

All Theses and Dissertations

2018-03-01

How Are U.S. Startups Using Instagram? An Application of Taylor's Six-Segment Message Strategy Wheel and Analysis of Image Features, Functions, and Appeals

Robert David Jenkins Brigham Young University

Follow this and additional works at: https://scholarsarchive.byu.edu/etd



Part of the Communication Commons

BYU ScholarsArchive Citation

Jenkins, Robert David, "How Are U.S. Startups Using Instagram? An Application of Taylor's Six-Segment Message Strategy Wheel and Analysis of Image Features, Functions, and Appeals" (2018). All Theses and Dissertations. 6721. https://scholarsarchive.byu.edu/etd/6721

This Thesis is brought to you for free and open access by BYU ScholarsArchive. It has been accepted for inclusion in All Theses and Dissertations by an authorized administrator of BYU ScholarsArchive. For more information, please contact scholarsarchive@byu.edu, ellen amatangelo@byu.edu.

How Are U.S. Startups Using Instagram? An Application of Taylor's Six-Segment

Message Strategy Wheel and Analysis of Image

Features, Functions, and Appeals

Robert David Jenkins

A thesis submitted to the faculty of
Brigham Young University
in partial fulfillment of the requirements for the degree of

Master of Arts

Pamela Brubaker, Chair Kristoffer Boyle Clark Callahan

School of Communications

Brigham Young University

Copyright © 2018 Robert David Jenkins

All Rights Reserved

ABSTRACT

How Are U.S. Startups Using Instagram? An Application of Taylor's Six-Segment Message Strategy Wheel and Analysis of Image Features, Functions, and Appeals

> Robert David Jenkins School of Communications, BYU Master of Arts

Social media and their accompanying smartphone apps have opened brands to consumers in unprecedented ways. Of these sites, none, with the exception of Facebook, are more popular than Instagram, a social networking app that is image-centric and image-driven. As a free platform for potentially reaching, attracting, and engaging with millions of consumers, Instagram offers brands an unprecedented avenue for free advertising—all on a relatively level playing field. This means that brands, even startups, have the same access to potential followers as larger, more established brands. This advertising is more fluid, more frequent, and more inconspicuous than traditional advertisements; e.g., magazine spreads, billboards, or commercials.

To better understand what elements are commonly found in startups image posts on Instagram, as well as to learn if or how those elements translated to engagement, this study employed a content analysis to deconstruct 438 image posts aggregated from the Instagram accounts of ten U.S. startups. Images were coded for salient image features, viral advertising appeals, fundamental image functions, and creative message segments as outlined by Taylor's seminal advertising model, the six-segment message strategy wheel (1999). Likes and comments were recorded during coding in order to measure engagement. Two approaches to analyzing the data were then taken. First, descriptive statistical analyses were applied to the data to determine how frequently elements appeared among startups' image posts. The second approach involved two phases. In Phase 1, crosstabs were conducted to discover what interrelationships exist among these elements. In Phase 2, a qualitative content analysis of the data compiled from the initial content analysis was conducted to determine if certain schema were commonly manifest among posts with high and low engagement in respects to likes and comments. The subsequent findings indicated that object(s) were the most common image feature, informing was the most common function, ration was the most common image function, and humor was the most popular viral advertising appeal, although as a whole, viral advertising appeals were rarely manifest. The qualitative content analyses suggested that more schema negatively affected engagement than schema that positively affected it, though several important themes and base combinations were perceptible among the top 10 percent of posts in relation to engagement.

Keywords: Instagram, startup, social media, images, Taylor's six-segment strategy wheel, viral advertising appeals, visual framing theory, engagement

TABLE OF CONTENTS

TITLE	i
ABSTRACT	ii
TABLE OF CONTENTS	iii
How Are U.S. Startups Using Instagram?	1
Literature Review	3
Social Media	4
Brands on Social Media	6
Defining Startup	7
Instagram	10
Images	12
Visual Framing Theory	14
Image Features	17
Image Function	19
Viral Advertising Appeals	21
Taylor's Six-segment Message Strategy Wheel	22
Engagement	26
Research Questions	28
Method	30
Instagram Image Posts	33
Coding	

Inter-coder Reliability	35
Data Analysis	37
Results	39
Research Question 1: Image Features	39
Research Question 2: Image Functions.	42
Research Question 3: Viral Advertising Appeals	44
Research Question 4: Message Segments	46
Research Question 5: Engagement	48
Phase 1: Crosstabs of various image elements	48
Phase 2: Qualitative content analysis	62
Discussion	65
Opportunity of Variety	65
Current Pitfall of Startups	65
Engagement	67
Broad Appeal vs Concentrated Appeal	68
Viral Advertising Appeals in Instagram	70
Conclusion	71
Limitations and Opportunities for Future Research	73
References	75
Appendices	82
Appendix A	82
Appendix B	84

Appendix C	88
Appendix D	92

How Are U.S. Startups Using Instagram? An Application of Taylor's Six-Segment Message Strategy Wheel and Analysis of Image Features, Functions, and Appeals

Social media and their corresponding smartphone applications (apps) have introduced brands to consumers in unprecedented ways. Such is the case for Instagram, an image-driven social networking site most commonly used as an app on a person's smartphone. It is an app where users can share personal images they have taken—images that capture every facet of human existence. More than ever, images and information about people, places, and things are accessible to historic numbers of people. Instagram not only facilitates this growing accessibility to images and information, it has proven to be a catalyst for shifting people's focus, dramatically increasing the importance people assign to images within communication. This shift, given the sheer number of Instagram users, has already had profound impacts on such areas as culture, human behavior, interpersonal communication, and, as is pertinent to this study, brand and consumer relations.

From an academic standpoint, Instagram has received relatively little attention, especially in comparison to the social network's growth (Casaló, Flavián, & Ibáñez-Sánchez, 2017). It was not until 2014, nearly four years after Instagram was founded, that an introductory examination of its image content and user types emerged (Hu, Manikonda, & Kambhampati, 2014). Since then, several studies have surfaced, forming the slowly expanding body of communication research. A recent 2016 study from Pittman and Reich examined the growth of Instagram among young adults and its impact on loneliness. Other recent studies have examined associations between exposure to "sexy online self-presentations and adolescents' sexual attitudes and behavior" (van Oosten, Peter, & Boot, 2015) and Instagram's overall impact on body image

satisfaction among youth (Ahadzadeh, Sharif, & Ong, 2016). No studies exist, however, that examine brands' use of Instagram as a means of promoting and advertising their brand, products, or services. Several studies do exist that investigate why brands are being drawn to Instagram (Carah & Shaul, 2016), how and why consumers engage with brands on the app (Casaló *et al.*, 2017), and what characteristics are common throughout all Instagram users, brands included (Araújo *et al.*, 2014), but this is among the first empirical investigations to take a multi-faceted, systematic approach to first deconstruct and then examine the content and nature of brands' visual creative messages on Instagram. Further, this is the first study to apply one of the most significant and comprehensive models in advertising from the last two decades of communications research, Taylor's six-segment message strategy wheel (1999), to brands' Instagram posts.

This study first discusses relevant existing literature within the context of social media and brands on social media. It then narrows its focus to a discussion on Instagram, followed by a close examination into images as powerful modes of communication. Visual framing theory is examined as an integral theory surrounding image control and manipulation. The tenets from visual framing theory provide the foundation for understanding how brands take complex messages strategies and condense them into bite-sized posts that convey a simplified and cohesive message: "The key function of...frames is to reduce the complexity of the world, and thereby render it comprehensible and meaningful" (Geise & Baden, 2015). An examination of image composition, image functions, construction of Taylor's six-segment message strategy wheel (1999), common viral advertising appeals as identified by Porter and Golan (2006), and engagement in the context of social media conclude this study's literature review and provide context for its research questions and method.

It is important to reiterate, before delving too far into existing literature, a point originally made by Dr. Taylor (1999), that "the term 'advertising' is often used in conjunction with 'creative strategy'; however, there is no reason to limit the consideration of strategic, promotional communication efforts to advertising." Accordingly, this study employs both the term "advertising" and the phrase "creative message strategies" to denote related yet distinct concepts. The term advertising in this study refers to its most general meaning, that of making something known, "especially by emphasizing desirable qualities so as to arouse a desire to buy or patronize" (Advertise, n.d.). Creative message strategies, on the other hand, refer to the specific relationships a message attempts to establish with the viewer. These message strategies, as Taylor (1999) suggest, should not be limited to traditional advertising efforts. Indeed, it is important to understand that creative message strategies play a key role in understanding how images can operate like basic advertisements on Instagram.

Literature Review

The following literature informs this study by discussing social media, brands use of social media, definition of a startup, Instagram as a whole, and the persuasive power of images. The literature review also addresses visual framing theory, image features, image functions, viral advertising appeals, Taylor's six-segment strategy wheel, and engagement.

Social Media

Consumers and brands are more connected to each other than ever before in history as digital, web-based technologies, channels, and platforms make communication more ubiquitous, convenient, effortless, and seamless with people's daily lives (Pittman & Reich, 2016). Indeed, never before have so many people been connected to so many brands globally than today—and each day surpasses the next. One of the most dramatic revolutions in this growing phenomenon

of human interconnectivity and communication is taking place within social media, whose accessibility and popularity is facilitated by the unparalleled expansion of the Internet. Social media (sometimes referred to as social networking sites, or SNSs) can be broadly defined as websites and smartphone apps that enable users to create accounts, share content, and create social ties (Ellison, Steifield, & Lampe, 2007). These websites and apps, such as Facebook, Twitter, Instagram, YouTube, and SnapChat, allow people to "subscribe," "follow," or "friend" other accounts, whether personal, organizational, or brand accounts, thus creating user-based networks within which each user can engage with the content by "posting," "liking," "sharing," or "commenting" (Haferkamp & Kramer, 2011; Phua, Jin, & Kim, 2017). The content users produce within social media is often referred to as "UGC," or "user-generated content" (Munar & Jacobsen, 2014).

Prior to the emergence of popular social media such as Facebook in 2004, people who used the Internet did so to consume content. They read it, watched it, and used it to "buy products and services; rarely did the average person go online to produce content to disseminate to a large group of people (Kietzmann, Hermkens, McCarthy, & Silvestre, 2011). As noted above, this passive relationship with the Internet has changed dramatically within the past decade with the advent of social media. Social media is not the only factor, however. Another major catalyst for this change has been the advent of smartphones (Carah & Shaul, 2016). Millions of consumers now possess smartphones, which grant them 24/7 access to social media in the form of apps. One age demographic in particular takes advantage of this more so than any other. A 2015 study by the Pew Research Center concluded "fully 91% of smartphone owners ages 18–29 used social networking on their phone at least once over the course of the study period, compared with 55% of those 50 and older" (Smith, 2015). Age is also a key factor in the

frequency and length of someone's social media use (Thayer & Ray, 2006). When it comes to which social networking sites and apps are the most popularity among this demographic, statistics indicate Facebook, Instagram, and Twitter are the most popular, respectively. (Duggan, Ellison, Lampe, Lenhart, & Madden, 2015). If Facebook and Twitter were attractive spaces to brands 2011 for reaching this demographic (Araujo & Neijens, 2011), they and other popular social media are only significantly more so now.

The interconnectivity that social media affords is one of their main features (Boyd, & Ellison, 2007; Munar & Jacobsen, 2014). Even more important than their interconnectivity, however, is their interactivity: "Social media employ mobile and web-based technologies to create highly interactive platforms via which individuals and communities share, co-create, discuss, and modify user-generated content" (Kietzmann et al., 2011). Social media's interactivity represents their major advantage over more traditional media such as television or newspaper, especially for consumers and brands (Phua et al., 2017). Not only does the process of "posting," "liking," "sharing," and "commenting" on UGC perpetuate and extend its reach as it can be continually "rebroadcast" to other networks, but it does so at an accelerated rate and relatively low cost (Phua et al., 2017; Qualman, 2013). As a result, the study of viral advertising, or the study of what makes promotional content instantly popular, among brands to consumers must shift towards social media as its petri dish. Indeed, a relatively recent phenomenon within the last decade is social media's hijacking of the term viral. Where once viral advertising scholars studied email campaigns, they must now examine how brands are using social media to creatively advertise their products and increase their popularity (Golan & Zaidner, 2008; Porter & Golan, 2006).

