBBP_R	0.199	0.076	0.016		0.150	0.073	0.060
ConVBBP_R	0.153	0.069	0.028		0.280	0.076	0.000
AD	-0.111	0.101	0.323		0.049	0.071	0.502
ComCF	0.222	0.143	0.122		0.138	0.147	0.345
ConCF	0.064	0.090	0.496		-0.047	0.110	0.681
NV	0.071	0.272	0.796		0.360	0.266	0.176

Note: Each column represents the estimates of the equation (1a) and (1b). Coefficient, robust standard error and p-value are reported accordingly.

The results indicate that the VBBP is indeed a co-creational process. First, ComVBBP_R and ConVBBP_R are dynamic and keeps evolving during the process. Second, the process is dyadic that a company and its consumers influence each other. The effect of the last time period's VBBP_Rs carry over and spill over on the current time period's VBBP_Rs. Both ComVBBP_R and ConVBBP_R increase during the VBBP co-creational process. A company is more likely to be influenced by both itself and consumers. The effect size of ComVBBP_R at time t-1 is large than that of ConVBBP_R (coefficient .199 is larger than .153). For ConVBBP_R, the effect size of ConVBBP_R at time t-1 is large than that of ComVBBP_R (coefficient .280 is larger than .150). During the co-creational process, although both ComVBBP_R and ConVBBP_R increase, the carryover effects are larger than the spillover effects.

Table 8 shows the results of Model 2. Model 2 tests how a set of marketing communication strategies influence VBBP_G over time while controlling for the carryover effect of VBBP_G at time t-1. We found strong support for hypotheses H3b, H3c, H3d. This indicates that by controlling the autocorrelational effect of VBBP_G, ComCF and ConCF have negative effects on VBBP_G, and NV has a positive effect on VBBP_G. Increasing ComCF and ConCF on social media can mitigate the VBBP_G. Increasing news volume on media can enlarge VBBP_G. However, AD does not have an effect on VBBP_G over time.

We successfully identify three marketing communication strategies to help the company to manage VBBP_G. The visual communication strategy has a positive effect on VBBP_G while the non-visual communication strategy has a negative effect on VBBP_G. Depending on whether companies intend to explore new markets or gain new consumers, they can adopt the marketing communication strategies appropriately. If a company intends to explore a new market, the company can reduce communication frequency on social media or create more news volume on other media to enlarge VBBP_G. If a company aims to maintain an existing customer base, the company can increase visual communication frequency or control and reduce news volume on other media. Unfortunately, advertising does not have an effect on VBBP_G.

Table 8. The Effect of Marketing Communication Strategies on VBBP_G

	Coef.	Std. Err.	t	P-value	95% Conf. Interval	
Intercept	-0.009	0.084	-0.110	0.914	-0.181	0.163
VBBP_G	0.158	0.053	2.960	0.003	0.053	0.262
AD	-0.189	0.092	-2.050	0.111	-0.447	0.068
ComCF	-0.103	0.045	-2.300	0.027	-0.193	-0.013
ConCF	-0.256	0.051	-5.010	0.000	-0.356	-0.156
NV	0.040	0.020	2.030	0.044	0.001	0.079

Note: the dependent variable is VBBP_G. Coefficient, robust standard error, t stats, p-value, and 95% confidence interval are reported accordingly.

CONCLUSION

Contributions and Implications

With the rapid growth of visual messages from OSM and ESM, images are useful for a company and its consumers to co-create brand perception on social media. To our best knowledge, this is the first study to examine VBBP co-creational process on social media. We made three contributions to the extant literature.

First, in the context of social media, companies have lost their pivotal roles as creators of brand stories. We conceptualize VBBP as a co-creational process. Relative to current research on brand perception, the co-creation of VBBP is dyadic and dynamic. We develop a set of visual attributes to measure VBBP on social media empirically. We utilized machine learning-based image mining to quantify visual content on social media where visual data from both a company and its consumers are readily available and in sheer volume. We found six visual attributes that represent VBBP on social media: human happiness, size, brightness, vividness, colorfulness, and brand focus. Although text-mining approaches have gained popularity in leveraging user-generated content for brand perception, image-mining approaches are still relatively new. This paper bridges the image-processing literature with the branding literature by proposing an approach for companies to monitor its VBBP through visual content from OSM and ESM.

Second, the interactivity between a company and its consumers are important to understand the VBBP co-creational process. We use MRT and SIP theories to explain the co-creational process of VBBP, especially to explain how the information richness changes over time. We demonstrated that both the company and consumer VBBP_R increase over time, and that the brand meaning becomes increasingly rich. Our results indicate that the company and consumer's VBBP_R positively influences themselves (dynamic communication) and each other (dyadic communication) over time. However, dynamic communication is stronger than dyadic communication. Thus, we suggest that companies may rely more on ESM instead of OSM to enrich their VBBP. In addition, the company should also find effective approaches to influence the consumer VBBP because consumers are more likely to form VBBP by using the messages within the community.

Third, we found the VBBP_G, a discrepancy between the company VBBP and consumer VBBP. The company and consumer VBBP are not always consistent. The discrepancy can either be on all visual attributes of VBBP or a certain visual attribute of brand perception. We adopted a set of marketing communication strategies to address how companies should manage the discrepancy of their VBBP on social media. We find that a visual communication strategy (i.e., company and consumer visual content posting frequency on social media) has a negative effect on VBBP_G, while non-visual communication strategy (i.e., new volume) has a positive effect on VBBP_G. Depending on whether companies need to mitigate or enlarge their VBBP_G, they can choose the appropriate marketing communication strategies. If a company intends to explore a new market, the company should enlarge its VBBP_G. Consumers will be aware that the brand stories change from the past. If a company aims to maintain an existing customer base, the company should mitigate the VBBP_G.

Limitations and Future Research

Despite its merits, this study leaves us with many unanswered questions. First, when mining for VBBP measures, we excluded some visual characteristics that require customized machine learning coding. The machine learning-based image processing methods presented in this paper provide a first step in analyzing rich image data. A meaningful future research direction could include more visual characteristics by using customized machine learning algorithms to investigate whether more visual attributes would represent VBBP.

Second, we focus on how visual marketing communication influences brand perception on social media. Future research can extend the application to analyze how visual marketing communication influences marketing outcomes. For example, we could analyze company sales to better understand the marketing communication effectiveness of visual cues.

Third, we examine the dynamic process of VBBP. However, the missing data limit us to examine the robustness of Model 1a, 1b, and 2 fully. We used multiple imputation to impute the missing data to estimate the PVAR model used in Model 1a and 1b, and panel model in Model 2. We are able to estimate the models, but we are not able to perform robustness checks such as root test, reverse impulse function, etc., on these models. Future research may adopt a Bayesian approach to compensate for the robustness issues of the linear models used in this study.

Fourth, we identified a set of marketing communication strategies to manage VBBP_G. Unfortunately, the advertising spending per ad, which represents the overall communication strategy, does not have an impact on VBBP_G. A possible explanation would be that social media ad spending differs from the overall advertising spending. In the future, we can focus on whether social media ad spending would influence VBBP_G as this has a more direct impact than the overall ad spending.

Last, video messages have become increasingly popular on social media. Video is a richer communication medium than visual. Video contains text, visual, and audio information in one self-contained medium, and it offers the richest form of information. Further research could explore video-based brand perception.

ESSAY 2. THE JOINT EFFECTS OF IMAGE AND TEXT ON CROWDFUNDING SUCCESS

INTRODUCTION

Crowdfunding and Kickstarter

The sharing economy is an economic model defined as a peer-to-peer based activity of acquiring, providing, or sharing access to goods and services that are facilitated by a community-based online platform. The sharing economy has significant traction among internet users. Crowdfunding is an emerging form of sharing economy. The U.S. millennial internet users who have used a sharing economy service have increased from 51% to 76% from 2015 to 2017 (eMarketer 2015, 2017); 5% of them have solicited crowdsourced funding from others in 2017 (eMarketer 2017). One of the most successful crowdfunding platforms is Kickstarter. Kickstarter is a project-based fundraising site for entrepreneurs and inventors to launch a product or start a creative endeavor. The platform focuses on offering backers rewards (i.e., finished product or service) to give the potential backers an incentive to support projects. Since its launch on April 28, 2009, 16 million people have backed a project, $4.1 billion has been pledged, and 157,791 projects have been successfully funded (Kickstarter 2019a).

Funding on Kickstarter follows an all-or-nothing model that no backers will be charged for a pledge towards a project unless the project reaches its funding goal in a certain time period (Kickstarter 2019b). The all-or-nothing funding model is a core part of Kickstarter, and has three advantages (Kickstarter 2019b). First, it offers fewer risks for everyone. If a project does not reach its funding goal, creators will not be expected to complete their project without the funds, and backers will not be charged. Second, adding a sense of urgency by adding project deadlines motivates the community to spread the word and rally behind a project. Third, the all-or-nothing model works because the projects either realize and surpass their goals, or they never fully take off. Funding success is important for creators and backers. Once the project achieves its funding goal, creators can complete and deliver products and services to backers.

Marketing Communication on Kickstarter

Online marketing communication on Kickstarter is unique in three ways. First, Kickstarter is a multimedia communication platform that allows creators to combine image, text, and video messages to tell compelling stories to potential backers. The platform suggests that besides text, image and video are helpful to bring potential backers inside the story (Kickstarter 2019c). Textual messages have been widely studied in the context of user-generated content including online reviews, Facebook postings, and Tweets (Dellarocas 2006; Goh, Heng, and Lin 2013; Liu, Singh, and Srinivasan 2016; Tirunillai and Tellis 2014). Visual messages have been widely studied in print and online advertising as well as emerging machine learning-based, image mining literature (Appendix A provides a summary of visual characteristics that are impactful in the marketing literature). It is important for creators to understand how to communicate through different media on the same platform effectively. By understanding this issue, it helps creators to choose the appropriate media to maximize communication effectiveness and ultimately achieve the funding goal. In this study, we focus on visual and textual communication. We also consider the mere presence effect of video communication that creators use videos to communicate with potential backers in projects.

Second, the study focuses on how visual and textual communication influence funding success both individually and jointly. Current studies focus on how visual and textual communication influence marketing constructs individually. For example, the impact of presenting full-color, black-and-white, and color-highlighted ad photo influences the persuasiveness of an ad (Meyers-Levy and Peracchio 1995). This study examines the individual effect of visual communication. In the context of online product reviews, affective content and linguistic style of online reviews can influence conversion rates (Ludwig et al. 2013). This study examines the individual effect of textual communication. To our best knowledge, little attention has been paid to study the joint effect of visual and textual communication. How should creators integrate visual and textual messaging to maximize communication effectiveness? Would the same messages communicated through both visual and textual media increase communication effectiveness? In this study, we examine both individual and joint effects of visual and textual communication on the duration of project success. It helps creators understand how media interact with each other and how to utilize multiple media effectively.

Third, Kickstarter provides an opportunity to examine how visual and textual communication directly influences a marketing outcome: the duration of funding success. A successful project requires backers to pledge enough money to exceed the funding goal in a certain time period. Thus, the duration of success is essential to barkers. The faster a project achieves its funding goal, the sooner a creator can start to complete and deliver their products and services. Although current studies demonstrate that visual and textual communication is impactful on several marketing constructs, the dependent variables are mainly based on perception (Maeng and Aggarwal 2018; Nam, Joshi, and Kannan 2017), attention (Howell, Breivik, and Wilcox 2007; Teixeira, Wedel, and Pieters 2012), memory (Hagtvedt and Brasel 2016; Unnava and Burnkrant 1991), attitude (Robson et al. 2013; van Rompay, de Vries, and van Venrooij 2010), choice (Mandel and Johnson 2002; Laura A. Peracchio and Meyers-Levy 2005), and decision (Sevilla and Townsend 2016; Yin, Bond, and Zhang 2014). The platform allows us to investigate how visual and textual communication influences a marketing outcome, the duration of funding success.

Research Questions and Contributions

We propose two research questions to study the unique marketing communication and the all-or-nothing funding model on Kickstarter. First, how does visual and textual marketing communication influence the duration of funding success individually? Second, how does visual and textual communication influence the duration of funding success jointly? By answering these research questions, we make two contributions to the current literature.

First, we contributed to the literature by understanding how creators should allocate messages on visual vs. textual communication media on Kickstarter. The information richness of visual and textual messages influences the duration of funding success differently. In this context, information richness refers to the amount of information contained in a communication medium. We empirically tested and support that visual and textual information richness affect the duration of funding success oppositely. Visual information richness shortens the duration, while textual communication prolongs the duration. The mere presence of video also shortens the duration. Therefore, creators should manage each medium differently. Creators should prioritize visual and video communication on Kickstarter to provide rich information and condenses messages on the textual medium.

Second, we contributed to the marketing communication literature by studying how to integrate multiple communication media on the same platform. The synergy effect refers to the relative amount of overlapping information between visual and textual media. For example, the overlapping information could be positive emotion expressed from both image and text. In this case, the visual and textual medium provides synergistic information on the dimension of emotion. The non-overlapping information could be a positive emotion expressed from images and an in-depth textual description. In this case, the visual and textual medium does not provide synergistic information. When the visual and textual communication media are synergistic, the project overall provides consistent information to potential backers. The visual and textual communication reinforce each other and shortens the funding duration. This provides insights to creators on managing the multimedia communication of visual and textual media. Therefore, creators should integrate visual and textual channel in a harmonic way to maximize communication effectiveness.

The rest of the study is organized as follows. First, we develop a conceptual model to describe the characteristics that influence the duration of funding success. Second, we introduce data and measures. Third, we specify the model, introduce estimation method, and report the results. Finally, we conclude this study with contributions, implications, limitations, and further research.

CONCEPTUAL FRAMEWORK

Lending Crowdfunding

Crowdfunding has become a popular form of sharing economy that attracts both funding seekers and backers to participate. There are three major crowdfunding types: donation crowdfunding, lending crowdfunding, and equity crowdfunding (Paschen 2017). In a donation crowdfunding model, the founder receives money from a crowd without any tangible return for that contribution (e.g., Indiegogo). Lending crowdfunding, often referred to as peer-to-business (P2B) or peer-to-peer (P2P) crowdfunding, raises money with the expectation that founders will repay supporters (e.g., Kickstarter). Equity crowdfunding, also referred to as investment crowdfunding, the venture raises money from a crowd in exchange for an ownership stake in the firm (e.g., AngelList).

Kickstarter is an example of lending crowdfunding. The creator (i.e., funder) offers finished products and services in return for a backer's pledge. Current literature on Kickstarter focuses on a variety of topics such as the determinants of funding success (Parhankangas and Renko 2017; Yuan, Lau, and Xu 2016), social impacts on crowdfunding (Kuppuswamy and Bayus 2017; Wessel, Thies, and Benlian 2016), and fraudulent behaviors (Siering, Koch, and Deokar 2016). Rather than investigating on how communication influences funding success (e.g., Parhankangas and Renko 2017), we focus on the duration of funding success as an outcome. Once the project achieves its funding goal, creators can deliver finished products and services to its backers. Current studies investigate how textual communication, such as linguistic style, influences crowdfunding outcomes (Parhankangas and Renko 2017). We extend the current literature to examine not only the individual effect of visual and textual communication but also the joint effect of visual and textual communication. Creators can better manage communication mediums by understanding the interactivity between visual and textual communication media.

Conceptual Model

We propose our conceptual model in Figure 6 for this study. Due to the nature of lending crowdfunding that backers expect rewards in return to pledge projects, we investigate the factors that influence the duration of funding success. The duration of funding success is critical in this study because the quicker a project reaches its funding goal, the sooner backers receive the final products and services as rewards. We propose that there are three types of factors that influence the duration of funding success: 1) marketing communication, 2) funding process characteristics, and 3) intrinsic project uniqueness.

First, how creators communicate to backers influences the duration of funding success. Creators should choose appropriate media and integrate them when communicating with target backers. Second, the funding process characteristics, such as the funding percentage and the number of backers, signal the attractiveness of projects. Third, the intrinsic project uniqueness also influences the duration of funding success. For example, a music album may have a different funding story relative to a high-end coffee maker. We discuss each factor in the following section.

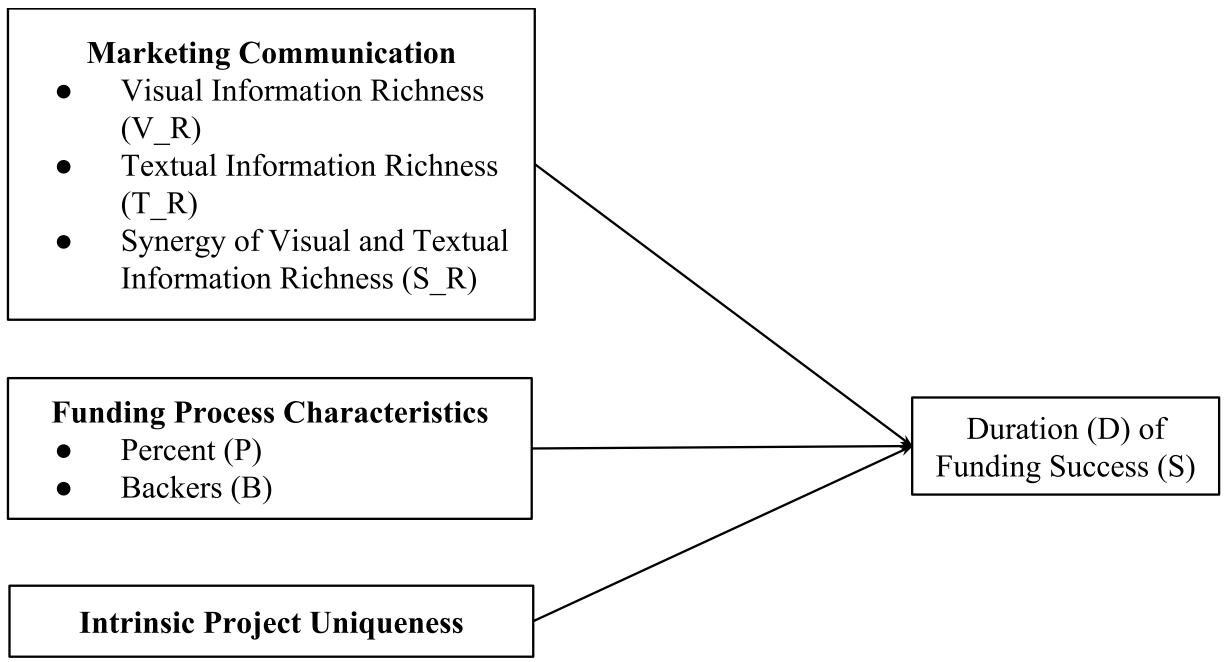

Figure 6. The Determinants of the Duration of Funding Success
Note: We propose that there are three types of factors that influence the duration of funding success: 1) marketing communication, 2) funding process characteristics, and 3) intrinsic project uniqueness.

Marketing Communication

This study focuses on visual and textual marketing communication on the platform Kickstarter. We study three types of communication: visual, textual, and joint communication via visual and textual media. We integrate MRT, cognitive load, and integrate marketing communication theories to conceptualize how marketing communication influences the duration of funding success.

Visual and Textual Communication

We adopt MRT to illustrate when visual and textual communication media are proper for communication. MRT is a framework to describe a communication medium's ability to reproduce the information sent to it. Under the MRT framework, Daft and Lengel (1986) first propose ranking and evaluating certain communication medium within an organization. When facing different levels of equivocality and uncertainty, Daft and Lengel (1986) suggest using proper communication media such as face-to-face, phone calls, and emails. Low equivocality and low uncertainty represent a clear, well-defined situation, resulting in using a leaner media. High equivocality and high uncertainty indicate ambiguous events that need clarification by managers, resulting in using a richer medium. Thus, richer media are more effective for communicating with equivocal and uncertain issues than leaner medium. The MRT has been adapted to new media communication such as video and online conferencing (Dennis and Kinney 1998).

The communication on Kickstarter between creators and backers is unambiguous and difficult. First, the project idea could be ambiguous and hard to articulate. Second, Kickstarter may be the only communication channel to reach potential backers because the proposed products or services are not afflicted with any brands. Third, creators do not have to chance to interact with directly backers. Fourth, backers are serious and cautious when pledging toward a project because they expect to receive the rewards. They hope the communication is clear to receive the intended product. In such an ambiguous situation, creators need a richer medium to communicate to backers. The visual medium is considered richer than textual medium because text cannot reproduce visual cues such as the specific shape, color, lighting, etc. Thus, visual communication is more effective than textual communication.