Brands on Social Media

Brands have been drawn to the Internet since its inception. This is particularly true for those operating in consumer and technology markets, due to the "competitive business environment and needing to solicit feedback to improve products and services" (Perry, Taylor, & Doerfel, 2003). According to Araujo and Neijens (2011), the same holds true for brands on social media, the next frontier of free advertising space. In 2009, approximately 17 percent of the top global brands used social media in some form (Peters & Salazar, 2010). Only two years later, that percentage increased dramatically to 64 percent (Araujo & Neijens, 2011). That percentage only continues to rise as social media use among everyone, brands included, becomes more integrated and integral with brands' communications campaigns (Qualman, 2013): "[D]igital marketers are increasingly incorporating SNSs as an indispensable part of their online brand strategy by raising brand awareness, driving engagement, and increasing conversions for their brands and products (Phua et al., 2017). With that in mind, Araujo and Neijens (2011) looked beyond simple usage of social media and focused on the growing importance of participation with social media. Specifically, they sought to identify which factors compel top global brands to participate. They learned that the "country in which the brand operates plays a significant role in the brand's likelihood of adopting SNSs," with brands in the US being "more likely to use SNSs than other countries" (2011). They also confirmed that the adoption of social networking sites and apps by brands continues to happen globally.

Content on social media is transmitted more quickly and more broadly than most traditional media, and at a much lower cost. Much of social media is free to use (Qualman, 2013). It is no wonder, therefore, that brands are drawn to these platforms as a way of disseminating their creative marketing strategies. This is especially true for new companies, or

startups, that enter industries and markets without much, if any, prior reputation or visible history. More and more, social media are becoming a tool for managers and communications specialists to grow the popularity of their brands, especially as people rely more heavily on social media than ever to reach not only their friends, but also brands (Rapp, Beitelspacher, Grewal, & Hughes, 2013). New and old companies alike can take full advantage of free services that allow for access to millions of potential customers without dedicating much, if any, of their marketing budgets—unlike with traditional advertising (i.e., newspaper ads, billboards, etc). Simply using social media, however, does not guarantee visibility and growth. There are a number of limiting factors. One major limiting factor is often the content being shared. Certain types of content generate more interest and engagement than others (McNely, 2012), and the brand, regardless of whether or not it is new or old, that understands how to compose engaging content will also be able to create an "external image that will stick in the minds of consumers, competitors, and other stakeholders within a given sector" (Faber, 2002). This postulation is fundamental to this research.

Defining Startup

Before continuing the discussion on social media and narrowing the focus to Instagram, it is important to understand that this study set out to learn what elements are prominent in the promotional images startups share on Instagram and how those images translate to, if not directly impact, engagement. Startups are of particular interest because their brand identity and marketing strategies are still in their infancy. A company that is only a few years old has not had sufficient time to develop its marketing strategies in the real world when compared to more established brands. Today's startups are interesting for another reason—they are emerging in a time with access to social media that, as previously discussed, can accelerate access and exposure to

millions of people in ways never before seen. But what is a startup business exactly? Merriam-Webster defines startup as simply a new business. Aside from being a new business, however, very little other qualifications seem to exist. New is a relative term. Can a five-year-old company be considered a startup? Can a 10-year-old company? In her Forbes article, "What is a Startup?" journalist Natalie Robehmed (2013) sought to answer that very question. She acknowledged that the age range for startups is not concrete, simply that they must be comparatively new, but she also looked for other characteristics. She interviewed fourteen founders of new businesses how they define the term startup. A few of their notable responses are highlighted in Table 1.

Table 1

New business founders offer their definitions of the term "startup"

Company	Person	Quote
littleBits	Ayah Bdeir, founder	"I think the first measure for a startup is: Is it something new – a process, a category, a business model, an ecosystem? Now matter what it is, it has to have not existed before[A] startup is always significantly resource constrained. Meaning it is trying to do way more than what it can afford, and that makes it have to be creative."
Venmo	Iqram Magdom-Ismail	"A startup is a group of people working towards a common goal, generally with limited time."
InteraXon	Ariel Garten, cofounder	"You know you are a startup when you are a small, high growth company based on a big idea. Often, this big idea centers around tech, and is disruptive which attracts visionary investors."
Homejoy	Adora Cheung, cofounder	"Startup is a state of mind. It's when people join your company and are still making the explicit decision to forgo stability in exchange for the promise of tremendous growth and the excitement of making immediate impact."
BaubleBar	Daniella Yacobovsky, cofounder	"There obviously isn't a formula [for what makes a startup], but it's some combination of how long you've been operating and how much of your business model you're still proving out. As an unproven brand/concept/business model, your life is dictated by answering all of those questions you had when you first started – will people buy my product? Can I convince the right talent to join me in building this company?"

From these answers and others, several perceptible themes emerge, including the notions of "newness," "rapid growth," "innovation," and "disruption" (Robehmed, 2013). For the sake of this study, the term startup will be applied to new companies, as identified by industry experts, that are attempting to either disrupt existing industries or create new ones, especially within the highly competitive emerging digital technology industries where social media are commonly integrated.

Instagram

Instagram is a unique social media app. It is more image-driven and visual-based than most, if not all, other social media: "Instagram, combined with the smartphone on which it runs, is an image machine that stimulates and captures the productive activity of producing, circulating, and attending to images" (Carah & Shaul, 2016). Instagram was released in October of 2010 and has accrued more than 150 million registered users since (Hu *et al.*, 2014). The most recent statistics from a Pew Research survey of 1,520 adults, conducted from March 7 to April 4, 2016, reveal that 32 percent of adults who are online use Instagram. When the total population is factored in, excluding the relatively few who do not use the Internet, Pew found that 28 percent of all adults in the United States who are online use Instagram (Greenwood, Perrin, & Duggan, 2016). Instagram is particularly popular among younger adults, who comprise the largest age demographic: "Roughly six-in-ten online adults ages 18-29 (59%) use Instagram, nearly double the share among 30- to 49-year-olds (33%) and more than seven times the share among those 65 and older (8%)" (Greenwood *et al.*, 2016).

The emergence of Instagram has played a considerable role in the democratization of content. Similar to many social networks, including Twitter, Instagram relies on its users to create profiles and generate content. At the forefront of this content are images, typically

photographs uploaded directly from one's smartphone. Instagram offers users built-in filters to manipulate and transform the images they post, and profile pages, whether for individuals, organizations, or brands, contain very little text (Carah & Shaul, 2016). For example, Instagram "bios," where a person can include a textual description of him or herself, are limited to 150 characters. Each image allows for an accompanying caption, although the caption is placed below the image. When the image is viewed in a user's stream of the most recent images (and videos) posted by the people he or she follows, only a few lines of the caption shows. In addition, a user is allowed to post an original image to Instagram without a caption, but he is she is not allowed to post original text without an image, unless it is a comment on another person's image (Hu *et al.*, 2014). This underscores Instagram's partiality to the visual over the textual.

It is important to note that Instagram is asymmetric by design. This means that if a user A "follows" user B, user B is not required to "follow" user A (Hu et al., 2014). This allows for users to accumulate millions in followers while never having to follow others. For example, a brand can accumulate one million followers while in turn only following a few people. Such is the case for celebrities, famous athletes, politicians, personalities, models, corporate executives, religious leaders and anyone else who has an account on the app. Users accounts are public by default, which means anyone who also uses the site or app can find their profile and follow them. Although, users are allowed to decide their privacy settings, and they can arrange to approve each follow request another user submits. Until the follow request is approved, the user who submitted the request is unable to see the images and captions posted by the user he or she desires to follow. Independent of followers and the followed, all images that visible to a particular user allow for him or her to "like" them and comment. Users can also use hashtags (#) in comments, as well as tag and mention others users by using their username, which is preceded

by the @ symbol. A log of a user's activity is kept within the app, as well the activity of others who interact with the user's posts (Hu *et al.*, 2014).

Despite Instagram's popularity and the fact that it has existed in much the same form since October 2010, it was not until 2014 that significant research into Instagram began appearing. A study conducted in 2014 by Hu, Manikonda, and Kambhampati, who at the time recognized that relatively "little research has been focused on Instagram," sought to lay the groundwork for understanding user activities on the platform: "To the best of our knowledge, we believe this is the first paper to conduct a deep analysis of photo content and user activities and types on Instagram" (Hu et al., 2014). They sought to learn what types of photos and videos people usually post on Instagram, what differences exist between users, and how those differences between users' photos relate to other user characteristics, such as the number of followers. Their analysis contributed in two substantial ways: (a) by characterizing the content of photos shared on Instagram, and (b), examining "how the content of photos is related to user types and characteristics" (Hu et al., 2014). They were even able to answer the question of what types of images are most commonly posted to Instagram: ones that include friends and "selfies," or images taken by the user of him or herself (Hu et al., 2014). It is worth noting that a similar study conducted that same year discovered that those same types of images, namely pictures containing the faces of people, are 38 percent "more likely to receive a 'like' and 32 percent more likely to receive a comment than those without" (Bakhshi, Shamma, & Gilbert, 2014).

Images

Instagram's popularity and wealth stems from its most abundant currency—images.

Images are a powerful medium in communication, and understanding an image from a visual standpoint is imperative to understanding Instagram's impact on brands' creative strategies for

growth on the app. A common maxim used both colloquially and even recently in research is that an image is worth a thousand words (Pittman & Reich, 2016; Hum et al., 2011). Images act as visual text, provide social communication, and "construct literal social space within and between frames and fields of which they're made" (Hartley, 1992). Images are "social, visual, spatial" and *always* communicative (Hartley's language in the 1992 study implies that images, specifically pictures, are sometimes communicative). While one can argue that not all images communicate messages of the same value (if we are to extend the currency metaphor further), an image "has only one language and is destined potentially for all" (Sontag, 2003). This language is one comprised of visual elements: colors, shapes, lighting, position, location, scope, frame, angle, depth, and more. These visual elements in turn act as "modes of communication" (Rodriguez & Dimitrova, 2011) that either "enhance or mitigate" the affect of the message being communicated (Messaris & Abraham, 2001). What makes an image so powerful as a visual mode of communication is that its language is a universal one: "Pictures speak a universal language and tell a news story in one frame" (Sontag, 2003). When paired with text, an image, whose message or messages can be communicated and processed much faster than lines of text that, has the capacity to overpower and override the text (Wischmann, 1987). This is the case with Instagram, where images are given greater emphasis and prominence than any other content: i.e., the optional caption located beneath the image.

Not only does Instagram place a greater emphasis on images, but evidence also suggests that images can be and often are more persuasive modes of communicating than text. A couple of key factors contribute to this. One factor is that an image is "sensory-specific because it is linked to the visual modality" (Pittman, & Reich, 2016). Compare this to a mental model that must rely on text. Pittman and Reich (2016) provide the example of someone using only text to

describe his or her vacation on the beach. This could invoke a mental model, a "mental picture" if we are to use the colloquial phrase, of the beach, but in regards to detail and vividness, it would pale in comparison to an actual picture of the beach. A mental model is able to integrate information from the different sensory modalities (i.e., visual, auditory, touch, taste, and smell), making it possible to construct spatial configurations. Nonetheless, it is still more "abstract" than an image (Schnotz, 2005).

The second factor is outlined in the MAIN model under the "realism heuristic," which "immediately determines that a photograph of something is inherently more real than text written about the same thing" (Sundar, 2008; Pittman, & Reich, 2016). Humans trust the visual modality more than the abstract mental model they must construct from text: "that is, we trust those things that we can see over those that we merely read about" (Sundar, 2008). Indeed, it is a principal supposition of the MAIN model "that our brains implicitly trust visual modalities such as images and video more than text," primarily because they trigger the aforementioned realism heuristic (Pittman, & Reich, 2016). The danger in this is apparent. People are placing great trust in images, believing they cannot lie. This leaves them susceptible to the manipulation of their perceptions, as images are easily manipulated. This power of images to not only communicate but also persuade underscores the value of examining Instagram as an image-driven app.

Visual Framing Theory

While images are more persuasive modes of communication than text, even images are limited. This is true for all images, including those on Instagram. Images can only capture a relatively small portion of a 360-degree environment in a frame. Consequently, each image unavoidably omits important elements in the photographer's overall narrative. More importantly, the photographer, or the person capturing the picture, has the power to manipulate what

messages are conveyed and how by the conscious inclusion, omission, or emphasis of specific elements.

One theory in particular provides the optimal framework for better understanding the implications of this control over the inclusion, omission, or emphasis of elements depicted in each image: visual framing theory. Visual framing theory provides an understanding of what factors actually contribute to that manipulation. Visual framing theory is an important branch of framing theory, which examines the process of "selecting some aspects of a perceived reality and make them more salient in a communicating text, in such a way as to promote a particular problem definition, causal interpretation, moral evaluation, and/or treatment recommendation" (p.52). Framing, therefore, is a communicative process that relies on "selection and salience" (Entman, 1993). It is commonly defined as a cognitive process with major implications in news media and journalism, where "certain words or phrases in a news message can lead to certain political preferences" and influence "how the public interprets and processes news reports" (Cappella & Jamieson, 1996; Scheufele, 1999; Hertog & McLeod, 2003; Druckman, 2004; Evans, 2010).