Information Richness of Visual, Textual, and Synergistic Communication

In this study, we focus on not only the choice of the medium but also the information richness of each medium. Information richness refers to the amount of information contained in a communication medium. Visual information richness (V_R) refers to the amount of visual information contained in a crowdfunding project. Textual information richness (T_R) refers to the amount of textual information contains in a crowdfunding project. We define the synergy of visual and textual information richness (S_R) as the relative overlapping information amount across visual and textual media in a crowdfunding project. The overlapping information, for example, could be positive emotion expressed from both image and text. The non-overlapping information, for example, could be a positive emotion expressed from images and an in-depth textual description. S_R is independent of V_R and T_R. For example, Project A may consist of rich visual messages and lean textual messages, but every element in textual messages overlaps with visual messages. Project B may consist of rich visual and textual messages, but neither of them overlaps with each other. In this case, S_R in project A is richer than that in project B.

Cognitive load theory explains that information from the sensory memory passes into the working memory, where it is either processed or discarded (Sweller 1988). Working memory can generally hold a limited amount of information (typically seven items or even fewer) at one time. Visual information attracts more attention than textual information (Pieters and Wedel 2004). Consumers learn more and process information faster through a richer medium (Lengel and Daft 1989). To reduce cognitive effort, we argue that creators should use a richer medium, i.e., visual medium for richer information because it helps potential backers learn and memorize more about the project. A picture is worth a thousand words. However, rich information via a textual communication medium increases backers' cognitive effort and distracts backers from focusing on visual information.

When examining the joint information richness between visual and textual communication media, we propose the S_R are likely to shorten the duration of funding success. S_R represents the communication consistency between visual and textual media in the context of integrated marketing communication, which uses marketing strategies to optimize the communication of a consistent message of the company's brands to stakeholders (Yeshin 2007). It suggests that the communication tools work better if they work together in harmony rather than in isolation. If backers are exposed to consistent information via both visual and textual media, the communication effectiveness will increase. If visual and textual communication emphasizes on the same aspects of the potential product or service, backers will learn about the product or service more easily. Therefore, V_R and S_R will shorten the duration of funding success while T_R will prolong the duration of funding success. Thus, we have:

H1a: The increase of V_R will shorten the duration of funding success.

H1b: The increase of T_R will prolong the duration of funding success.

H1c: The increase of S_R will shorten the duration of funding success.

Funding Process Characteristics

Aside from marketing communication, the duration of funding success is also influenced by the funding process characteristics. The funding process on Kickstarter follows two patterns. The project either realizes or exceeds the funding goal, or the project never takes off. The process is similar to the normal product life cycle as most of the new products fail (Day 1981). Some studies suggest a failure rate of 95% in the U.S. (Kotler and Keller 2006).

Backers are motivated to receive finished products and services as their rewards due to the nature of lending crowdfunding. During the funding process, the funding percentage and the number of backers change over time. Some projects are more likely to succeed during the funding process. First, the funding percentage increasing over time signals that the project is approaching its funding goal. Backers are more likely to pledge toward these types of projects because they are likely to receive the finished products and services. Second, the increasing number of backers over time helps the projects accumulate popularity. Backers are more likely to pledge because they are likely to follow the crowd. Therefore, we hypothesize:

H2a: The increase in funding percentage is likely to shorten the duration of funding success.

H2b: The increase in the number of backers is likely to shorten the duration of funding success.

Intrinsic Project Uniqueness

We argue that the intrinsic project uniqueness is also likely to have an impact on the duration of funding success. For example, a music album may have a different funding pattern or process from a high-end coffee maker. The literature has discussed that different product types: such as utilitarian and hedonic product (Kronrod and Danziger 2013), search and experience goods (Mudambi and Schuff 2010). The different product types would influence marketing outcomes differently. Therefore, we should also consider that the intrinsic project uniqueness across each project could have an impact on the duration of funding success.

METHODOLOGY

Data Collection

We collected all live projects on a daily basis on Kickstarter from April 3, 2018, to July 31, 2018. When a creator launches a project, potential backers often read the project description. These descriptions include funding goal, funding deadline, and an assortment of backer rewards determined by project creator, visual, textual and video messages about the project. A potential backer chooses his or her level of support for the project; that person's pledge goes toward the funding goal. Kickstarter updates the amount of funding pledged and the numbers of backers in real time. The visual, textual, and video messages are static once the creator launches the project. Therefore, the funding amount and number of backers change over time while marketing communication information remains the same over time.

We collected three types of data: (1) visual description of a project, (2) textual description of a project, and (3) project characteristics. Since visual and textual information are static, at the end of each project, we crawled the images, text, and videos of each project to derive the measures of V_R, T_R, and S_R. We collected the static project characteristics – project id, funding goal, funding amount, and the number of backers – when a project launched. We also collected two funding process characteristics: the funding amount and the number of backers daily. To ensure a comprehensive understanding of projects evolving process, we kept the projects which launched and finished within the data collection time frame. This resulted in 5,446 projects with 129,867 project-day observations.

Data Processing and Measurement

V_R

All visual information richness measures are static, and the visual data was originally collected in a single snapshot at the image level. We followed the similar approach of Essay 1 to construct the measures of V_R and aggregated them into project level.

First, at the image level, we used computer measures of the visual characteristics summarized from the marketing literature. Table 9 summarizes the image processing sources, measures, and descriptive statistics for each visual characteristic. We do not measure the visual characteristic brand logo because the brand effect is not present for crowdfunding projects. Second, we separated face-related visual characteristics from other characteristics at the image level. Attribute human happiness is identified using face related visual characteristics. We use the proportion of human happiness as the initial measure. We then conducted an EFA to extract other attributes. We extracted the same six attributes as Essay 1 (i.e., human happiness, size, brightness, vividness, colorfulness, and brand focus). We calculated factor scores of each attribute as the initial measure of each attribute. Third, we aggregated the six attributes from the image-level to the project level. At the project level, we collected the image number and number of images contained in a project as an additional measure of V_R. Fourth, we rescaled the seven measures of visual information richness into a range of 0 to 1. We rescaled each visual attribute using: Rescaled Attribute = [Attribute + Min(Attribute)] /Max(Attribute) – Min(Attribute)]. We construct V_R using rescaled values of all attributes which is: V_R = (human happiness + size + brightness + vividness + colorfulness + brand focus + image number)/7.

We use the video number and number of videos containing in a project as a control variable to partition out the mere presence effect of video in the projects. Kickstarter recommends project creators to utilize videos to best communicate with potential backers. Therefore, we'd like to control this effect in this study.

T_R

All textual information richness measures are static, and the textual data was collected in a single snapshot at the project level. We follow the similar steps of how to construct V_R to derive the measures of T_R. All measures are at the project level.

Table 9. Visual Characteristics Measures and Descriptive Statistics

Visual Attribute	Visual Characteristic	Image Processing Source	Computer Measure	Mean	Standard Deviation	Observations
Color	The Number of Colors	Microsoft Azure Vision API	binary: black and white:0, color:1	0.916	0.277	72,069
	Dominant Foreground Color	Microsoft Azure Vision API	red (1), orange (2), yellow (3), green (4), teal (5), blue (6), purple (7), pink (8), white (1), gray (9), brown (9), black (9)	8.759	1.229	56,038
	Dominant Background Color	Microsoft Azure Vision API	red (1), orange (2), yellow (3), green (4), teal (5), blue (6), purple (7), pink (8), white (9), gray (9), brown (9), black (9)	8.707	1.380	57,335
	Hue	Python Library	0 to 360 degrees	0.323	0.319	72,069
	Saturation	Python Library	from 0% to 100%	0.180	0.193	72,069
	Lightness	Python Library	from 0% to 100%	0.555	0.248	72,069
	Value	Python Library	from 0% to 100%	0.602	0.246	72,069
Domain-Specific Object	Image-Text Integration	Microsoft Azure Vision API	binary: 1: present, 0: absent	0.487	0.500	72,069

Note: The image processing source, computer measures, and the descriptive statistics are provided for each visual characteristic. All V_R measures are static, and the data was collected at a single snapshot. The descriptive statistics of each visual characteristic was measured at the image level.

(Table cont'd)

Visual Attribute	Visual Characteristic	Image Processing Source	Computer Measure	Mean	Standard Deviation	Observations
Face	Happiness Emotion	Microsoft Azure Face API	likelihood from 0 to 1	0.438	0.429	10,528
	Sadness Emotion	Microsoft Azure Face API	likelihood from 0 to 1	0.021	0.063	10,528
	Fear Emotion	Microsoft Azure Face API	likelihood from 0 to 1	0.006	0.032	10,528
	Disgust Emotion	Microsoft Azure Face API	likelihood from 0 to 1	0.004	0.016	10,528
	Surprise Emotion	Microsoft Azure Face API	likelihood from 0 to 1	0.025	0.099	10,528
	Anger Emotion	Microsoft Azure Face API	likelihood from 0 to 1	0.027	0.102	10,528
Size	Image Width	Microsoft Azure Vision API	the number of pixels	589	372	72,069
	Image Height	Microsoft Azure Vision API	the number of pixels	500	420	72,069
	Image Area	Microsoft Azure Vision API	the dimension of an image calculated by multiplying width and height	336,184	380,042	72,069
Sharpness	Sharpness	Python Library	the average gradient magnitude	9.718	6.128	72,019

First, we summarized a list of textual information characteristics in the marketing literature. Since textual communication has been well studied in the context of crowdfunding (Parhankangas and Renko 2017) and electronic word of mouth (Goes, Lin, and Au Yeung 2014; Tirunillai and Tellis 2014; Yin, Bond, and Zhang 2014), we only focus on examining the widely studied textual characteristics. Table 10 summarizes text processing sources, measures, and descriptive statistics for each characteristic. Second, we conducted an EFA and confirmed that four textual attributes are extracted: complexity, emotion, length, and sentiment. We calculated factor scores of each attribute as the initial measure of each attribute. Third, we rescaled the three T_R measures, and they range from 0 to 1 using the same formula used to rescale V_R measures. Fourth, we measure T_R = (happiness + length + complexity)/3 at the project level.

We use sentiment as a control variable because studies demonstrate the effect of sentiment on various marketing constructs (Archak, Ghose, and Ipeirotis 2011; Salehan and Kim 2016; Schweidel and Moe 2014). We excluded this attribute as a measure of T_R because positive information is not necessarily richer than negative information.

S_R

S_R is also measured at the project level because we use measures of V_R and T_R to construct it. We construct the synergistic effect of visual and textual communication by calculating the percentage of overlapping information between V_R and T_R. The emotion happiness appears in both the measure of V_R and T_R. In addition, image size and image number from V_R overlap with text length from T_R. Thus, S_R = (image human happiness + text happiness + image size + image number + text length)/ (V_Rx7 + T_Rx3).