If framing is the process of selecting specific aspects of a reality in order to make them more salient, then a frame can be defined as the final product or selection of those aspects, providing the perimeters for the messages communicated within it via its elements. Gamson, Croteau, Hoynes, and Sasson explained how frames can diagnose, evaluate, and prescribe (1992). Entman (1993) further detailed how frames serve multiple functions. He outlined four key ones: a) Frames can define problems by determining what a causal agent is doing with what costs and benefits, usually measured in terms of common cultural values"; b) they can diagnose causes by identifying "the forces creating the problem"; c) they can also make moral judgments

by evaluating "causal agents and their effects"; and d) they can suggest remedies by offering and justifying "treatments for the problems and predict their likely effects" (Entman, 1993). It is important to note that Entman argued for discretion when searching for and identifying frames. He argued that a sentence in a text "may perform more than one of these four framing functions," but that "many sentences in a text may perform none of them" (Entman, 1993).

Much of Entman's seminal work focused on framing through text, and his emphasis on its implications on new media, where a "certain reality is perceived by the public which could lead to a biased view upon the world's current events," spawned further research interested in text-based news media framing (1991; Evans, 2010). Entman himself, however, acknowledged early on in his research that "frames can be detected by probing for particular words and visual images" (1991).

Similar to framing theory, what research that does exist on visual framing theory is commonly applied to journalism. Remember the line from Sontag: "Pictures speak a universal language and tell a news story in one frame" (2003). Studying visual framing theory in the context of other arenas of communication, however, "provides an important new direction for theory building and future research," especially considering the growing popularity of Instagram and other social networking sites and apps that rely heavily on user-generated images and videos (Coleman, 2010). The theory's importance is magnified, too, when one examines the growing number of framing studies only to realize that "the tenets of framing theory have been applied mainly to analyzing texts" (Rodriguez & Dimitrova, 2011). This has consequently left the question of how narratives, issues, and events are presented and framed through the use of images, whether standing alone or accompanied by text, relatively untouched and under-

developed (Bell, 2001). If that was the case prior to the rise of Instagram and other popular social media networks, it is certainly the case now.

Though this analysis of visual framing theory seems to focus on the limitations of images, this limitation, when understood, is integral to this study. Indeed, this study relies on visual framing theory as foundational for its approach to analyzing its sample of images. Specifically, this study focuses on the salient aspects of an image because it maintains the assumption that images framed on Instagram, like any image, "reduce the complexity of available information by discriminating between relevant and irrelevant information based on a comprehensible 'central organizing idea'" (Gamson & Modigliani, 1987; Entman, 1993). Therefore, it stands that elements of an image were, to some degree, intentionally selected and thus irrefutably relevant.

Image Features

This study focuses on a number of salient elements in an image to better understand the messages meant to be garnered from startup's image posts on Instagram. Included in these elements are image features, which range from objects to location to people. In their 2014 study, Hu, Manikonda, and Kambhampati identified the most salient image features that were common in images posted on Instagram. They found "that Instagram photos can be roughly categorized into eight types based on their content: self-portraits, friends, activities, captioned photos (pictures with embedded text), food, objects, fashion, and pets, where the first six types are much more popular." To identify these types of contents, or features, the researchers collected a random sample of photos from random users displayed on Instagram's public time, a feature showing which media was most popular at that time. From these users, who were mostly celebrities, the accounts of their followers and followees were mined to form a list of 95,343

users. From this list, a random sample of 50 users was created that featured only regular and active Instagram users whose accounts were also public. From each user, 20 image posts were selected, making the total sample of image posts 1,000. Once the sample was collected, the researchers employed the use of computer vision techniques, namely the Scale Invariant Feature Transform (SIFT) algorithm, "to detect and extract local discriminative features from the photos in the sample" (Hu *et al.*, 2014). Through this process, the researchers were able to identify numerous codebook vectors, from which they, using "k-means clustering," were able "to obtain 15 clusters of photos where the similarity between two photos are calculated in terms of Euclidean distance between their codebook vectors" (Hu *et al.*, 2014). Lastly, this process was refined with two human coders who were either able to group each photo into a distinct group or combine groups. The result was the eight-category coding scheme previously outlined: self-portraits, friends, activities, pictures with embedded text, food, objects, fashion, and pets.

This study adopted their research but also added two key categories identified by the researcher during preliminary reviews of images on Instagram: *location* and *graphic*. For this study, however, some of the language and terms were modified. For example, *self-portrait* was broadened slightly to include the presence of a single person, regardless of whether or not it was exclusively a self-portrait. The presence of body parts signifying the presence of a person was classified in this group. Likewise, what Hu *et al.* (2014) termed friends, this study term termed *multiple people* to included groups of people that may or may not be friends. *Food* was left unchanged, as were *pets* and *object(s)*. However, the researcher would like to clarify that for the sake of this study, *object(s)* included any single or multiple man-made objects or gadgets other than buildings and similar structures. In other words, the term *object(s)* included but was not limited to furniture, vehicles, gadgets, signs, bags, sports equipment, silverware, flatware, and

art. The term text encompassed any text that was embedded, emphasized, or superimposed on an image so that it became a part of the image. For this study, only legible text that was clearly intended to be read was classified as a feature. Activity was harder to consistently distinguish, but it encompassed one or multiple actors, whether people, animals, or some other personified agent, performing some sort of action. This included activities like hiking, camping, gaming, texting, talking, painting, running, reading, and a myriad of others. Fashion represented the emphasis of clothes in the light of fashion and was applied to clothes or accessories that were either being worn or displayed in such a way as to convey a sense of fashion. It is worth noting that fashion was not considered a relevant feature simply because someone was wearing clothes. Again the emphasis had to be on the clothes or accessories as desirable fashion items. Location typically included such destinations as cityscapes and landscapes that were captured within the frame of the image, although it also included indoor spaces such as home interiors, museums, libraries, or retail spaces. Similar to fashion, the emphasis had to be on the space as a whole and was not considered simply because the image highlighted other features that existed within a setting or space. Lastly, the term *graphic* signified any digitally created features either embedded or superimposed on the image. These artificial features included logos, digitally altered backgrounds, animated characters, and borders.

Image Function

An image's meaning and overriding message is not solely determined by the elements framed within, however salient they are. Rather, an image's meaning is also determined by the salient relationships of elements to each other. This is particularly true for advertising, where brands are striving to create cogent, compelling messages that connect with viewers. According to Porter and Golan (2006), an ad, whether a digital ad or television ad, can have one of several

functions: *branding*, *calling-to-action*, or *informing*. Golan and Zaidner (2008) later sought out these same functions in their study of creative strategies in viral advertising when they analyzed 360 images based on a number of questions, including, "Was the ad's primary purpose branding, Call-to-action or to provide information about the product or service?" For images on Instagram that function like ads, these same functions apply. As a result, this study designates these functions as "image functions" rather than ad functions.

In a separate study, McNely (2012), found that brands' images, particularly those shared on Instagram, commonly display characteristics of what he described as six image functions or processes categories: i.e., orienting, humanizing, interacting, place-making, showcasing, and crowdsourcing. The similarities are evident. For example, what McNely termed orienting and place-making, Porter and Golan (2006) termed branding. For this study, the use of the term branding is used synonymously with orienting and refers to the use of external artifacts or landmarks that act "a pivot related to organizational image (McNely, 2012). For example, a product displayed on a basketball court brands it as "sporty" or "athletic" while a product displayed in the mountains brands it as "outdoorsy" and/or "rugged." Similarly, interacting and crowdsourcing correspond to calls-to-action. In concert with other studies, this study defines a call-to-action as an explicit solicitation of a response from the viewer, whether in the form of liking, commenting, or performing some other specified action (e.g., "Visit us" or "Go to") (Golan & Zaidner, 2008). The term *showcasing* denotes the display or demonstration of a product or service and corresponds with Golan and Zaidner's (2008) informational ad function informing, which this study has adopted. Informing is just that—it describes the act of providing information about a product or service. Indeed, only humanizing is a function not explicitly identified or employed by Golan, Porter, and Zaidner (2006; 2008). For reference, humanizing

denotes the act or process an ad performs to transform the brand into something much more human, thereby making it more relatable, amenable, and approachable. This is often accomplished by featuring a spokesperson or by highlighting employees, although it can be accomplished just as easily by using other people or other elements that are expressly human. Essentially, *humanizing* designates the function by which a brand seeks to assign a personality and a face to its name (McNely, 2012).

For the sake of this study, a combination of these researchers' functions was considered for a total of four image functions: *branding* (*orienting* and *place-making*), *call-to-action* (*interacting* and *crowdsourcing*), *informing* (showcasing), and *humanizing*.

Viral Advertising Appeals

Porter and Golan's (2006) study was also one of the first to analyzing viral email advertising campaigns. In the study, they defined viral advertising as "unpaid peer-to-peer communication of provocative content originating from an identified sponsor using the Internet to persuade or influence an audience to pass along the content to others" (Porter & Golan, 2006). In short, viral advertising pertains to Internet based content that becomes popular. As a result of that same study, which examined 501 advertisements and 250 viral ads, they concluded that viral advertisements usually contain at least one of the following "meme" factors (Dawkins, 1967), which they labeled as advertising appeals: *sex*, *nudity*, *violence*, *humor*, *animals*, *children*, and *animation* (Porter & Golan, 2006).

As has already been established, social media has hijacked the notion of viral advertising to where the phrase almost exclusively pertains to content shared and re-shared via social media sites and apps. Regardless, it follows that while social media have enhanced contents ability to become popular by fostering it in a highly populated and connected network, they have not

changed the nature of those advertising appeals. In other words, it is understood that while the mediums may have changed, the principles, or rather the elements, of advertising that may propel promotional content to virality have not changed. Therefore, this study prescribes to those appeals and considers them essential elements in brands' images on Instagram in order to better understand how those brands, particularly startups, craft visually appealing images to advertise themselves, their products, and their services on Instagram. For the sake of this study, however, sex and nudity were combined into one term, sexuality. Animation was also excluded as an element characteristic of video advertisements.

Taylor's Six-segment Message Strategy Wheel

In 1999, advertising scholar Ronald Taylor introduced his six-segment strategy wheel. According to Taylor, his model "draws from the theoretical work of James Carey and John Dewey, from Kotler's summary of social science literature, from Vaughn's FCB Grid, from Frazer's creative strategy summary, and from Laskey, Day, and Crask's typology of main message strategies" (1999). However, his model "is more comprehensive than any currently published in the literature, and it is able to subsume" those existing theoretical works (Taylor, 1999). For this reason, the follow discussion will focus specifically on Taylor's model and how it applies to brands' creative messaging strategies, and it will not attempt to delineate its complex lineage of origination.

Taylor's model is comprised of two levels. The first level identifies two general, macrocosmic views of creative message strategies: the transmission view and the ritual view. The transmission view encapsulates the types of messages that can be classified or perceived as informational and appealing "to one's cognition or logic," while the ritual view, on the other hand, encapsulates the message's emotional or sensory appeals (Golan & Zaidner, 2008). Taylor

himself put it simply when he wrote, "Under a transmission view, news is information; under a ritual view, news is drama that portrays an arena of dramatic forces and action" (1999). He envisioned the transmission view and ritual view as two halves of a circle, or wheel, and the two are often represented as such (see Figure 2.1).

The second level to Taylor's model is a more specific, microcosmic perspective where each side of the wheel, the transmission view and the ritual view, are composed of three individual segments, making six segments in total. Ration, acute need, and routine segments comprise the transmission view, while ego, social, and sensory segments comprise the ritual view (see Figure 2.2). It is important to note that the terms "strategy" and "segment" are often interchangeable in this context. This is because each of the segments identified and developed by Dr. Taylor represent messages that attempt to strategically connect with viewers. In other words, one can analyze advertisements and other creative messages brands disseminate by the type of relationship the messages purposefully seek to establish with the viewer. For further clarity, each segment is detailed below.

Ration (transmission view): Messages that appeal to a consumer's need for information (Golan & Zaidner, 2008). In this segment, the role of messages is to not only inform but also persuade, as consumers are to be considered "rational, conscious, calculating, deliberative individuals" (Taylor, 1999).

Acute Need *(transmission view):* Messages that appeal to the immediate situations of a consumer and the subsequent needs: e.g., guests stop by unannounced for dinner and you need to order food. In this segment, the role of messages is to create brand recognition so that when consumers are limited by time and information and in immediate need of a product or service, they will choose the one with which they are the most familiar (Taylor, 1999).