Table 10. Textual Characteristics Measures and Descriptive Statistics

Textual Attribute	Textual Characteristic	Text Processing Source	Computer Measure	Mean	Standard Deviation	Observations
Complexity	Flesch	Python Library	the Flesch Reading Ease Score, which has a range of 0–100, with 0 meaning very hard and 100 meaning very easy to read (Thomas, Kincaid, and Hartley 1975)	32.062	80.93	5,522
	Smog	Python Library	the SMOG index measured by the years of education a person needs to understand the project description (McLaughlin 1969)	12.927	5.087	5,522
Emotion	Happiness	Python Library	likelihood from 0 to 1	0.021	0.023	5,522
Length	Word	Python Library	the number of words in a project	622.897	522.63	5,522
	Sentence	Python Library	the number of sentences in a project	18.471	17.388	5,522
Sentiment	Polarity	Python Library	A continuous measure ranges from -1 to 1. The number closes to -1 means very negative, while the number closes to 1 means very positive.	0.171	0.089	5,522
	Subjectivity	Python Library	A continuous measure ranges from 0 to 1. The number closes to 0 means very objective, while the number closes to 1 means very subjective.	0.487	0.08	5,522

Note: The text processing source, computer measures, and the descriptive statistics are provided for each visual characteristic. All T_R measures are static, and the data was collected at a single snapshot. The descriptive statistics of each visual characteristic was measured at the project level.

Project Characteristics

We collected data on the project characteristics directly from Kickstarter. Some of the characteristics change over time while others do not. We collected the funding percentage and number of backers, funding success daily. Funding percentage, named as percent, is measured by the percentage of funding goal achieved. We named the number of backers as backers. We name funding success as success, which refers to whether the project achieves its funding goal. We measure other characteristics such as project ID and funding goal in a single snapshot. Project ID is a unique number assigned to each project. Funding goal is the amount of money needed for the creators to finish their project. Table 11 describes the labels and measures of the constructs in the main study including V_R, T_R, S_R, project characteristics and control variables.

Table 11. Construct Label and Measures

Construct	Label	Measure	Measure Type
Visual Information Richness	V_R	V_R = (human happiness + size + brightness + vividness + colorfulness + brand focus + image number)/7	Static
Video Number	V	The number of videos in a project	Static
Textual Information Richness	T_R	T_R = (happiness + length + complexity)/3	Static
Sentiment	Sen	The factor score of sentiment	Static
Synergy of Visual and Textual Information Richness	S_R	R = (image human happiness + text happiness + image size + image number + text length)/ (V_Rx7 + T_Rx3).	Static
Project ID	ID	A unique number assigned to each project	Static
Date	D	The time when data is collected	Dynamic
Backers	B	The number of backers that pledged a project	Dynamic
Percent	P	Percent= the funding amount/ funding goal	Dynamic
Success	S	Binary variable: 0 is fail, and 1 is success	Dynamic

Note: The construct label, measure, and measure type used for the main study are provided. All measures are at the project level. V_R, T_R, and S_R are rescaled.

Model Specification

We adopt a survival model to test hypotheses because survival analysis is a set of methods for analyzing data where the outcome variable is the time until the occurrence of an event of interest (Wooldridge 2010). In this study, the event of interest is funding success. We used a hazard rate function to test our hypotheses. Hazard rate is defined as the rate of success for a project at age (t). A hazard rate is the conditional likelihood of a project's success in the time period t, given the project has not succeeded through the time t – 1. We propose a sequence of four models to test our hypotheses. Table 12 provides a summary of the conceptual and methodological differences between the four models.

Model 1 is the base mode since the focus of the study is online communication effectiveness. In this model, we solely focus on how visual and textual communication influences the duration of funding success. We test static marketing communication variables (i.e., V_R, T_R, and S_R) in this model. We use a survival analysis with a single duration from the project launch to project deadline. The static model is suitable as a base model because all the marketing communication variables are static. However, conceptually, Model 1 leaves out the important factor: funding process characteristics.

Building upon Model 1, Model 2 also takes funding process characteristics into account. Since the measures of funding process characteristics change over time, we use a repeated survival model to capture the time-varying covariates. Thus, we use the dynamic dataset collected for this study in this model. Model 2 allows testing both H1 and H2. Although Model 2 is comprehensive to test all of our hypotheses, it failed to compensate for the factor intrinsic project uniqueness.

Table 12. A Summary of Conceptual and Methodological Differences of the Three Models

	Model 1	**Model 2**	**Model 3a**	**Model 3b**
Conceptual	Marketing communication	• Marketing communication • Funding process characteristics	• Marketing communication • Funding process characteristics • Intrinsic project uniqueness	• Non-linear effect of marketing communication • Funding process characteristics • Intrinsic project uniqueness
Data	Cross-sectional	Dynamic	Dynamic	Dynamic
Covariate	Time-invariant covariates	• Time-invariant covariates • Time-varying covariates	• Time-invariant covariates • Time-varying covariates	• Time-invariant covariates • Time-varying covariates
Method	Survival analysis with a single duration	Repeated survival analysis	• Multilevel survival analysis • Unique baseline hazard rate for each project	• Multilevel survival analysis • Unique baseline hazard rate for each project
Statistical Benefit	Capture the effects of marketing communication variables	• Capture the effect of the marketing communication variables • Also capture the dynamic funding variables	• Capture the effect of the marketing communication variables • Also capture the dynamic funding process variables • Compensate for intrinsic project uniqueness	• Capture non-linear effects of the marketing communication variables • Also capture the dynamic funding process variables • Compensate for intrinsic project uniqueness

Note: a summary of how four models differ conceptually and methodologically is provided.

Relative to Model 2, Model 3a includes intrinsic project uniqueness to have a complete understanding of the conceptual model. To compensate for intrinsic project uniqueness, Model 3a is a multi-level survival model that assigns a unique baseline hazard rate for each project to capture the unobserved uniqueness. A conceptual enrichment is whether marketing communication variables need to pass or be under a certain threshold to be effective. For example, a project with a couple of words as the textual description may offer little information to help the project achieve its funding goal. On the other hands, a project with overloaded images may be too overwhelmed for the potential backers to process as well. Therefore, we added quadratic functions of V_R, T_R, and S_R to Model 3b to detect the threshold effect. Each model is specified below.

To capture the main focus of this study and the effects of marketing communication, we propose a time-invariant hazard rate's function using cross-sectional data as the based model. The event of interest is funding success. In this model, we treat all constructs as static using a single observation from each project. We adopt the values of success using the last date of data collection for each project. We only include marketing communication variables in this model. We control for the mere presence effect of video and the text sentiment. The hazard rate of project i in the time period t_i depends on the baseline hazard rate function and a project i's covariate values at the time period t_i, $\mathbf{x}_i$. A project i's hazard rate at the time period t_i can be expressed as below in Model 1.

$$\lambda(t_i, \mathbf{x}_i) = \lambda_0 \exp(\beta_0 + \beta_1 V\_R_i + \beta_2 T\_R_i + \beta_3 S\_R_i + \beta_4 V_i + \beta_5 Sen_i) \qquad \text{Model (1)}$$

Building upon model 1, we consider both marketing communication and funding process characteristics in Model 2. Percent and backers change over time during the crowdfunding process. Model 1 considers only time-invariant covariates. We propose a model treating percent and backers as time-varying covariates by using the longitudinal data. A widely recognized benefit of hazard rate analysis is that it represents the impact of both time-varying and time-invariant covariates (Bellera et al. 2010). Overall, the hazard rate of project i at the time period t_i depends on the baseline hazard rate function and a project's time-varying covariates percent and backers as well as time-invariant marketing communication covariates at the time period t_i, $\mathbf{x}_i(t_i)$. A project i's hazard rate in the time period t_i can be expressed as:

$$\lambda(t_i, \mathbf{x}_i(t_i)) = \lambda_0 \exp(\beta_0 + \beta_1 V\_R_i + \beta_2 T\_R_i + \beta_3 S\_R_i + \beta_4 P_i(t) + \beta_5 B_i(t) + \beta_6 V_i + \beta_7 Sen_i) \quad \text{Model (2)}$$

In Model 3a, we add the intrinsic project uniqueness into consideration as well. We control for the intrinsic project uniqueness of each project. Building upon Model 2, we allow different baseline hazard rates for each project in Model 3. To capture the intrinsic project uniqueness, a project i's hazard rate at the time period t_i can be expressed as:

$$\lambda(t_i, \mathbf{x}_i(t_i)) = \lambda_0 \exp(\beta_0 + \mu_i + \beta_1 V\_R_i + \beta_2 T\_R_i + \beta_3 S\_R_i + \beta_4 P_i(t) + \beta_5 B_i(t) + \beta_6 V_i + \beta_7 Sen_i) \quad \text{Model (3a)}$$

In Model 3b, we add the quadratic terms of marketing communication variables to detect whether very lean or very rich communication would still work. A project i's hazard rate at the time period t_i can be expressed as:

$$\lambda(t_i, \mathbf{x}_i(t_i)) = \lambda_0 \exp(\beta_0 + \mu_i + \beta_1 V\_R_i + \beta_2 V\_R_i^2 + \beta_3 T\_R_i + \beta_4 T\_R_i^2 + \beta_5 S\_R_i + \beta_6 S\_R_i^2 + \beta_7 P_i(t) + \beta_8 B_i(t) + \beta_9 V_i + \beta_{10} Sen_i) \quad \text{Model (3b)}$$

DATA ANALYSIS AND RESULTS

Since the study aims to provide suggestions to project creators on how to utilize different communication mediums, we standardized each variable to compare the effect size within a model. Table 13 shows the results of Model 1, Model 2, Model 3a and Model 3b. The positive coefficient means the increase of the variable is likely to shorten the duration of funding success, while the negative coefficient means the increase of the construct is likely to prolong the duration of funding success. Hazard ratio provides us a detailed explanation on the coefficient. For example, the hazard rate of V_R in Model 1 is 1.310. Thus, one standard deviation increase in V_R is associated with a 31% (1.310-1=.31) increase in the expected hazard. If we did not standardize the variables, the explanation would be one unit increase in V_R associated with a 31% increase in the expected hazard. Taking the hazard rate of T_R in Model 1 as another example, it shows that one standard deviation increase in T_R is associated with 7.3% (1-.927=.073) decrease in the expected hazard.

Model 1 reports the results accounting for the marketing communication effect using a single snapshot data. In a cross-sectional setting, consistent with hypothesis 1a, 1b, and 1c, V_R and S_R shorten the duration of the funding success while T_R prolongs the duration. V also has a positive effect on the funding duration. This model, however, does not consider the funding process characteristics and intrinsic project uniqueness. The results limit the interpretation of our conceptual model.

Table 13. Model Comparison and Results

	Model 1			
	Coef.	Hazard Ratio	Std. Err. (Coef.)	P-value
V_R	0.270	1.310	0.020	0.000
T_R	-0.076	0.927	0.035	0.030
S_R	0.171	1.186	0.038	0.000
V	0.151	1.163	0.009	0.000
Sen	0.025	1.025	0.021	0.227

Note: The coefficients, hazard ratios, standard errors of coefficients, and p-values are reported in each model for each construct. All of the variables are standardized.

(Table cont’d)

Model 2				
	Coef.	Hazard Ratio	Std. Err. (Coef.)	P-value
V_R	0.432	1.541	0.005	0.000
T_R	0.051	1.052	0.009	0.000
S_R	0.035	1.035	0.010	0.001
P	0.036	1.037	0.001	0.000
B	0.076	1.079	0.001	0.000
V	0.155	1.168	0.002	0.000
Sen	0.040	1.041	0.005	0.000
Model 3a				
	Coef.	Hazard Ratio	Std. Err. (Coef.)	P-value
V_R	0.165	1.179	0.015	0.000
T_R	-0.110	0.896	0.031	0.000
S_R	0.182	1.200	0.030	0.000
P	0.780	2.181	0.178	0.000
B	0.235	1.265	0.049	0.000
V	0.157	1.170	0.024	0.000
Sen	0.020	1.020	0.016	0.200
Model 3b				
	Coef.	Hazard Ratio	Std. Err. (Coef.)	P-value
V_R	0.425	1.530	0.108	0.000
V_R^2	-0.266	0.766	0.098	0.007
T_R	0.055	1.057	0.057	0.332
T_R^2	-0.101	0.904	0.050	0.045
S_R	0.178	1.195	0.041	0.000
S_R^2	-0.069	0.933	0.037	0.064
P	0.776	2.172	0.179	0.000
B	0.237	1.267	0.050	0.000
V	0.156	1.169	0.024	0.000
Sen	0.020	1.020	0.016	0.205

Building upon Model 1, Model 2 includes the funding process characteristics by treating P and B as time-varying covariates using longitudinal data. Both P and B shorten the duration of the funding success. Thus, hypotheses 2a and 2b are supported. The hazard rate of V_R, S_R, and V increase in Model 2 while the effect of T_R is inconsistent. T_R has a positive effect on the duration of funding success in Model 2. Thus, H1a and H1c are supported while H1b is not supported. The intrinsic project uniqueness may confound this result. Therefore, Model 2 is not applicable to interpret the result either. Therefore, we use a unique baseline hazard rate for each project in Model 3a to partition the unobserved effect out.

Model 3a captures marketing communication, funding process characteristics, and intrinsic project uniqueness. This is the most comprehensive model to test the hypotheses and interpret the results. For marketing communication media, the increase of V_R shortens the duration of funding success while the increase of T_R prolongs the duration of funding success. S_R has a positive effect on the duration of success. Thus, H1a, H1b, and H1c are supported. Looking into the funding process characteristics, both P and B have positive effects on the duration of funding success. Thus, H2a and H2b are supported. By taking into account for time-varying covariates and compensating for intrinsic project uniqueness, the mere presence of video has a positive impact on the duration of success. It is consistent with Kickstarter's recommendation that creators should use videos and images to tell a compelling story to attract potential backers.

Within the model, the effect size of V_R and V are similar, implying that video and pictures are equally important to shorten the funding duration. The effect of S_R is slightly higher than V_R and T_R, showing the synergized marketing communication media online is indeed important. The effect of T_R is smaller than that of V_R and S_R, so the positive effects of visual and synergy communication outweigh the negative effect of T_R.

Model 3b captures the threshold of when marketing communication becomes useful and when it is not. The quadratic terms of V_R and T_R are negatively significant while that of S_R is not significant. This implies that a rich S_R is associated with funding success all the time. The positive effect of V_R will be strongest if the project has an adequate number of images.

Although T_R has a negative effect on funding duration, too few or too many textual messages will not help achieve the funding goal either.

Our results suggest that when communicating rich information, creators should prioritize visual and video media. Rich visual information catch backers' attention and helps them learn faster while rich textual information increases the cognitive load of backers. Integrated marketing communication suggests that creators should use multiple communication tools in a harmonic way. The synergistic effect of visual and textual communication is the most effective approach when used online. Our results support that funding process characteristics are associated with funding success.

CONCLUSION

Contributions and Implications

Building on online marketing communication research in fundraising and crowdfunding, our study suggests that the duration of funding success is influenced by three types of factors: 1) marketing communication, 2) funding process characteristics, and 3) intrinsic project uniqueness. Based on the MRT, cognitive load theory, and integrated marketing communication theory, our results suggest that when communicating rich information, a visual medium outstands a textual medium. Rich visual information catch backers' attention and helps them learn faster while rich textual information increases the cognitive load of backers. Integrated marketing communication suggests that creators should use multiple communication tools in a harmonic way. Our research extends current literature by studying the joint effect of image and text on crowdfunding. We demonstrate that the synergistic effect of visual and textual communication is the most effective communication format online. Integrated marketing communication is important on the same platform. The mere presence effect of video is as important as visual communication. In addition, consistent with current studies, we confirm that the funding process characteristics are associated with funding success. Although both funding percentage and the number of backers have positive effects on funding durations, funding percentage has a much higher likelihood that leads to funding success.

From a practical point of view, our results provide guidelines for creators to communicate effectively on Kickstarter. Creators must understand that not all communication mediums are created equally. The synergy effect is the most effective on Kickstarter. Therefore, they should send consistent communication messages across visual and textual media. They should prioritize the use of synergy communication. Second, they should use visual and video messages more than textual messages. It facilitates backers' learning process as well as attracting their attention. They should avoid creating too little or too many textual messages. The adequate amount of textual information would help the backers understand the project. However, too many textual messages would cause information overload. The creators should also understand that the effect of marketing communication is limited as backers assign a larger weight to funding process characteristics because the platform is reward based. The backers are motivated to receive the final products and services.

Limitations and Future Research

Despite its merits, this study leaves us with many unanswered questions. First, we consider the visual and textual information richness as a combined value from all dimensions. An interesting avenue for future research would be to investigate to information richness of each element from visual and textual media. We can examine whether the synergy effect still holds. Furthermore, the topic modeling technique has been widely used in online chatters (e.g., Tirunillai and Tellis 2014). This technique can actually summarize textual messages into different topic categories and can be applied to visual messages as well. It would be interesting to see how the synergistic effect of how visual and textual content could influence the duration of funding success. In this way, we can understand not only how but also what project creators should communicate with potential backers.

Second, we only consider the aggregate value of funding percent and the number of backers to understand the funding process characteristics. However, on Kickstarter, the backer can pledge at different levels. For example, a project may provide rewards at two levels with 1 dollar vs. 20 dollars. A meaningful future research direction would be to examine whether the funding and backers coming from different levels could influence the funding duration differently.

Third, although we controlled for intrinsic project uniqueness in Model 3, we are not clear which intrinsic attributes affect the funding success. Current literature investigates many different types of product, cost, quality, value, etc. Thus, a potential avenue for future research would be to identify other relevant project intrinsic characteristics to enrich the topic. A possible character would be the product category. The funding process of a 10 dollar plate may be very different from a 200 dollar coffee maker. Moreover, Kickstarter reveals where the project is created. There might be some country or region effects as well. Furthermore, some projects may have social causes or person-related motivations. A potential question would investigate whether those projects with social causes or person-related motivations influence the duration of funding success differently.

Fourth, the mere presence of video increase the likelihood of funding success and shorten the duration across three models in our results. It is also consistent with the suggestion provided by Kickstarter that creators should focus on videos to tell a compelling story. In the future, it would be interesting to incorporate the measures of video information richness in the study. An interesting question would be how video information richness influences the duration of funding success and how video media interact with visual or textual media.

Last, in this study, we assumed the effect of the three divers on the duration of funding success were constant over time. Future research could focus on whether the effects are time-varying. For example, marketing communication may have a stronger effect when the project launches as not so many backers have pledged the project yet, while the funding process characteristics may have a stronger effect when the project is approaching the deadline. This is becasue because this may be the strongest evidence on whether the project will reach its funding goal.

DISCUSSION

The center focus of the dissertation is online marketing communication effectiveness. We examine both one-way and two-way marketing communication. Essay 1 investigates the dyadic and dynamic communication between a company and its consumers, which is a two-way visual communication. A VBBP is co-created by a company and its consumers. We contribute to the theory by illustrating that during the co-creational process, both the company and consumer VBBP_Rs increase and the VBBP_G exist. The brand meaning keeps increasing during the co-creational process, but the company and consumer VBBPs are not always consistent during the process. Essay 2 focuses on one-way communication: the project creator communicating to potential backers. We demonstrate how different communication media interact with one another. We contribute to the theory by illustrating that the synergistic effect of multiple media is effective on a marketing outcome. This dissertation is grounded under the MRT and related theories. The dyadic and dynamic-based brand perception motivate current studies to re-conceptualize brand-related constructs by considering both parties. When communicating through multiple media, integrated marketing communication is the most effective online.

The dissertation offers two important managerial implications. First, brand perceptions between a company and its consumers are not always consistent. If a company intends to explore a new market, the company should keep brand perception inconsistent. Consumers will be aware that the brand stories change and differ from the past. If a company aims to maintain an existing customer base, the company should mitigate the gap. We offer visual and non-visual communication strategies to manage the inconsistency. Increasing visual communication frequency helps mitigate the gap while increasing third-party news volume (non-visual communication) enlarges the gap. Second, companies should synergize multiple media in a self-contained online platform to maximize communication effectiveness. The consistent content communicated via different media has a positive impact on the marketing outcomes. Companies should prioritize visual and video messages because they outperform textual messages.

The dissertation contributes to the methodological domain by using a machine learning-based image mining approach to empirically measure brand perception and information richness. The sheer volume of images readily available online provides us an opportunity to mine meaningful visual information automatically. By using these sets of measures, companies can constantly manage their brands, products, services, and enrich their visual metrics. Furthermore, the empirical measures are validated by comparing computer measures with human coders. The results support that the empirical measures are close to human perceptions. The image mining technique can be applied to various contexts and research topics.