Routine (transmission view): In this segment, messages appeal to the consumers' habitual needs by emphasizing how a certain product or service fits in with his or her routine. Once a consumer is using that product and service as part of his or her routine, messages are designed to reinforce and perpetuate the behavior. Factors such as convenience and usability are common themes (Taylor, 1999). Messages designed to sell products such as cleaning supplies or other household items often focus on their fit within a consumer's routine (Golan & Zaidner, 2008).

Ego (*ritual view*): The ego segment is characterized by messages that target a consumer's emotional needs, as well as his or her identity. Messages are commonly constructed around the idea of how the product or service, or more importantly, the brand, makes them look. In other words, the messages reinforce the relationship of the brand with the consumer's identity (Taylor, 1999). Luxury items are commonly advertised with ego-laden messages (Golan & Zaidner, 2008).

Social (*ritual view*): Similar to the ego segment, the social segment is characterized by messages that target a consumer's emotional needs, but only as it pertains to that consumer's need to be noticed or gain social approval: "The role of advertising is to create the appropriate social situation within the advertising that motivates the consumer and thus transforms the product into the appropriate emotion such as love, affection, affiliation, noticing, or admiration" (Taylor, 1999).

Sensory (*ritual view*): As its name suggests, the sensory segment is characterized by messages that attempt to communicate how a product, service, and/or relationship with a brand "produce sensory pleasure." These message appeal to any or all of consumers' fives senses: taste, sight, hearing, touch, and smell (Taylor, 1999).

Figure 1

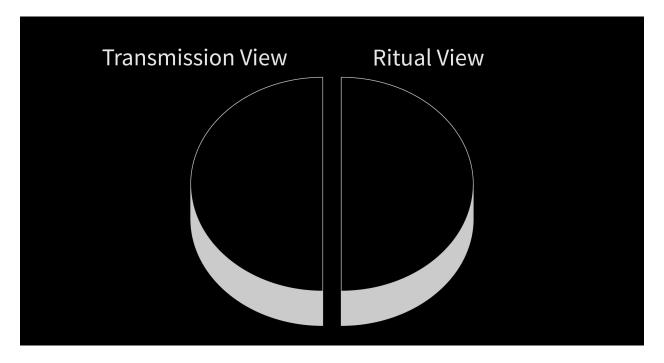
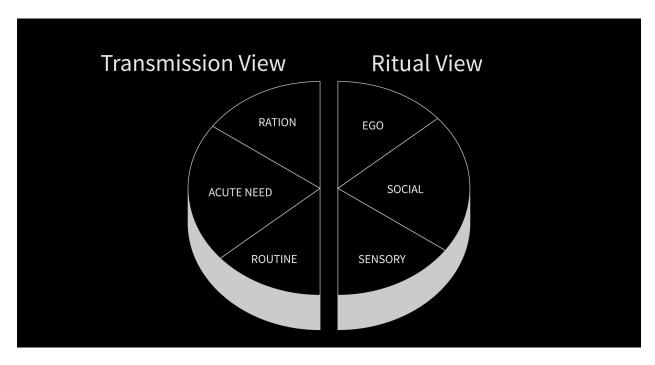


Figure 2



Engagement

Consumers are active on social media and because they are "motivated to join brand communities to fulfill their social and identification needs" (Phua *et al.*, 2017). Simply, people generally seek out content that is congruent with their attitudes and behavior. Conversely, they generally avoid content that is incongruent with their attitudes and behavior (van Oosten *et al.*, 2015). Research, therefore, validates this ostensibly intuitive principle, that the majority of people who follow brands on social media are genuinely interested in those brands. Even further, it validates the assumption that images posted by brands must be congruent in large degree with their followers' own perceptions of the brand. Otherwise there would be no reason to follow the brand's account.

The number of followers an account has certainly speaks to its broad popularity, but engagement goes well beyond followers. As previously outlined, Instagram allows users to "like" a post by tapping twice on the image. A "like" is limited to one user. Users can also leave a brief comment that is attachment to the post, and unlike "likes," a single user can leave multiple comments. Users can also "tag" other users in the comments by using their handles, which notifies them. Both likes and comments are recorded and attached to the post for others to see, meaning how many likes and/or comments a post received is public information (Hu *et al.*, 2014). More importantly, likes and comments provide quantifiable metrics for brands to measure how well a post is received (Coelho, Santos de Oliveira, & Severo de Almeida, 2016; Peters, Chen, Kaplan, Ognibeni, & Pauwels, 2013). Further, posts that garner numerous likes and comments are more likely to be promoted by Instagram due to its feed algorithm. This means posts that receive numerous likes and comments have a greater likelihood of being seen by others, including those not following the profile of the user who posted (Coelho *et al.*, 2016).

This particular notion of engagement is unique to the online world, especially within social media. Again, likes and comments provide built-in and quantifiable metrics for how well any piece of content, whether text, an image, or a video, is received. This is why engagement has become a buzzword in recent years in the world of advertising and online marketing where professionals are obsessed with maximizing the efficacy of the content they create and share. That said, there is some controversy over the challenges the academic community faces in best measuring engagement, sometimes referred to as "interaction," not only on Instagram but also all of social media. (Coelho et al., 2016; Weller, 2015). Numerous metrics exist (Peters et al., 2013). To measure the impact certain image features and message elements have on the success of an image post shared by a startup on Instagram, this study adopted a straightforward approach by measuring engagement in terms of likes (like engagement) and comments (comment engagement). Not only is this the simplest approach, it is also the easiest to replicate for future research because it involves uniform, quantifiable data readily available to all researchers. Additionally, it is worth noting that instead of combining the two to create one metric (e.g., 10 likes plus 3 comments would equal an engagement score of 13), this study has kept each metric separate. This is based on the fact that the two metrics require different actions from those viewing the content. A like requires a quick double-tap and nothing more. On the other hand, leaving a comment on an image requires more time and effort on behalf of the viewer. Indubitably, the two actions require slightly different motivations and incentives for acting, with liking ostensibly being more popular than commenting because it requires less time and effort. In short, each metric has unique value, and this study seeks to preserve that value in its representation of the data.

Research Questions

There are two main purposes to this study. The first purpose is to learn what types of elements, from image features to functions to message strategies, are common among startups' posts on Instagram. The second purpose is to understand if certain thematic combinations of these elements, or schema, are tied to higher rates of engagement as measured by likes and comments. These two purposes provide the foundation for five key research questions.

Before addressing these research questions, however, it is important to reiterate several crucial assertions drawn from existing literature. First, it is evident from an examination of visual framing theory that how an image is framed (i.e., what is included, its position, and other subtle factors) serves to highlight important features and hone in on a certain message. This study relies on the salience of elements within an image, asserting that if they are salient, they are the most important elements in the image. Second, this study posits that the act of a brand posting an image to Instagram qualifies as advertising in that the brand is using the image strategically to promote products, services, or brand qualities that it sees as beneficial to its business and/or central to its brand image. Third, this study accepts that, using established and proven processes and models, images can be deconstructed into the individual elements discussed previously. Fourth, this study asserts that the engagement a post garners in the forms of likes and comments is affected, if not entirely then at least mostly, by the appeal of the images elements to those who view it.

This study has focused its scope on U.S. startups with multi-million dollar capital investments for a couple of reasons. Test startups, especially ones with large capital investments, are ideal test subjects because they have the most to lose financially if they do not adequately advertise their brand and products. Recent tech startups are ideal for another reason, though: their

birth within the modern tech industry suggests a proclivity to use digital social media like Instagram, or, if not a proclivity, then at the very least a familiarity with digital social media. This is especially true for those startups that rely on mobile apps or digital interfacing to both interact with current customers and attract new ones. As a result, they are more inclined to use Instagram, given its popularity among mobile users, in their overriding creative message strategies.

The five key research questions that dictated the execution of this study are as follows:

- RQ1: What image features are used in startups' Instagram image posts?
- RQ2: Are there differences in the image functions used in startups' Instagram posts: *branding*, *call-to-action*, *informing*, or *humanizing*?
- RQ3: What viral advertising appeals (i.e., *sexuality*, *humor*, *violence*, *children*, and *animation*) are used in startups' Instagram posts?
- RQ4: Are there differences in the message strategies used in startups' Instagram posts: *ration*, *acute need*, *routine*, *ego*, *social*, *sensory*?
- RQ5: Are there set combinations, or schema, of image features, ad functions, appeals and messages strategies that are common among posts that received high engagement and posts that received low engagement in respect to likes and comments?

Method

To systematically answer these research questions, this study employed a content analysis to identify and categorize the elements of visual composition and message conveyance of Instagram posts shared by startups companies on their respective Instagram accounts. The images examined consisted of those shared from 10 separate, U.S. startups. These startups were selected from a total of 73 startups that were initially compiled from three distinct lists of startups recognized by news media in 2017. These startups reflected a convenience sample aggregated from these lists which appeared in articles published by three leading business- and economic-oriented news sites: Business Insider, Bloomberg, and Forbes. These articles are titled "18 of the hottest under-the-radar startups to watch in 2017," "These Are the 50 Most Promising Startups You've Never Heard Of," and "These Are The Startups You should Watch In 2017," respectively (Hartman, 2017; Huet, 2017; Armstrong, 2017). Aside from the clout and prominence Business Insider, Bloomberg, and Forbes carry within the business industry, these articles identified startups based on several key factors. The journalists who compiled the lists consulted investors and experts, focusing on startups that were well-funding and showing promise outside of the tech hatcheries known as Silicon Valley (San Jose, California) and Silicon Allies (New York, New York) (Hartman, 2017). All 73 startups began with multi-million dollar capital investments. Huet (2017) based her list on market research from Quid, a market research platform that identified startups – all founded in the past six years – that "have been raising money at an impressive clip—typically once every nine months, suggesting heavy interest among investors." Armstrong (2017) identified promising U.S. startups based on his extensive industry experience as a business adviser and author on disruptive technologies and startups.

Substantial investments and mentions in prominent publications suggested these startups are under considerable pressure to succeed. For those startups built around selling products or services to consumers (B-to-C), this implies growing their national consumer bases. The fact that these startups are well-funded yet still "under-the-radar" (Hartman, 2017) or unheard of indicates they both have the financial capability to hire communications personnel to manage their social media and the need to implement some sort of strategic marketing plan in order to continue growing their consumer base. As a free and readily accessible social media app, Instagram offers unparalleled reach among millions of people, especially within the United States—the kind of reach of which communications personnel would be negligent not to take advantage. This is reflected in the sample, which was condensed by selecting B-to-C startups over those that primarily sell products or services to other businesses (B-to-B). Focusing exclusively on startups based in the U.S. that own and maintain Instagram accounts condensed the sample further. Lastly, this study focused on startups selling products or services in, on, or pertinent to digital technologies. The remaining 10 startups, in fact, either operate entirely as an app or offer complementary apps that are instrumental with consumer interaction. This is important because it suggests each startup has if not a proclivity than at least a familiarity with social media apps like Instagram.

Each account was found and verified as belonging to its respective startup by visiting each startup's official website, locating its listed social media accounts, and opening the Instagram account using the Instagram icon. The startups used for this study, as well their account handle and other basic account information, are listed in Table 2.

Table 2
Startups and their Instagram accounts, number of posts, followers, and first post date

Startup	Intagram Handle	Posts	Followers	First Post
Hudl	@hudl	7	101,000	March 10, 2014
Starry	@starryinternet	30	762	January 27, 2016
Nowait	@nowaitapp	1	542	July 8, 2016
Bellhops	@bellhopsmoving	65	3,257	May 13, 2014
OfferUp	@offerup	149	628,000	May 3, 2017
Simple	@simple	126	13,700	March 22, 2014
Lola	@lolatravel	1	487	June 26, 2016
Instamotor	@instamotorofficial	10	967	January 22, 2015
NewStore	@newstoreinc	24	231	October 1, 2015
Look App	@looklivecam	25	970	July 17, 2016

Note. Posts indicate the total number of posts from January 1, 2017, to December 31, 2017. Followers represent the total number of followers as recorded on December 31, 2017. Also, it is important to know when the number of followers exceeds 9,999, Instagram rounds the number to the nearest hundred. Followings in the hundreds of thousands are rounded to the nearest thousand, and followings in the millions are rounded to the nearest hundred thousand. For example, a following of 10,503 would be rounded to 10,500 and would be displayed as 10.5k (k signifying thousands). A following of 161,099 would be displayed as 161k. This makes it almost impossible to know the exact number of followers for those accounts with large followings and is the reason why several of the followings of startups listed above are rounded to either the nearest hundred or thousand.