APPENDIX A. VISUAL CHARACTERISTICS AND MEASURES

Camera Angle

Camera angle refers to whether an image is shot at an upward, downward, or eye-level angle (Meyers-Levy and Peracchio 1992; Laura A. Peracchio and Meyers-Levy 2005). Meyers-Levy and Peracchio (1992) find that when processing motivation was low, evaluations were most favorable when the viewer looked up at the product, least favorable when he or she looked down at the product, and moderate when the product was at eye level. Further, when processing motivation was moderate, eye-level shots produced the most favorable evaluations. The industry findings show that online shoppers feel confident in their purchase decisions if they can see the product from multiple angles (Conard 2010), and that a person shot at an upward-looking angle in photo conveys a positive and friendly demeanor (Harrison 2016).

Color

Color is one of the most studied visual attributes in the literature search. One stream of literature treats color as a categorical visual attribute. The other stream operationalizes color as a continuous visual attribute by studying Hue-Saturation-Lightness (HSL) and Hue-Saturation-Value (HSV) color models.

The literature has operationalized color as a categorical visual attribute in three ways. First, the studies compare the number of colors used in an image. In the print advertising literature, researchers studied the difference between black and white and color ads (Finn 1988; Gardner and Cohen 1964; Lee et al. 2014, 2017; Meyers-Levy and Peracchio 1995; Pollay 1985). Wedel and Pieters (2015) further compared black and white, greyscale, inverted, and inverted background images, bringing more opportunities to study the number of colors in an image. Usually, color ads evoke more favorable evaluations. Second, the studies compared the effects of different dominant colors of an image or an ad on marketing constructs. The comparison applies to both image foreground and background. Dominant foreground color refers to the most attention-grabbing color in front of an image. Dominant background color refers to the attention-grabbing color at the back of an image. A widely used comparison is between warm and cool colors. For example, red or blue as the foreground or background of an image (Bagchi and Cheema 2013; Gardner and Cohen 1964; Mandel and Johnson 2002). For example, a red (vs. blue) background elicits higher bid jumps. But red (vs. blue) backgrounds decrease price offers in negotiations (Bagchi and Cheema 2013). An extension of dominant color study is to examine the color contrast between foreground and background (Van Ittersum and Wansink 2012). Reducing the color contrast between dinnerware and a tablecloth solves the problems of underserving and overserving (Van Ittersum and Wansink 2012). Third, another stream of study is on color association (Macklin 1996). Color association refers to the degree to which a color is associated with brands, senses, language, objects (or forms), personality characteristics, etc. For example, color can be associated with product attributes. Mandel and Johnson (2002) used red and orange flames to prime the color association with safety and green bills to prime color associated with price. They found that for novices, priming drives differences in external search that, in turn, drive differences in choice. For experts, differences in choice are not mediated by changes in external search. Industry results showed that good images allow shoppers to see the product in every color combination possible (Conard 2010). In addition, color becomes an important element on Pinterest's visual search functionality that allows pinners to use part of the image or the entire image to search for related images (Kane and Pear 2016).

The continuous visual attribute of color mainly comes from HSL and HSV color models. A color's hue is the degree to which a stimulus can be described as similar to or different from stimuli that are red, green, blue, and yellow. It is often described as a 360-degree color wheel, which range from red (0 degrees), yellow (60 degrees), green (120 degrees), to blue (240 degrees)[3]. A color's saturation, also called chroma, refers to the degree of intensity or purity of a color. A color with high saturation are perceived as more vivid and stand out more, but one with low saturation looks dull and greyish (Hagtvedt and Adam Brasel 2017). Increasing color saturation increases size perceptions(Hagtvedt and Adam Brasel 2017). A color's lightness refers to the degree of blackness and whiteness in a given color (Hagtvedt and Brasel 2016; Hagtvedt and Brasel 2017). A color with low lightness is nearly black, but one with a high lightness is nearly white. High frequency (low frequency) sounds guide visual attention toward light-colored (dark-colored) objects (Hagtvedt and Brasel 2016). A color's value refers to the degree of darkness in a given color. A color with a low value is nearly black, but one with a high value is "pure" and fully saturated[4].

Domain-Specific Object

A domain-specific object refers to the focal subject of interest contained in an image in a category such as people, animals, plants, representation of concepts, etc. The visual characteristics from the writing domain are image-text integration, image-text consistency, and image-text interactivity. Image-text integration refers to whether the textual message is integrated into an image (Peracchio and Meyers-Levy 1997). The type of ad copy used in an ad along with the physical layout of the ad can affect the degree to which a balance is achieved

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[3] Hagtvedt and Brasel (2017) introduced hue from HSL and HSV models, but did not study the effect of a color's hue. In the previous studies, hue was treated as a categorical variable. We keep this visual characteristic as it is part of the HSL and HSV model.

[4]Hagtvedt and Brasel (2017) introduced value in the appendix, but did not study the effect of value on perpception directly. We keep this visual characteristic in this study as it is part of the HSV model.

between the resources one makes available for processing versus those required by the ad for processing (Peracchio and Meyers-Levy 1997). Image-text consistency refers to the degree to which the text and image convey a consistent message (Edell and Staelin 1983; Houston, Childers, and Heckler 1987; Luna and Peracchio 2001). Image-text interactivity refers to the degree to which the textual message is interactive with an image (Luna and Peracchio 2001). A high level of congruity between picture and text facilitates conceptual processing messages, increasing memory for ads and thereby reducing the impact of language asymmetries on memory (Luna and Peracchio 2001). The other visual characteristics are from the symbol domain such as brand logo and warning sign icon. Brand logo refers to whether a brand logo appears in an image[5]. Cian and colleagues (2015) studied how the dynamism of warning sign icons alter people's perceptions and behaviors. A warning sign icon refers to whether a warning sign icon appears in an image.

The industry perceives domain-specific objects as important elements in the image (Carton 2015). Brand logo detection, such as identifying an image of someone holding a Coca-Cola can, is useful for marketers to uncover consumer preference, which allows them to send out targeted ads (MacMillan and Dwoskin 2014). Facebook researchers studied people who post dog and cat images and concluded that "on average, dog people have 26 more Facebook friends than cat people" and "cat people get invited to more events" (Plomion 2017). Moreover, objects from images allow us to retrieve information. Google Goggles, an image-recognition app introduced in 2009, lets users identify and retrieve information about a book or landmark by taking a photo (Koh 2015).

[5] Researches did not directly study whether a brand logo appears in an image but studied brand logo size and brand logo location that depend upon the presence of a brand logo. Thus, we keep the visual characteristic brand logo for further study.

Facial Feature

A stream of literature focuses on the effect of facial features. Xiao and Ding (2014) proposed an eigenface method to classify facial features into 12 general types. Other studies focused on the specific facial features a face contains, for example, a babyface feature and a celebrity face feature. Babyface feature refers to the degree to which a person has a child-like face in an image. A CEO with a babyface feature, in general, are perceived as less competent (Gorn, Jiang, and Johar 2008). Celebrity face feature refers to the degree to which a stranger's face was blended with a celebrity's facial features in an image. Tanner and Maeng (2012) concluded that an unfamiliar face blending with celebrity facial features increases trust. The industry believes that facial recognition is a better technology with more security compared to password protection; facial recognition has implications in a large area (Mims 2017). For example, Apple’s iPhone X models adopted the Face ID as new cell phone security technology.

The other stream of literature focuses on the emotion expressed from faces in an image. The universally understandable emotions across cultures that have been studied are happiness, neutral, sadness, fear, disgust, surprise, and anger (Landwehr, McGill, and Herrmann 2011; Lu, Xiao, and Ding 2016; Small and Verrochi 2009; Teixeira, Picard, and el Kaliouby 2014; Teixeira, Wedel, and Pieters 2012). In the context of this study, emotion refers to the degree to which a human face detected in an image expresses happiness, sadness, fear, disgust, surprise, or anger. The studies either investigated some of the emotions or all of them. Researchers mainly studied the intensity of an emotion at a given moment. Teixeira, Wedel, and Pieters (2012) also studied the velocity (change) of an emotion, indicated by the first-order derivative of the emotion trace. Happiness is an equivalent visual characteristic as smile intensity, entertainment, or joy (Chih et al. 2013; Lu, Xiao, and Ding 2016; Small and Verrochi 2009; Teixeira, Picard, and el Kaliouby

2014; Teixeira, Wedel, and Pieters 2012; Wang et al. 2016). A marketer displaying a broad smile, compared to a slight smile, is more likely to be perceived by consumers as warmer but less competent (Wang et al. 2016). Surprise and joy effectively concentrate attention and retain viewers (Teixeira, Wedel, and Pieters 2012). People "catch" the emotions displayed on a victim's face are sympathetic and likely to donate when they see sad expressions versus happy or neutral expressions (Small and Verrochi 2009). Some companies use software to scan photos to identify whether the person in the image is smiling to allow marketers to send targeted ads or conduct market research (MacMillan and Dwoskin 2014).

Size

Size refers to the amount of space that an image or an object in an image takes up. It has been operationalized in three ways. First, studies focused on the image/ad size. Image/Ad size refers to the amount of space that an image/print ad takes up. The size of an image/ad is measured as pages, a fraction of a page (Finn 1988; Hanssens and Weitz 1980; Pollay 1985; Silk and Geiger 1972), or by square-decimeters (Aribarg, Pieters, and Wedel 2010; Pieters and Wedel 2004). Second, a couple of studies examined brand logo size. Brand logo size refers to the space a brand logo takes up in an image (Aribarg, Pieters, and Wedel 2010; Pieters and Wedel 2004). Third, size ratio refers to the relative space proportion of a focal object in an image. The examples are (1) the relative space proportion of the white space (negative space) in an image (Pracejus, Olsen, and O'Guinn 2006), (2) the relative space per product in an image (Sevilla and Townsend 2016), (3) diameter ratio between the target serving size and the dinnerware (Van Ittersum and Wansink 2012), and (4) face width-to-height ratio (Maeng and Aggarwal 2018). Size, in general, has a positive influence on attention.

Object Location

A couple of studies focused on the location of an object in an image such as product location and brand logo location. Product location refers to the placement of a product in an image. Location of the product image on a package facade influences consumers' perception of the visual heaviness of the product and evaluations of the package. The "heavier" ("lighter") locations are on the bottom (top), right (left), and bottom-right (top-left) of the package (Deng and Kahn 2009). Brand logo location refers to the placement of a brand logo in an image. Brand logos and product depictions capture greater fluency when they change location in an advertisement from one exposure to the ad to the next, so logo preference and brand choice are enhanced (Shapiro and Nielsen 2013).

Wedel and Pieters (2015) studied image sharpness by manipulating image blur, the opposite of image sharpness. Sharpness refers to the amount of details an image contains. Color enables consumers to continue to perceive the gist of ads accurately when the exposure is blurred (Wedel and Pieters 2015). This characteristic does not belong to any visual attributes summarized above. We kept it as a stand-alone image characteristic as it reflects the amount of information in an image.

Table 14. A Summary of Visual Characteristics and Measures

Visual Attribute	Visual Characteristic	Measurement	Result	Author
Camera Angle	Camera Angle	Low angle vs. high angle	A high, downward-looking camera angle can impart either a relatively negative concept like weakness or a fairly positive one like naturalness.	Peracchio and Meyers-Levy 2005
	Camera Angle	Look up, look down, eye level	When processing motivation was low, evaluations were most favorable when the viewer seemed to be looking up at the product, least favorable when he or she looked down at the product, and moderate when the product was at eye level. However, when processing motivation was moderate, eye-level shots produced the most favorable evaluations.	Meyers-Levy and Peracchio 1992
Color	The Number of Colors	Black and white vs. color	The ads with color evoked more positive reactions to the merchandise and were more often identified with higher status stores.	Gardner and Cohen 1964
	The Number of Colors	Black and white, two colors, four colors	Though there is little difference between two-color and black and white ads, the use of four colors has a substantial impact on all measures of effectiveness for important products and a significant but weaker impact in ads for unique products. Four colors have a greater impact on recall and readership measures than on inquiry generation	Hanssens and Weitz 1980
	The Number of Colors	Black and white (1) vs. color (2)	Conceptual paper	Pollay 1985

Note: The visual attributes, visual characteristics, measurements, results and authors used in the paper are listed in each row.

(Table cont'd)

Visual Attribute	Visual Characteristic	Measurement	Result	Author
Color	The Number of Colors	Treated as an interval variable, with black and white ads coded as 1. black and white plus a single color as 2, black and white plus two colors as 3, and full color as 4.	The number of colors contained in the ad has a positive effect on audience readship (attention received).	Finn 1988
	The Number of Colors	Black and white vs. color	When viewers devote few resources to processing, ads with some color outperform black-and-white ads. However, when viewers engage in more effortful ad processing, attitudes are sensitive to the match between available and required resources.	Meyers-Levy and Peracchio 1995
	The Number of Colors	Black and white vs. color	Black-and-white (BW) versus color imagery is cognitively associated with high-level versus low-level construal, respectively.	Lee et al. 2014
	The Number of Colors	Full color, grayscale, inverted, inverted background	Color contributes little to gist perception when sufficient visual detail is available, and ads are typical, but color enables consumers to continue to perceive the gist of ads accurately when the exposure is blurred.	Wedel and Pieters 2015
	The Number of Colors	Black and white vs. color	When consumers visualize the distant (vs. near) future, they engage in processing that captures shape (vs. color): namely, imagery that is relatively more black and white (vs. colorful).	Lee et al. 2017
	Dominant Foreground Color	Blue vs. yellow, blue vs. red	Colors that induce more relaxed feeling states lead to greater perceived quickness.	Gorn et al. 2004
	Dominant Background Color	Red vs. blue	A red (vs. blue) background elicits higher bid jumps. By contrast, red (vs. blue) backgrounds decrease price offers in negotiations.	Bagchi and Cheema 2013

(Table cont'd)

Visual Attribute	Visual Characteristic	Measurement	Result	Author
Color	Dominant Foreground and Background Color	Low contrast vs. high contrast	Reducing the color contrast between dinnerware and a tablecloth (1) reduces overserving when the diameter ratio between the serving size and the dinnerware is smaller than 0.5 (but larger than 0), typically with larger dinnerware. (2) reduces underserving when the diameter ratio between the serving size and the dinnerware is larger than 0.5 (but smaller than 1), typically with smaller dinnerware.	Van Ittersum and Wansink 2012
	Color Association	Associated vs. unassociated of brand names	When visual cues are provided in addition to brand names that are prior-associated in children's memory structures, children better remember the brand names.	Macklin 1996
	Color Association	Car web site: red and orange with flames (to prime safety) vs. green with dollars (to prime price). sofa Website: blue with clouds (to prime comfort) vs. green with pennies (to prime price)	For novices, priming drives differences in external search that, in turn, drive differences in choice. For experts, differences in choice are not mediated by changes in external search.	Mandel and Johnson 2002
	Saturation	High vs. low	Increasing color saturation increases size perceptions.	Hagtvedt and Brasel 2017
	Lightness	Light-colored vs. dark-colored	High frequency (low frequency) sounds guide visual attention toward light-colored (dark-colored) objects.	Hagtvedt and Brasel 2016

(Table cont'd)

Visual Attribute	Visual Characteristic	Measurement	Result	Author
Domain-Specific Object	Image-Text Integration	Ad copy and ad picture are integrated or separated	The type of ad copy used in an ad along with the physical layout of the ad can affect the degree to which a balance is achieved between the resources one makes available for processing versus those required by the ad for processing.	Peracchio and Meyers-Levy 1997
	Image-text Consistency	Pictorial unframed: an ad in which the verbal message does not relate the picture to the brand. pictorial framed: an ad in which the verbal message relates the picture to the brand.	When subjects saw the unframed pictorial advertisements, fewer evaluative thoughts were given, and when given, the attributes mentioned were rarely the attributes the subject had indicated in advance that s/he would use to evaluate the brand.	Edell and Staelin 1983
	Image-Text Consistency	Consistent verbal content (i.e., copy that described the same attribute portrayed in the picture). discrepant verbal material (i.e., copy that described an attribute different from the one represented in the picture).	Superior recall for ads in which the picture and copy convey discrepant information about the product attributes when the picture and brand name are linked interactively.	Houston et al. 1987
	Image-text Consistency Image-text Interactivity	Ad copy and ad picture are consistent vs. inconsistent. ad copy and ad picture are interactive vs. non-interactive	A high level of congruity between picture and text facilitates conceptual processing of second language messages, increasing memory for second-language ads and thereby reducing the impact of language asymmetries on memory.	Luna and Peracchio 2001

(Table cont'd)

Visual Attribute	Visual Characteristic	Measurement	Result	Author
Domain-Specific Object	Warning Sign Icons	Lower vs. higher dynamism	Features of static visuals can lead to perceived movement (via dynamic imagery) and prepare the observer for action.	Cian et al. 2015
Facial Features	Babyface Feature	Baby-faced CEO vs. mature-faced CEO	Babyface facial characteristic affects the perception of a CEO's honesty/innocence and, hence, the credibility of the denial of wrongdoing.	Gorn et al. 2008
	Celebrity Face Feature	An unfamiliar face blending with celebrity facial features (Tiger Woods and George Bush)	Trustworthiness ratings of the composite faces are clearly influenced by celebrities.	Tanner and Maeng 2012
	Emotion	Sad, happy, or neutral	People "catch" the emotions displayed on a victim's face and they are particularly sympathetic and likely to donate when they see sad expressions versus happy or neutral expressions.	Small and Verrochi 2009
	Emotion	The level of an emotion is its intensity at a given moment during ad exposure. The velocity (change) of an emotion is indicated by the first-order derivative of the emotion trace.	Surprise and joy effectively concentrate attention and retain viewers. However, the level rather than the velocity of surprise affects attention concentration most, whereas the velocity rather than the level of joy affects viewer retention most.	Teixeira et al. 2012
	Emotion	A seven-expression scheme (i.e., neutral, happiness, sadness, fear, disgust, surprise, and anger)	The system uses a camera to capture a shopper's behavior in front of the mirror to make inferences about her preferences based on her facial expressions and the part of the garment she is examining (region of interest) at each time point.	Lu et al. 2016

(Table cont'd)

Visual Attribute	Visual Characteristic	Measurement	Result	Author
Facial Features	Emotion	Smile intensity	Entertainment (smile intensity) has an inverted U-shape relationship to purchase intent.	Teixeira et al. 2014
	Emotion	Smile intensity: slight vs. broad	A marketer displaying a broad smile, compared to a slight smile, is more likely to be perceived by consumers as warmer but less competent.	Wang et al. 2017
Size	Ad Size	1/16, 1/8, 1/4, 3/8, 1/2, and 1 (fraction of page)	there is an inverted U shape between advertisement size and exposure to print advertising.	Silk and Geiger 1972
	Ad Size	Combined photo and illustration space in the ad as a proportion of the page size of the magazine.	Ad illustration size has a positive effect on audience readship (attention received).	Finn 1988
	Image Size	Surface size (dm^2)	The pictorial is superior in capturing attention, independent of its size. The text element best captures attention in direct proportion to its surface size.	Pieters and Wedel 2004
	Image Size	Surface size (dm^2)	The ad size has a positive effect on attention.	Aribarg et al. 2010
	Brand Logo Size	Surface size (dm^2)	The brand logo size has a positive effect on attention.	Pieters and Wedel 2004
	Brand Logo Size	Surface size (dm^2)	The brand logo size has a positive effect on attention.	Aribarg et al. 2010
	White Space Ratio	Low vs. high	White space has a positive effect on brand perception.	Pracejus er al. 2006

(Table cont'd)

Visual Attribute	Visual Characteristic	Measurement	Result	Author
Size	Face Width-to-height Ratio	Low vs. high face width-to-height ratio (fWHR: bizygomatic width divided by upper-face height)	Like human faces, product faces with high (vs. low) f WHR are perceived as more dominant. However, while human faces with high f WHR are liked less, product faces with high f WHR are liked more as revealed by consumer preference and willingness-to-pay scores.	Maeng and Aggarwal 2018
Object Location Object Location	Brand Logo Location	Location of the brand logo	Brand logos and product depictions capture greater fluency when they change location in an advertisement from one exposure to the ad to the next. As a consequence, logo preference and brand choice are enhanced.	Shapiro and Nielsen 2013
	Product Location	Heavier (bottom, right, bottom-right) vs. lighter (top, left, top-left)	Location of the product image on a package facade influences consumers' perception of the visual heaviness of the product and evaluations of the package. The "heavier" ("lighter") locations are on the bottom (top), right (left), and bottom-right (top-left) of the package.	Deng and Kahn 2009
Sharpness	Sharpness	Blur (opposite to sharpness): normal, low, medium, high, very high	Color contributes little to gist perception when sufficient visual detail is available, and ads are typical, but color enables consumers to continue to perceive the gist of ads accurately when the exposure is blurred.	Wedel and Pieters 2015

APPENDIX B. VISUAL ATTRIBUTE VALIDATION

Face Validity

We followed the procedure of Böttger and colleagues (2017) to conduct a face validity check using expert opinions. To ensure the visual characteristics measuring each visual attribute are relevant to researchers and marketers, the panel included five marketing academics from universities and five visual and graphics design professions. These experts rated each visual characteristic of a visual attribute using a seven-point scale with a range from "very bad fit" (1) to "very good fit" (7). Textual description and visual illustration are provided to help describe each visual characteristic. A sample survey question to test the face validity of the visual attribute brightness is listed in Figure 7. We constructed two separate scores, academic score and professional score, by taking the average rating of the responses of academics and professionals. We retained visual characteristics that both the academic score and the professional score are favorable (> 4.0). We kept all the visual characteristic for each visual attribute based on the selection criteria in Appendix E. The favorable scores provide face validity to the method.