Instagram Image Posts

Because each of these startups was identified at the beginning of 2017 as a promising yet relatively unknown startup to watch for 2017, the researcher was most interested in examining the image posts from each of the above listed startups during that year. Excluding videos, a sample of 438 Instagram image posts were compiled from the startup's posts for 2017 (January 1, 2017, to December 31, 2017), providing a sufficient sample to test the research questions (compare to Golan and Zaidner's 2008 study sample of 360 viral advertisements). Instagram allows for multiple images to be posted at one time as a slideshow; however, for the sake of this study, only the first image, visible first in the feed and on the brand's profile, was collected and coded. Coding of these Instagram posts focused exclusively on the content framed within the image, meaning any text in the caption or otherwise separate from the image was not considered. This was done in order to better understand an image's initial and immediate efficacy from a viewer standpoint.

Coding

To gather the necessary data, the researcher first compiled screenshots of each startup's Instagram image posts that were posted between the dates of January 1, 2017, and December 31, 2017. The total, as mentioned previously, was 438 image posts from the ten startups. The screenshots were inserted into a shareable document and numbered 1-438, with headings designating which startup the screenshot belonged to. Images from the startups were grouped together for the sake of organization and data analysis. Using the survey and analytics service Qualtrics, a private survey of ten questions (see Appendix B) was created mirroring the Coding Sheet (see Appendix A). Once inter-coder reliability was established, Coder 1 and Coder 2 were given access to the digital survey to conveniently and quickly code the sample. When the coders

were given access, a total of 199 posts were assigned to Coder 1 and 239 posts were assigned to Coder 2. For the 44 images coded as a test sample, the data from Coder 1 was chosen and the 44 images were integrated into Coder 1's total sample of 199, meaning that once inter-coder reliability was established with the sample of 44, Coder 1 was only expected to code 155 additional images. A more detailed explanation of the coding process each coder was instructed to follow is included below.

During the coding process, the coder first identified him or herself and the startup to which the image belonged. The image post was then coded for salient image features (RQ1) using those identified by Hu et al. (2014). These features, which were modified slightly for the sake of clarity and operationalization, included the presence of a single person, multiple people, food, objects, text, pets, activities, and fashion. Destination and graphics were added as amendments based on a preliminary review of Instagram posts to make the list more comprehensive and complete. Next, coders recorded an image's function (RQ2) based on a combination and adaptation of two existing scales used in other studies: branding, calls-toaction, informing, and humanizing (Golan & Zaidner, 2008; McNely, 2012). To review, branding refers to the use of external artifacts or landmarks that act "a pivot related to organizational image" (McNely, 2012). A call-to-action is an explicit solicitation of a response, whether in the form of liking, commenting, or performing some other specified action (e.g., "Visit us" or "Go to") (Golan & Zaidner, 2008). *Informing* is just that—informing or educating the viewer about some aspect of the brand, product(s), and/or services. *Humanizing* is a function designed to make the brand more relatable by making it seem more human. This is often done by featuring a spokesperson or highlighting employees, essentially giving a face to the name (McNely, 2012).

Next, the coders employed the techniques used to by Golan and Zaidner's (2008) seminal study of advertising appeals and message strategies in viral advertising (RQ₄). Specifically, they recorded the presence of advertising appeals as discovered in Porter and Golan's (2006) study of viral advertising: i.e., sexuality, violence, humor, animals, and children. Sexuality was defined as any image feature designed to elicit a sexual response from the viewer: e.g., provocative clothing, attractive model, suggestive pose, exposed body parts such as legs, or intimate interactions between people. Violence incorporated volatile emotions (i.e., anger) and physical acts such as punching or shooting, as well as verbal cues indicating immediate harm to someone or something. For *animals* to be considered as an advertising appeal, either a single animal or multiple animals needed to be a salient feature of the image. Further, the animal(s) must have been used in such a way as to evoke an emotional response from viewers, commonly ones of adoration ("So cute!") or affection. Similarly, to consider *children* as an advertising appeal, either a single child or multiple children must have been a salient feature of the image and emphasized in such a way as to evoke an emotional response from the viewer (i.e., young children). These appeals were listed as dichotomous variables to indicate if the post portrayed a specific appeal or did not portray it, with 0 signifying the appeal was absent and 1 signifying it was present. This allowed for an accurate capturing of all relevant advertising appeals that may have been present, as these appeals were not mutually exclusive and therefore multiple appeals may have been present in one post (e.g., animated children in a humorous situation).

An application of Taylor's six-segment message strategy wheel followed in order to understand each post's strategic message strategy (RQ₄). Each image was assigned one of Taylor's six segments – *ration*, *acute need*, *routine*, *ego*, *sensory*, and *social*. Lastly, the engagement metrics for each image post were recorded, namely the amount of likes and

comments garnered by the post at time it was coded (RQ5). This was done last to avoid having the coder affected too early by possible perceptions of popularity or unpopularity.

Inter-coder Reliability

Before the entire sample was coded, Coder 1 and Coder 2 were each given a copy of the researcher's Codebook (see Appendix B), as well as supplemental research of the concepts discussed in this study's literature review: e.g., an outline of Taylor's six-segment model. The coders were trained together and shown examples of image posts from other brands on Instagram not a part of the sample of 10 startups (e.g., Toyota, Nike, and Papa John's). Once confident the coders were in agreement on certain concepts, they were each given the same sample of 44 random posts from the total sample of 438, or 10 percent of the total sample.

As coding employed only two coders and the variables comprising the content analysis were categorical, Cohen's Kappa (κ) was applied to each question to test for inter-coder reliability. In order for inter-coder reliability to be achieved and approval to be given to the coders to begin coding the entire sample, each questions was expected to attain a coefficient equal to or greater than .80 ($\kappa \ge .80$). Although inter-coder reliability was not attained on every question with the first test sample, Coder 1 and Coder 2 were given a brief re-training, and the process was repeated with a new sample of 44 image posts. Cohen's Kappa was again applied and inter-coder reliability was achieved. For multiple questions, a coefficient of 1.0 was attained ($\kappa = 1.0$), signifying perfect inter-coder reliability. These questions included Question 1 (coder), Question 2, Question 3, Question 8, and Question 9. As there should have been no variance in the data coded for these variables, inter-coder reliability of $\kappa = 1.0$ was not only expected, but required. For Questions 4 through 7, slight variance of interpretation among coders was

anticipated; however, a high level of reliability with coefficients equaling or exceeding .80 ($\kappa \ge$.80) was still expected. Their inter-coder reliability coefficients are detailed below.

Ouestion 4 contained multiple parts because the various features were coded as dichotomous variables, meaning they were either were present or not present, and various combinations of the features were possible. Subsequently, inter-coder reliability was employed for each feature rather than for the question as a whole. For features single person, multiple people, food, text, pet, fashion, and location, $\kappa = 1.0$. The Kappa coefficients for the remaining features were as follows: object(s), $\kappa = .95$; activity, $\kappa = .79$; and graphic, $\kappa = .90$. Although $\kappa <$.80 for activity, the difference of 0.01 is marginal. Also, greater variance for activity was expected for two reasons: a) numerous variations of activities were possible, and b), as an action and not a physical feature, interpreting what constitutes an activity is inherently harder in an image. Therefore, .79 was deemed permissible. For Question 5, a reliability of $\kappa = .93$ was found. Similar to Question 4 where multiple combinations of features were possible, Question 6 contained multiple parts and thus, each function was tested separately. Only for humor, however, was a coefficient score of less than 1.0 found ($\kappa = .83$), meaning for sexuality, violence, children, and animals, $\kappa = 1.0$. Lastly, for Question 7, which asked for the image's most salient creative message segment out of six possible, $\kappa = .83$.

Data Analysis

This study was exploratory in nature and relied primarily on a quantitative analysis, namely a descriptive statistical analysis of the data. For RQ1 through RQ4, the primary purpose of analyzing the data was to determine the frequency of features, functions, viral advertising appeals, and creative message segments among the sample of 438 images. Subsequently, data for RQ1 through RQ4 were aggregated, organized, analyzed, and displayed in such as way as to best

highlight both their frequencies and their percentages relative to the total sample. Single-sample chi-square tests were performed on RQ2 and RQ4, where only one element was possible, to examine differences. To sufficiently answer RQ5, data analysis involved a two-part process, Phase 1 and Phase 2. In Phase 2, crosstabs were performed on each possible pairing of elements: 1) Image Features and Image Function, 2) Image Features and Viral Advertising Appeal, 3) Image Features and Creative Message Segments, 4) Image Function and Viral Advertising Appeal, 5) Image Function and Creative Message Segments, and 6) Viral Advertising Appeal and Creative Message Segments. This was done prior to Phase 2 of RQ5 to determine what interrelationships exist among the various elements that might prove to comprise important thematic combinations, or schema. In Phase 2, a qualitative content analysis, similar to that conducted by McNely (2012) in his study of branded image functions on Instagram, was conducted on the coded sample data to determine if prevalent schema translated to higher or lower engagment. To fairly compare schemas' impact on engagement across startups whose number of followers varied from 231 to 628,000, likes and comments were converted into percentages of the number of total followers for each respective startup. For example, a startup that has 1,000 followers posted an image that garnered 100 likes (10% of the total number of followers) and 15 comments (1.5%). At the same time, another startup with 10,000 followers posted an image that garnered 200 likes (2%) and 30 comments (0.3%). While the second startup's image garnered double the amount of likes and comments as the first startup's image, the first startup's image performed better comparative to its followers.

Once likes and comments were converted into percentages of the respective startup's number of followers as of December 31, 2017, the data was organized two separate times using Microsoft Excel. First, it was organized in descending order from highest percentage of likes-to-

followers to the lowest. An initial qualitative content analysis then assessed the top 44 posts (10% of the total sample) and bottom 44 posts to identify potentially important schema that may correspond to higher levels of like engagement. The top 10 percent was designated Segment 1 and the bottom 10 percent was designated Segment 2. The data was then reorganized in descending order from highest percentage of comments-to-followers to the lowest. A second qualitative content analysis then examined the top 44 posts (Segment 3) and bottom 44 posts (Segment 4) to identify potentially important schema that may correspond to higher levels of comment engagement. Segments 1 and 3 were then compared to determine if certain schema translated to higher engagement for both likes and comments. Similarly, Segments 1 and 4 were compared to determine if certain schema translated to lower engagement for both likes and comments.

Results

There were two purposes to this study as addressed previously. The first purpose was to learn what elements of image composition, ranging from features to function and message strategy, are common among startups on Instagram. The second purpose was to understand if certain schema, comprised of combinations of image features, appeals, functions, and message segments, related to higher rates of engagement as measured by likes and comments.

Reseach Question 1: Image Features

The first research question of this study, RQ1, sought to better understand what image features are most common in startups' Instagram image posts. Images were coded to learn what features and combinations of features were present. Once collected, the data, as shown in Table 3, indicated several important in regards to feature frequency. The most important finding, for example, was that of the 10 possible image features an image post may contain, *object(s)* were

markedly the most popular, occurring in 230 of 438 image posts, or 52.5 percent of the total sample. This means that more than half of all the images that comprised the total sample featured a man-made object of some kind. The next most popular image features were *location* with 89 instances (20.3%) and *multiple people* with 81 instances (18.5%). *Single person* and *text* followed closely and occurred at identical frequencies—79 instances each (18%). *Activity* and *graphic* features were next in regards to frequency at 77 instances (17.6%) and 73 instances (16.7%). *Food, fashion*, and *pet(s)* occurred with the least frequency, with 26 (5.9%), 16 (3.7%), and 13 (2.9%) instances, respectfully. One point to reiterate is that for this variable, various combinations of features were possible for each image. In fact, 223 of the 438 images included multiple features. Conversely, 215 images portrayed a single feature. Only two features were considered mutually exclusive: *single person* and *multiple people*. Consequently, the total sum of the frequencies is not 438, nor is the total sum of the percentages listed in Table 3.

Table 3
Frequency distribution of image features

Image Feature	Frequency (n = 438)	Percentage of Sample
Object(s)	230	52.5%
Location	89	20.3%
Multiple People	81	18.5%
Single Person	79	18%
Text	79	18%
Activity	77	17.6%
Graphic	73	16.7%
Food	26	5.9%
Fashion	16	3.7%
Pet(s)	13	2.9%

Note. Each percentage is rounded to the nearest tenth decimal.

Research Question 2: Image Functions

To answer RQ2, each image post was coded for one of four possible image functions: branding, call-to-action, informing, or humanizing. During this process, only one image function was selected for each image as its most prevalent or salient function. When the data was analyzed, a single-sample chi-square revealed significant differences in the frequencies of functions. Table 4 indicates that of the four, informing was the most popular with a frequency of 173 instances, accounting for 39.5 percent of the total sample. Branding followed as the second most common image function with a frequency of 141 instances (32.2%). Humanizing occurred at a frequency of 113 instances (25.8%). Calls-to-action were by far the least common image function as it was employed in only 11 images, accounting for only 2.5 percent of the total sample.