Computer-Human Convergent Validity

The visual cues can sometimes alter customer perception. Customers perceive a package as heavier (lighter) if the product image is placed at on the bottom (top), right (left), and bottom-right (top-left) (Deng and Kahn 2009). Increasing color saturation increases size perceptions (Hagtvedt and Adam Brasel 2017). Colors that induce more relaxed feeling states lead to the greater perceived quickness of time (Gorn et al. 2004). To understand whether computer measures are consistent with human perceptions in this study context, we validated the image processing method by comparing the measure generated by computer agents and human coders.

We compared the measures across multiple computer agents, namely, Microsoft API, Google API, Python, and two trained human coders.

The following items are used to measure the image attribute: brightness. *Brightness* refers to the perception elicited by the luminance of a visual target.

Color lightness refers to the degree of blackness and whiteness in a given color. A color with a low lightness is nearly black, but one with a high lightness is nearly white (Image 1).
Color value refers to the degree of darkness in a given color. A color with a low value is nearly black, but one with a high value is the pure, fully saturated color (Image 2).

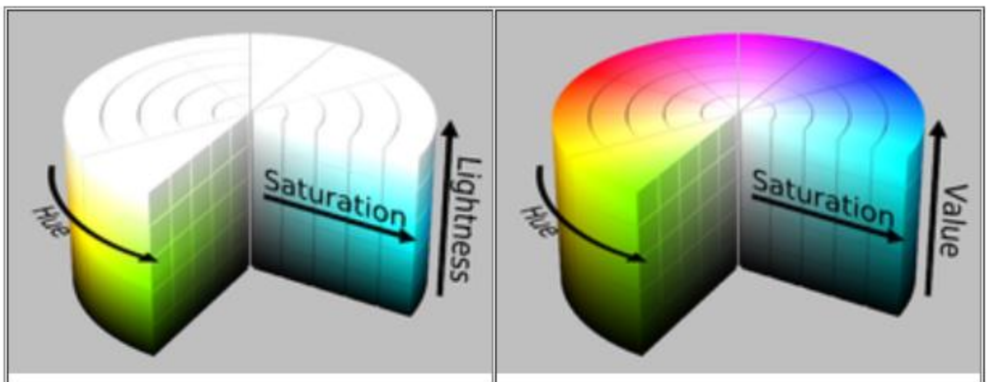

Image 1	Image 2

Please rate whether the items mentioned above are a good fit to measure the image attribute: *brightness* in the marketing and/or business field. Please note that the definitions, text and image examples are only provided to help you understand the meaning of the items.

	Very Bad Fit	Bad Fit	Somewhat Bad Fit	Neutral	Somewhat Good Fit	Good Fit	Very Good Fit
Color Lightness	○	○	○	○	○	○	○
Color Value	○	○	○	○	○	○	○

Figure 7. Sample Survey of Questions to Test Content and Face Validity
Note: This is a sample survey question to test content and face validity of the visual attribute: brightness. The attribute includes two characteristics: color lightness and color value.

We picked one visual characteristic from each visual attribute to keep the task operational to coders by following two criteria. First, we chose the visual characteristic that can be processed by the maximum number of computer agents (Table 15) to examine the consistency among multiple parties. Second, if multiple visual characteristics satisfy the second requirement, we picked the visual characteristic with the highest academic score of the face validity test. We randomly selected 50 images from each brand. Two coders were given the task of viewing each image to assign values to each visual characteristic. Appendix E provides the coding guideline. We provided the coders with visual characteristic definitions, coding instructions, and illustrative image examples of the visual characteristic measures. We demonstrated the convergent validity of the dimensions by showing the inter-rater reliabilities. We calculated three sets of inter-rater reliabilities: R1 is Scott's pi between computers agents. R2 is Scott's pi between coders. R3 is the Fleiss' kappa between computer agents and coders.

First, the selection criteria resulted in six visual characteristics that represent the visual attributes: (1) human happiness, (2) the number of colors, (3) dominant foreground color, (4) lightness, (5) image-text integration, and (6) size. Second, we converted the coding results from computer agents using human coding guidelines (Table 16) so that the coding results are comparable. Table 15 shows that measures across computer agents and human coders are largely consistent because the inter-rater reliabilities are at least greater than .50. The R1 values are around .80, except for the visual characteristic image-text integration. The R2 values are overall high, indicating consistent perceptions between human coders. The R3 values are higher for human happiness, the number of colors, image-text-integration, and size while lower for dominant foreground color and color lightness. Overall, the consistency provides convergent validity to the method.

Table 15. Validation of Visual Attributes

Visual Attribute	**Visual Characteristic**	**Face Validity Test**		**Coding Agent Assessment Ability**				**Inter-Rater Reliability**		
		Academic Score	Professional Score	Microsoft API	Google API	Python	Human Coders	R1	R2	R3
Happiness	Happiness	5.83	5.83	Yes	Yes	No	Yes*	0.80	0.88	0.69
Colorfulness	The Number of Colors	5.00	5.50	Yes	No	Yes	Yes*	0.79	0.77	0.72
	Hue	5.67	5.17	No	No	Yes	Yes			
Vividness	Dominant Foreground Color	5.33	5.33	Yes	No	No	Yes*	N/A	0.62	0.53
	Dominant Background Color	4.33	4.50	Yes	No	No	Yes			
Brightness	Lightness	5.17	6.17	No	No	Yes	Yes*	N/A	0.74	0.51
	Value	4.33	5.67	No	No	Yes	Yes			
Brand Focus	Brand Logo	5.67	6.00	No	Yes	No	Yes			
	Image-Text Integration	5.67	4.33	Yes	Yes	No	Yes*	0.50	0.90	0.66
Size	Image Width	5.17	6.33	Yes	No	Yes	Yes			
	Image Height	4.50	6.17	Yes	No	Yes	Yes			
	Image Area	5.50	5.17	Yes	No	Yes	Yes*	1.00	0.87	0.91

Note: The face validity of visual attributes is tested by academics and professionals. Yes and No are used to denote whether a visual characteristic can be assessed by computer agents and human codes. *Denotes the visual characteristic is selected to code by the two coders. R1 is Scott's pi between computers agents. R2 is Scott's pi between coders. R3 is the Fleiss' kappa across computer agents and coders. N/A is not available due to only one computer agent available.

External Validity

We demonstrate external validity by comparing the company postings with consumer postings. We compare whether the dimensions of visual attributes derived from consumer postings are consistent with company postings.

Table 17 reports the descriptive statistics of mean, standard deviation, and observations of each visual characteristic. The results of customer postings are highly consistent with companies' postings. The results of the extracted visual attributes are in panel B of Table 4. The extracted dimensions are identical to those of companies with similar variance explained and factor loadings. The consistency provides external validity to the method. We concluded that consumer and firm generated images illustrate consistent dimensions of visual attributes.

Table 16. Coding Criteria for Human Coders

Visual Characteristic	**Coding Criteria**
Human Happiness	0: the absence of a smiling face
	1: the presence of a smiling face
	2: the absence of a face in an image
The Number of Colors	0: black and white image
	1: color image
Dominant Foreground Color	0: neutral colors: black, white, grey, brown
	1: warm and cool colors: red, orange, yellow, green, teal, blue, purple, pink
Lightness	0: dull and greyish color
	1: pure and fully saturated color
	2: bright and white color
Image-Text Integration	0: the absence of text in an image
	1: the presence of text in an image
Size	0: small-sized image
	1: large-sized image

Note: Two human coders were trained by the coding guideline. The definition of each visual characteristic and illustrative image examples are provided to help them understand the coding procedure.

Table 17. Descriptive Statistics of Consumer-Generated Images

Visual Attribute	Visual Characteristic	Mean	Standard Deviation	Observations
Color	The Number of Colors	0.869	0.337	6,689
	Dominant Foreground Color	8.401	1.721	6,689
	Dominant Background Color	8.446	1.595	6,689
	Hue	113	67	6,689
	Saturation	0.318	0.205	6,689
	Lightness	0.442	0.171	6,689
	Value	0.510	0.179	6,689
Domain-Specific Object	Image-Text Integration	0.180	0.384	6,689
	Brand Logo	0.006	0.078	6,689
Face	Happiness Emotion	0.427	0.425	1,361
	Sadness Emotion	0.023	0.069	1,361
	Fear Emotion	0.002	0.014	1,361
	Disgust Emotion	0.003	0.013	1,361
	Surprise Emotion	0.026	0.096	1,361
	Anger Emotion	0.008	0.027	1,361
Size	Image Width	922	211	6,689
	Image Height	865	260	6,689
	Image Area	833,607	376,327	6,689
Sharpness	Sharpness	7.973	5.639	6,689

Note: The descriptive statistics of mean, standard deviation, and observations are provided for each visual characteristic.

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VITA

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Her research focuses on digital marketing/social media, big data, crowdfunding by using machine learning and econometric methods. Her papers are published at the Journal of Interactive Marketing. She has presented her papers at the Marketing Science, Winter AMA, AMICS, and Academy of Marketing Science (AMS) conferences. Subrina is also actively engaged in academic activities. She was an American Marketing Association Sheth Doctoral Consortium Fellow in 2017 and an ad hoc reviewer for Summer AMA and AMS conferences. She has taught courses in Marketing Analytics and Marketing Research.