Table 4
Frequency distribution of image functions

Image Function	Frequency (n = 438)	Percentage of Sample
Informing	173	39.5%
Branding	141	32.2%
Humanizing	113	25.8%
Call-to-action	11	2.5%

 $[\]chi^2 (df = 3, N = 438) = 134.60, p < 0.001$

Research Question 3: Viral Advertising Appeals

RQ3 asked if any advertising appeals common in viral advertisements were also present in startups' Instagram image posts. As with image features, combinations of viral advertising appeals were possible (e.g., an animal with a young child in an ostensibly humorous situation). When these appeals were coded, however, only three of the five appeals were evident in the sample. Visual portrayals of *violence* and *sexuality* were not found. Of the three appeals that were found, *humor* was by far the most common, although it occurred in only 33 images, or seven and a half percent of the total sample. *Animals* and *children* occurred at 13 (2.9%) and 6 (1.4%) instances. It is worth noting, too, that while combinations of these appeals were possible, a combination of two appeals only occurred in one image. Overall, viral advertising appeals appeared in only 51 images, or 11.6 percent of the total sample. Table 5 shows the frequency distribution of these appeals.

Table 5
Frequency distribution of viral advertising appeals

Appeals	Frequency (n = 438)	Percentage of Sample
Humor	33	7.5%
Animals	13	2.9%
Children	6	1.4%
Sexuality	0	0%
Violence	0	0%

Research Question 4: Message Segments

To answer RQ4, each image was also coded for a single, predominant message segment. A single-sample chi-square revealed a significant difference in the frequency distribution of the six possible segments. Coding of the images for creative message segments revealed that the predominant message segment was ration, accounting for 38.4 percent of the total sample, or 168 instances. The *sensory* message segment was the second most common and accounted for 21.2 percent of the sample, or 93 instances. The *social* and *ego* segments occurred at frequencies of 77 (17.6%) and 51 (11.6%) instances, respectfully. The two least common message segments were routine at 39 instances (8.9%) and, lastly, acute need at only 10 instances (2.3%). While ration, a component of the transmission view, was by far the most common single segment, the sensory, social, and ego segments – components of the ritual view – were the second, third, and fourth most common segments. When considering the segments in context of their respective views, the transmission view appeared in 217 of the 438 images (49.5%). Conversely, the ritual view appeared in 221 images (50.5%). This indicates that while *ration* was the most common message segment, on a macrocosmic level the total sample was split almost evenly between the transmission view and the ritual view.

Table 6
Frequency distribution of creative message segments

Message Segments	Frequency (n = 438)	Percentage of Sample
Ration	168	38.4%
Sensory	93	21.2%
Social	77	17.6%
Ego	51	11.6%
Routine	39	8.9%
Acute Need	10	2.3%

 $[\]chi^2 (df = 5, N = 438) = 23.652, p < 0.001.$

Research Question 5: Engagement

To answer RQ5 and understand if any set combination of image features, image functions, appeals and messages strategies are common among posts that received the most and least engagement in relation to likes and comments, the data was analyzed in two phases. In the first phase, Phase 1, six separate crosstabs were performed between the variables: 1) Image Features and Image Function, 2) Image Features and Viral Advertising Appeal, 3) Image Features and Creative Message Segments, 4) Image Function and Viral Advertising Appeal, 5) Image Function and Creative Message Segments, and 6) Viral Advertising Appeal and Creative Message Segments. In the second phase, Phase 2, a qualitative content analysis was performed to better understand the image features, functions, appeals, and strategies employed in posts that received both high and low levels of engagement in the form of likes and comments. The results of the crosstabs for each pairing are detailed below.

Phase 1: Crosstabs of various image elements.

Phase 1 of RQ5 involved performing crosstabs with the six combinations of image elements. These crosstabs were important in identifying patterns of interrelationships among the elements that would validate contingent combinations of these elements among posts with high and low engagement, as identified in Phase 2. In the first combination, image features were examined in relation to image functions, revealing several key findings. Table 7 shows the frequency distributions of image features among image functions and illustrates the important relationships. Most apparent from the table, too, is that of the 173 images whose function was *informing*, 154 of them, or 89 percent, featured *object(s)*. Only *text* (45 instances = 26%) and *graphic* (38 instances = 21.9%) appeared with any other notable frequency. The table also indicates that of the images whose function was determined as *branding*, *location* and *object(s)*

were the two most common features, accounting for 47.5 percent and 34.8 percent of the 141 images, respectfully. Understandably, *calls-to-action* were only distinguishable or discernable if they involved overlaid or salient *text* (100%), although *graphic* (9 instances = 81.8%) and *location* were other common features (5 instances = 45.5%). As expected, for the 113 images whose function was *humanizing*, the majority involved either *multiple people* (64 instances = 56.6%) or a *single person* (45 instances = 39.8%). Behind *multiple people*, *activity* occurred with the second most frequency: 50 of the 113 images, or 44.2 percent, involved some sort of *activity* that contributed to the image functioning as a *humanizing* instrument for the startup.

Table 7

Crosstabs displaying frequency distributions of image features in relation to image functions

	Features										
Function	SP	MP	Food	Object	Text	Pet	Act	Fash	Loc	Gra	Total
Branding	20	12	15	49	19	7	16	5	67	18	141
Call-to- action	1	1	1	1	11	0	1	0	5	9	11
Informing	13	4	3	154	45	1	10	6	2	38	173
Humanizing	45	64	7	26	4	5	50	5	15	8	113
Total	39	81	26	230	79	13	77	16	89	73	438

 $[\]chi 2$ (df = 27, N = 438) = 508.21, p < .001. *Note*. The bivariate chi-square approximation may be inaccurate due to expected frequency less than 5. SP = Single Person; MP = Multiple People; Act = Activity; Fash = Fashion; Loc = Location; Gra = Graphic.

When compared to image features, several significant groupings of the relatively few instances of viral advertising appeals emerged, as seen in Table 8. As revealed previously, *humor* was by far the most common advertising appeal, occurring almost three times as often as *animals* (13 instances) and more than five times as often as *children* (6 instances). *Sexuality* and *violence* were not present. When *humor* was present in a post, three image features were also present with similar frequency: *text* (22 instances = 66.7%), *object(s)* (21 instances = 63.6%), and *graphic* (20 instances = 60.6%). *Fashion* was never present, and *pet* and *location* were each present only once. When *children* were used as an advertising appeal, half of the six images, or 50 percent, featured a single child while the other half featured multiple children. *Object(s)*, *activity*, and *location* were also present at frequencies of 2 (33.3%), 3 (50%), and 1 (16.7%) instances, respectfully. Unsurprisingly, each use of *animals* as a viral advertising appeal corresponded to each feature of a pet or pets in an image (13 instances = 100%). A *single person* (3 instances = 23%), *multiple people* (3 instances = 23%), *object(s)* (3 instances = 23%), and *activity* (1 instance = 7.7%) were also present among the 13 instances of *animals*.

Table 8

Crosstabs displaying frequency distributions of image features in relation to viral ad appeals

	Features										
Appeals	SP	MP	Food	Object	Text	Pet	Act	Fash	Loc	Gra	Total
Humor	9	3	4	21	22	1	3	0	1	20	33
Sexuality	0	0	0	0	0	0	0	0	0	0	0
Violence	0	0	0	0	0	0	0	0	0	0	0
Children	3	3	0	2	0	0	3	0	1	0	6
Animals	3	3	0	3	0	13	1	0	0	0	13
Total	15	9	4	25	22	13	7	0	2	20	51

 $[\]chi^2(df = 36, N = 438) = 81.80, p < .001$. Note. The bivariate chi-square approximation may be inaccurate due to expected frequency less than 5. SP = Single Person; MP = Multiple People; Act = Activity; Fash = Fashion; Loc = Location; Gra = Graphic.

Table 9 displays the frequency distributions of image features among the possible creative message segments and indicates that when ration was an image's predominant message segment, object(s) was the most common image feature, occurring in 149 of 168 images (88.7%). The second most common feature was text (44 instances = 26.2%), followed by graphic (37 instance = 22%). The remaining features occurred at frequencies of 12 or fewer instances. When acute need was coded as an image's message segment, which accounted for only 10 out of 438 images, object(s), text, activity, and graphic occurred and at similar frequencies: 6 (6%), 5 (5%), 4 (4%), and 5 (5%) instances, respectfully. *Routine* exhibited a much more diverse spread and inclusion of image features: single person (10 instances = 25.6%); multiple people (5 instances = 12.8%); food (3 instances = 7.7%); object(s) (19 instances = 48.7%); text (8 instances = 20.5%); activity (9 instances = 23.1%); fashion (2 instances = 5.1%); location (12 instances = 30.8%); graphic (9 instances = 23.1%). The ego, social, and sensory segments also showed a diverse spread and inclusion of image features. Indeed, when social was the predominant message segment, each image feature was present in at least three separate images. Unsurprisingly, the presence of *multiple people* most commonly portrayed a message of sociality, occurring 61 times in 77 images (79.2%). Activity was also common, although less so: 38 times (49.4%). Similarly, when *sensory* was the most conspicuous message segment, each image feature was present in at least two images. Most were more common, however. For example, location and object(s) appeared 38 (40.8%) and 29 (31.2%) times, respectfully. Of note, too, is the fact that *food* appeared as an image feature more frequently for *sensory*-laden images than for those employing another message segment: 15 of the 26 images featuring some type of food corresponded to the sensory segment. Lastly, when an image's message segment

was coded as *ego*, *location* and *single person* were the most common features (30 instances = 58.8% and 25 instances = 49%).

Table 9

Crosstabs displaying frequency distributions of image features in relation to message segments

	Features										
Segments	SP	MP	Food	Object	Text	Pet	Act	Fash	Loc	Gra	Total
Ration	12	2	2	149	44	0	10	5	4	37	168
Acute Need	3	1	1	6	5	0	4	0	0	5	10
Routine	10	5	3	19	8	0	9	2	12	9	39
Ego	25	6	1	15	7	0	14	4	30	5	51
Social	13	61	4	12	3	4	38	3	5	6	77
Sensory	16	6	15	29	12	9	2	2	38	11	93
Total	79	81	26	230	79	13	77	16	89	73	438

 $[\]chi^2(df = 45, N = 438) = 567.67, p < .001$. *Note*. The bivariate chi-square approximation may be inaccurate due to expected frequency less than 5. SP = Single Person; MP = Multiple People; Act = Activity; Fash = Fashion; Loc = Location; Gra = Graphic.

The crosstabs between image functions and viral advertising appeals, as exhibited in Table 10, indicates that when *humor* was present as an appeal, it corresponded much more frequently with the image function *informing* (20 instances = 60.6%) than with the other functions: *branding* (7 instances = 21.2%), *call-to-action* (1 instance = 3%), and *humanizing* (5 instances = 15.2%). When *children* were present as an appeal, they were exclusively linked to *humanizing*. When *animals* were present, however, they corresponded to *branding* (7 instances = 53.8%), *humanizing* (5 instances = 38.5%), and *informing* (1 instance = 7.7%). As mentioned previously, neither *sexuality* nor *violence* was evident in the sample.

Table 10

Crosstabs displaying frequency distributions of image functions in relation to viral ad appeals

	Function						
Appeals	Branding	Call-to-action	Informing	Humanizing	Total		
Humor	7	1	20	5	33		
Sexuality	0	0	0	0	0		
Violence	0	0	0	0	0		
Children	0	0	0	6	6		
Animals	7	0	1	5	13		
Total	13	1	21	16	51		

 $[\]chi^2(df = 12, N = 438) = 27.45, p < 0.05$. *Note*. The bivariate chi-square approximation may be inaccurate due to expected frequency less than 5.

When image functions were compared to creative message segments, several key findings emerged. Most notably, Table 11 illustrates the incontrovertible link between ration as an image's predominant message segment and *informing* as that image's predominant function. Of the 168 images categorized as ration, 155, or 92.3 percent, were coded as informing. The remaining 13 images coded as ration were divided among branding (11 instances = 6.5%), callto-action (1 instance = 0.6%), and humanizing (1 instance = 0.6%). For the 10 images coded as acute need, the corresponding functions varied: i.e., two (20%) were coded as branding, one (10%) was coded as *call-to-action*, four (40%) were coded as *informing*, and three (30%) were coded as humanizing. For routine, the most compelling link to image function seemed to be that of branding, which accounted for 18 of the 39 images (46.2%). The same compelling link was found for those images coded as ego. Of the 51 images coded as ego, 30 (58.8%) were also coded as branding. This pattern held true for the sensory segment, as 78 of the 93 images (83.9%) coded as sensory were also coded as branding. For the social segment, however, an undeniable yet unsurprising link was established with the *humanizing* function: 73 of the 77 images (94.8%) coded as social were also coded as humanizing.

Table 11

Crosstabs displaying frequency distributions of image functions in relation to message segments

-	Function								
Segments	Branding	Call-to-action	Informing	Humanizing	Total				
Ration	11	1	155	1	168				
Acute Need	2	1	4	3	10				
Routine	18	0	11	10	39				
Ego	30	4	1	16	51				
Social	2	2	0	73	77				
Sensory	78	3	2	10	93				
Total	141	11	173	113	438				

 $[\]chi^2(df = 15, N = 438) = 551.57, p < .001$. Note. The bivariate chi-square approximation may be inaccurate due to expected frequency less than 5.

Viral advertising appeals occurred in only 51 total images, or 11.6 percent of the total sample. When a crosstabs between viral advertising appeals and creative message segments was performed, however, as shown in Table 12, several important relationships emerged. Most notable is the relationship among the images whose predominant message segment was *ration*. Specifically, *humor* was the only appeal to occur in connection to *ration*. *Humor* did appear in connection with other segments, though less frequently: two instances under *routine*, three instances under *ego*, five instances under *social*, and three instances under *sensory*. Of the six instances where *children* were used as an advertising appeal in the sample, two instances corresponded to the *routine* segment, one to the *social* segment, and three to the *sensory* segment. The 13 instances of *animals*, on the other hand, were weighted more heavily under the ritual view and corresponded only to the *social* (4 instances) and *sensory* (9 instances) segments.

Table 12

Crosstabs displaying frequencies of viral ad appeals in relation to message segments

		Viral Advertising Appeals							
Segments	Humor	Sexuality	Violence	Children	Animals	Total			
Ration	20	0	0	0	0	20			
Acute Need	0	0	0	0	0	0			
Routine	2	0	0	2	0	4			
Ego	3	0	0	0	0	3			
Social	5	0	0	1	4	10			
Sensory	3	0	0	3	9	14			
Total	33	0	0	6	13	51			

 $[\]chi^2$ (df = 20, N = 438) = 33.74, p < .05. Note. The bivariate chi-square approximation may be inaccurate due to expected frequency less than 5.

Phase 2: Qualitative content analysis.

Following Phase 1, a second phase, Phase 2, provided additional analysis to fully answer RQ5. In Phase 2, data was analyzed using a qualitative approach to determine if there were prevalent schemas that positively affected the top 10 percent of posts that received high levels of engagement in the form of likes (See Appendix D: Segment 1). Surprisingly, no identical combinations of features were clearly manifest. Nonetheless, several salient elements and observable patterns did emerge. First, a number of the most engaging posts, at least in relation to likes, incorporated the *humanizing* image function paired with a *social* message segment. In fact, this combination accounted for almost half of the top five percent of liked posts. Many of these posts also featured *multiple people* as a common image feature, drastically more so than a *single* person. Second, despite only occurring in 18% of the total sample, text appeared as another prevalent yet surprising feature in the top 10 percent of liked posts and was often found in conjunction with either the *call-to-action* or *informing* functions. Third, there appeared to be a fairly even distribution of functions among the top 10 percent when viewed as a whole. Humanizing, call-to-action, and informing have already been noted, but branding was also equally prevalent. Similarly, there appeared to be an even distribution of message segments, with the *sensory* segment seemingly occurring with the least frequency. Fourth, only one advertising appeal, humor, was present in the top 10 percent of posts that received high like engagement. Lastly, seven out of the 10 total instances of the acute need function appeared in the top 10 percent of liked posts and were commonly paired with *text*.

While many of these interactions may not be surprising based on the interrelationships and frequency distributions discovered in the preceding crosstabs, what is important to note is that groupings of these variables appear together in the top 10 percent of liked posts. In

summary, among the top 10 percent of liked posts, the notable thematic elements included multiple people, text, humanizing, call-to-action, informing, branding, social, acute need, ration, ego, and routine.

Perhaps even more telling than the analysis of the top 10 percent of liked posts was the analysis of the bottom 10 percent of liked posts (See Appendix D: Segment 2). Indeed, while exact combinations failed to appear with any frequency, one key combination of elements (with a couple of slight variations) was overwhelmingly manifest: *Object + Informing + Ration*. The two variations included the additional presence of *text* in a few instances and, surprisingly, *humor*. As evident in data, the *humor* appeal was not only clustered in the bottom 10 percent of liked posts, but it was more so clustered towards the bottom half of the 10 percent. In other words, *humor* was much more common among the least liked posts than anywhere else in the data.

When the data was reorganized by percentage of comments relative to followers and a second qualitative content analysis conducted, similar patterns to those found in the top and bottom 10 percent of posts in regards to comment engagement. For example, in the top 10 percent of posts that received the most comments, a variety of combinations of image features, functions, and message segments manifested themselves overall (See Appendix D: Segment 3). No set combinations stood out with clarity or salience. Following the pattern of the first qualitative content analysis, however, more insights into schema correlating to comment engagement were gleaned from examining the bottom percent of posts or the posts that received the fewest comments (See Appendix D: Segment 4). In this case, the bottom 10 percent all received no comments. Indeed, an analysis of this bottom percentage revealed several unforeseen patterns in the data. Most notably, *multiple people* and a *single person* were common features of

posts that received no comments. Further, *branding* and *humanizing*, though popular functions among the most liked image posts, were even more popular among posts with no comments, especially when accompanying *multiple people* or a *single person*. Similarly, the *social* and *sensory* segments, though popular segments among the most liked image posts, were by far the most common segments among the posts that received no comments. Specifically, many of the combination of features that negatively translated to comment engagement either mirrored or were a slight variation one of two general combinations: *Multiple People + Humanizing + Social* and *Single Person + Branding + Sensory*.

As outlined previously under the section Data Analysis, the last steps of the quantitative analyses involved comparing the top 10 percent of posts that received high like engagement with those that received high comment engagement, as well as comparing the bottom 10 percent of posts that received low like engagement with the posts that received the lowest comment engagement. This was done in order to determine if certain schema positively or negatively translated to engagement. When the top 10 percent of liked posts was compared to the top 10 percent of posts that received comments, two key but related findings emerged. First, 24 posts that appeared in the top 10 percent of like engagement also appeared in the top 10 percent of comment engagement. That means 24 of 44 posts, or 54.5 percent the top engaging posts for both likes and comments, were the same post. These image posts were, by post number, 394, 392, 391, 418, 38, 398, 417, 35, 424, 436, 425, 423, 421, 434, 393, 399, 400, 410, 430, 438, 420, 416, 422, and 431. Of these images, no obvious schema stand out apart from those previously identified. In other words, a variety of combinations of elements comprise these images. Conversely, when the bottom 10 percent of liked posts was compared to the bottom 10 percent of posts that received few or no comments, not a single post that appeared in the bottom 10 percent

of like engagement appeared in the bottom 10 percent of comment engagement. In brief, schema identified as negatively affecting like engagement showed no comparable or perceptible negative influence on comment engagement.

Discussion

Opportunity of Variety

As determined by this study, the main takeaway for startups is that Instagram provides an opportunity to show a variety of features other than simply products, employ a variety of functions, and communicate a variety of strategic messages and still positively impact engagement. Startups should feel comfortable in experimenting with different schema to see what may works best for them without falling into the trap of repeatedly posting about their product or service with the intent of informing or with a ration-oriented strategy, the schema most tied to poor engagement, especially like engagement. This pitfall is discussed in more depth in the following paragraphs. When a startup finds images that perform particularly well with engagement, this study provides them with the tools necessary to consistently and methodically deconstruct those images in order to understand what features, functions, appeals, and message segments compose them. The knowledge gained from deconstructing those images can in turn provide them with a formula for strategically creating content that will drive engagement.

Current Pitfall of Startups

RQ1 examined the image features in startups' Instagram posts, and one of the most discernable results indicated that more than half (52.5%) of all images in the total sample featured an object or objects of some kind. Since the sample is comprised of startups offering consumer products or services, this is understandable. Most of the startups in the sample, including the most prolific in terms of sheer number of posts, either offer a physical product or a

service that is accessed via a product: e.g., cell phone or computer. Some startups, like OfferUp and Instamotor, offered a service that involved selling others' things, from furniture to gadgets to cars. This suggests that startups are focusing a lot of posts on an object or objects, such as their product(s) or the products their service offers. What is interesting and important for those seeking to grow their own startup's presence on Instagram, however, is that the feature of an object or object in a post showed no perceptible positive impact on either like engagement or comment engagement. *Object(s)* were present in a number of the top 10 percent of both metrics, of course, but it was features like *multiple people* and even *text* that proved more prevalent among higher engaging posts.

Two other key discoveries support the finding that startups are primarily *object(s)* or product-oriented. First, frequency statistics revealed that among the four possible image functions, *informing* was the most frequent. This is compelling due to the fact alone that previous advertising studies revealed that *branding* is traditionally the most common (Porter & Golan, 2006; Golan & Zaidner, 2008). Bivariate chi-squares also revealed a significant link between image features and function, and the interrelationship between *object(s)* and *informing*, as exposed in the crosstab, is irrefutable. This connection is also intuitive. When highlighting a certain object or objects, especially its product(s), the natural inclination of the person or people posting the image for the startup may often be to inform people, whether current or potential customers. Conversely, those posting for a startup may feel the need to inform people about it, and the most intuitive way to do this is to highlight the product(s). Second, frequency statistics indicated the most common message segment was that of *ration*, a component of the transmission view that is information-oriented (Taylor, 1999). It makes sense that image posts intending to inform viewers about a particular object or product would also rely on a message

segment like *ration* as the complementary message strategy. Bivariate chi-square analyses support the relationship between *object(s)* and *ration* and *informing* and *ration*. Unsurprisingly, qualitative content analyses revealed that *object* + *informing* + *ration* was indeed a common combination of elements for image posts, especially those shared by OfferUp, an app for users to sell various personal items.

Engagement

When it comes to engagement, however, analyses also revealed that this schema (object + *informing* + *ration*) received dramatically less like engagement than any other schema. This schema did perform slightly better in relation to comment engagement, but even then it does not appear in the top 10 percent of comment engagement. As a result, communications professionals in charge of a startup's Instagram should avoid heavy repetition of this schema and instead focus on other combinations of features, functions, and message segments more conducive to higher like and comment engagement. For like engagement, this includes using more combinations of multiple people and text as features, a mixture of humanizing, call-to-action, informing, and branding as image functions, and social, acute need, ration, ego, and routine as message segments. Simply put, there is a wide variety of schema to choose from that may encourage higher like engagement from users, though the best schema for a particular startup may vary according to other factors such as the startups product, service, culture, mission, and core values. Unfortunately, combinations of multiple people, humanizing, branding, and ritual view segments such as ego, social, and sensory do ostensibly translate to low comment engagement. This intimates that communications professionals should thoroughly understand that certain types of images may have opposite effects on likes and comments. They should be encouraged to tailor

their content creation to specific engagement objectives, both for individual image posts and for more general Instagram campaigns.

Broad Appeal vs Concentrated Appeal

Concerning like and comment engagement, an additional, unexpected, and suggestive find was that, with very exceptions, those startups in the sample with the most followers failed to attract any noteworthy engagement. Indeed, there seemed to be two distinct categories for classifying startups based on the relationship of engagement to number of followers: broad appeal and concentrated appeal. In this context, the term appeal does not relate to the viral advertising appeals discussed heavily in this study. Rather, appeal refers to a startup's engagement compared to its popularity. Startups with broad appeal are those that have large numbers of followers but received low engagement on their image posts, while startups with concentrated appeal were able to garner higher levels of engagement from fewer followers. This finding became increasingly apparent after the data was ranked in order of most engaging to least engaging for both metrics. Qualitative content analyses on the data confirmed that for both, the startups with the least amount of followers, specifically those under 1,000 followers like Newstore, Look App, and Starry, comprised the majority of startups ranked in the top 10 percent of both metrics. Only one startup with more than 1,000 followers – Simple with 13,700 followers - was able to attract enough likes on one post and comments on another to make the top 10 percent for both metrics. Beyond that, the only other startup with more than 1,000 followers to make the top 10 percent was Bellhops, which had 3,257 followers and had one post with relatively high engagement in respects to comments. In short, startups with fewer followers garnered higher rates of engagement in relation to their number of followers. This suggests that the startups with the most followers, particularly Hudl (101,000 followers) and OfferUp

(628,000 followers), failed to grow their engagement proportionately to the growth of their followers.

One logical explanation for this is that a startup's initial followers can be compared to early adopters, a marketing concept describing those people who are first to buy a product or technology. It is commonly accepted that early adopters tend to be more proactive and engaged and often act as brand champions, a term describing loyal consumers or customers of a brand. Gradually over time, as the product or technology becomes more well known, more people adopt it, though with much less enthusiasm as the early adopters. Similarly, the initial followers of a startup may represent a more concentrated number of followers with an early adopter-type attitude who are generally more engaged with the startup's posts than the majority of people who followed or will follow much later. Thus, failure to grow engagement at the same rate as one's following may be a natural phenomenon characteristic of many different types of Instagram accounts with large and growing followings. That said, other factors could be in play, too. Paid advertising on Instagram, TV ads, or earned media attention in other mediums are just a few factors that may increase the general popularity of a startup on Instagram without driving engagement to the images the startup is posting. Regardless of all the factors, though, it is the challenge for those communications professionals, whether marketers, public relations specialists, or social media strategists, who maintain a startup's Instagram to grow engagement as they attract new followers. This requires not only understanding what general schema contribute to like and comment engagement, but also what specific schema work for their Instagram audiences.

Advertising Appeals in Instagram

Another finding worth noting from this study that merits discussion is the conspicuous lack of viral advertising appeals. Viral advertising appeals appeared in only 51 posts, or 11.6 percent of the total sample. Of these, most focused on *humor*. More importantly, when viral advertising appeals were present, no positive impact on like or comment engagement seemed to exist. Instead, when a viral advertising appeal was included, engagement seemed negatively affected. This was especially true for *humor*, which was more heavily concentrated in the bottom percentage of liked posts than elsewhere in the sample. There are several interpretations for these findings. For one, startups may not view Instagram as an advertising platform and are avoiding, whether intentionally or unintentionally, the use of viral advertising appeals in their posts. In other words, advertisers and other communications professionals may not view Instagram in the same class of mediums that have traditionally supported viral advertisements: e.g., TV, magazines, billboards, etc. This may be due to the fact that Instagram offers levels of engagement not seen in other mediums and including these viral advertisements represents more of a risk that could potentially backfire. Startups may want to especially avoid this risk because they do not have the same reputation and resources to survive negative attention that a larger brand has.

When startups do include viral advertising appeals, the low engagement commonly associated with the appeals may indicate startups are failing to execute the appeal appropriately, such as attempting humor but not succeeding in capturing something actually humorous. Another possibility is that although Instagram offers a medium for advertising in a literal sense of the term, people on Instagram do not respond well to images that appear too much like traditional viral ads. This may only apply to startups, however, from which people expect more authenticity

than to be bombarded with images constructed like a viral advertisement. More research should be done by replicating this study with larger, more diverse samples of brands to determine if this holds true across the board or if viral advertising appeals are more common among certain sizes of companies, in specific industries, or in both. In the meantime, startups may want to avoid *humor* altogether as it may actually translate to lower engagement.

This study is among the first empirical studies to deconstruct startups' Instagram image posts in order to better understand how previously established features, functions, appeals, and message strategies are leveraged on Instagram. As previously discussed, the data revealed several potentially consequential takeaways for startups looking to create an Instagram-specific social media strategy and researchers interested in studying brands' strategic use of the app. Researchers and marketers alike, however, should remember that while the implications of the findings from this study may be relevant to some degree to brands as a whole, the focus of this study was on results that were specific to startups.

Conclusion

Images are powerful means of communication. Though inherently limited in their scope, images present communications professionals a vivid tool for communicating salient and compelling messages. This is especially true for image-based advertisements found within a variety of channels. One such channel is Instagram, an image-centric and image-driven social media platform that offers brands an unprecedented alternative for advertising. However, what few studies exist that focus on brands' uses of Instagram tend to adopt a consumer-oriented approach or view the app as a public relations tool. This study adamantly advocates Instagram, as well as other social media, should be viewed as an advertising tool for brands. Indeed, Instragram provides brands with a significant opportunity to reach millions of potential

consumers without having to spending large amounts of marketing dollars. Instead, engagement, popularity, and brand reputation can be grown and cultivated over time without sophisticated or expensive equipment (other than a smartphone) and with a simple understanding of advertising-oriented images and their elemental composition, as outlined in this study.

By applying a content analysis to deconstruct 438 image posts aggregated from the Instagram accounts of 10 U.S. startups during 2017, this study found that certain elements of image posts were indeed common. Specifically, *object(s)* were the most common salient image feature as opposed to features such as *people*, *locations*, *text*, *graphics*, and *pets*, although various combinations of these features were common, too. This study also found that *informing* was the most common image function and *ration* the most common message segment. Further, bivariate chi-square tests indicated a significant relationship between these elements, as well as significant relationships among all the elements. Qualitative analysis of the data collected from the content analysis revealed that more fixed schema translated to negative engagement in terms of likes and comments than did positive engagement.

In summary, this study exposed what may be an inhibiting factor to startups' engagement on Instagram: too often, startups focus too much on informing their Instagram audiences about a product or object by highlighting such qualities like its specifications or design. This study's findings also revealed that startups do not often include traditional advertising appeals, but when they do, these appeals, especially *humor*, can have negative affects on engagement instead of the positive affects they may have in other mediums. By avoiding this schema and mixing in a variety of schema comprised of other features, functions, and segments, startups have an unique opportunity to not only find what types of images work best for their strategic communications

goals on Instagram, but also to develop a template for creating image content that will consistently help them realize those goals.

Limitations and Opportunities for Future Research

A necessary limitation of this study was its focused examination on U.S. startups. As a result, it not only excluded a variety of international startups, but also more established brands. This presents an opportunity for researchers to study these same elements on a wider sample of brands that can span numerous industries and be applied to brands of varying size and popularity. For example, it may be interesting to learn what features, functions, appeals, and message strategies large athletic apparel companies such as Nike, Adidas, and Under Armor employ on Instagram to promote their brand and products on Instagram. Again, this formula can be applied to a variety of brands on Instagram. More random samples may also be beneficial, as this study used a convenience sample. One limitation of the convenience sample is that it presented startups with a wide range of followers. Future research should examine brands of equal social media followings to determine if certain findings of this study continue to hold true. Comparing brands with broad appeal may reveal findings that vary significantly with findings from brands of concentrated appeal. On a related note, it may prove more beneficial in future research to examine an equal number of images from each account as each account varies in terms of how often it posts.

Future research into Instagram as an advertising platform for brands should also focus on consumers' experiences. This research could potentially highlight discrepancies between what functions and/or strategies a brand believes it is posting and what the consumer perceives as the function and/or strategies. It could also reveal what types of content consumers expect or want to see from startups and provide a more robust and effective template for startups to use in creating

content for their Instagram. Yet another opportunity for future research may be found in the seemingly subtle trend to video on Instagram. Videos are becoming more and more popular on the app, and future research should focus on if, and if so, how, startups and brands are promoting themselves and their products or services via this medium. Lastly, a limitation of this study that presents itself as an opportunity for future research is this study's focus on organic images. Instagram allows for brands to disseminate paid advertisements to Instagram audiences. These paid advertisements may prove to be more consistent with previous advertising research into ad functions and message strategies.

References

- Advertise (n.d.) Retrieved February 7, 2017, from https://www.merriamwebster.com/dictionary/advertise
- Ahadzadeh, A., Sharif, S. & Ong, F. (2016). Self-schema and self-discrepancy mediate the influence of Instagram usage on body image satisfaction among youth. *Computers in Human Behavior*, 68, 8-16.
- Araújo, T., & Neijens, P. (2012). Friend me: Which factors influence top global brands participation in social network sites. *Internet Research*, 22(5) 626-640.
- Araújo, C., Corrêa, L., Couto da Silva, A., Prates, R., & Meira, W. (2014). It is not just a picture:

 Revealing some user practices in Instagram. 9th Latin American Web Congress, Ouro

 Preto, Brazil, Oct. 22-24.
- Armstrong, P. (2017, January 3). These Are The Startups You Should Watch In 2017. *Forbes*. Retrieved from https://www.forbes.com/sites/paularmstrongtech/2017/01/03/these-are-the-startups-you-should-watch-in-2017
- Bakhshi, S., Shamma, D., & Gilbert, E. (2014). Faces engage us: Photos with faces attract more likes and comments on Instagram. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*.
- Bell, P. (2001). Content analysis of visual images. In T. Van Leeuwen & C. Jewitt (Eds.), *Handbook of visual analysis* (pp. 10–34). Thousand Oaks, CA: Sage.
- Boyd, D., & Ellison, N. (2007). Social network sites: definition, history, and scholarship. *Journal of Computer-Mediated Communication*, 13(1), 210-230.
- Brown, J. D. (2007). The self. New York, NY: Psychology Press.

- Cappella, J., & Jamieson, K. (1996). News frames, political cynicism, and media cynicism. *The Annals of the American Academy of Political and Social Science*, *546*, 71-84.
- Carah, N., & Shaul, M. (2016). Brands and Instagram: Point, tap, swipe, glance. *Mobile Media & Communication*, 4(1) 69-84.
- Casaló, L., Flavián, C., & Ibáñez-Sánchez, S. (2017). Understanding consumer interaction on Instagram: The role of satisfaction, hedonism, and content characteristics.
 Cyberpsychology, Behavior, and Social Networking, 20(6) 369-375.
- Coelho, R., Santos de Oliveira, D., & Severo de Almeida, M. (2016). Does social media matter for post typology? Impact of post content on Facebook and Instagram metrics. *Online Information Review*, 40(4), 458-471.
- Coleman, R. (2010). Framing the pictures in our heads: Exploring the framing and agenda-setting effects of visual images. In P. D'Angelo and J.A. Kyupers (Eds.), *Doing news framing analysis: Empirical and theoretical perspectives* (pp. 233-261). New York, NY: Routledge.
- Dawkins, R. (1976). The selfish gene. New York, NY: Oxford University Press.
- Druckman, J. (2004). Political preference formation: Competition, deliberation, and the (ir)relevance of framing effects. *American Political Science Review*, 98(4), 671-686.
- Duggan, M., Ellison, N., Lampe, C., Lenhart, A., & Madden, M. (2015). Social media update 2014. In *Pew Research Center*. Retrieved from http://www.pewinternet.org/2015/01/09/social-media-update-2014/
- Ellison, N., Steifield, C., & Lampe, C. (2007). The benefits of Facebook 'friends': Social capital and college students' use of online social network sites. *Journal of Computer-Mediated Communication*, *12*(4), 1143-1168.

- Entman, R. (1991), Symposium framing U.S. coverage of international news: Contrasts in narratives of the KAL and Iran air incidents. *Journal of Communication*, *41*(4), 6–27.
- Entman, R. (1993). Framing: Toward clarification of a fractures paradigm. *Journal of Communication*, 43(4), 51–58.
- Evans, M. (2010). Framing international conflicts: Media coverage of fighting in the Middle East. *International Journal Of Media & Cultural Politics*, 6(2), 209-233.
- Faber, B. (2002). Community Action and Organizational Change: Image, Narrative, Identity.

 Carbondale, IL: SIU Press.
- Gamson, W., & Modigliani, A. (1987). The changing culture of affirmative action. In R.G.

 Braungart & M. M. Braungart (Eds.), *Research in Political Sociology* (Vol. 3, pp. 137-177). Greenwhich, CT: JAI Press.
- Gamson, W., Croteau, D., Hoynes, W., & Sasson, T. (1992). Media images and the social construction of reality. *Annual Review of Sociology*, *18*, 373-393.
- Geise, S., Baden, C. (2015). Putting the image back into the frame: Modeling the linkage between visual communication and frame-processing theory. *Communication Theory*, 25(1), 46-69
- Golan, G., & Zaidner, L. (2008). Creative Strategies in Viral Advertising: An Application of Taylor's Six-Segment Message Strategy Wheel. *Journal of Computer-Mediated* Communication, 13, 959-972.
- Greenwood, S., Perrin, A., & Duggan, M. (2016, November 11). Social Media Update 2016:

 Facebook usage and engagement is on the rise, while adoption of other platforms holds steady. In *Pew Research Center*. Retrieved from http://www.pewinternet.org/2016/11/11/social-media-update-2016/

- Haferkamp, N., & Kramer, N. C. (2011). Social comparison 2.0: Examining the effect of online profiles on social-networking sites. *Cyberpsychology, Behavior, and Social Networking*, 15(4), 309-314.
- Hartley, J. (1992). *The politics of pictures: The creation of the public in the age of popular media.* New York, NY: Routledge.
- Hartmans, A. (2017). 18 of the hottest under-the-radar startups to watch in 2017. In *Business Insider*. Retrieved from http://www.businessinsider.com/18-hottest-startups-flying-under-the-radar-2017-1/
- Hertog, J., & McLeod, D. (2003). A multi-perspectival approach to framing analysis: A field guide. In S. D. Reese, O. H. Gandy, & A. E. Grant (Eds.), *Framing public life* (pp. 139–162). Mahwah, NJ: Lawrence Erlbaum Associates, Inc.
- Hu, Y., Manikonda, L., & Kambhampati, S. (2014). What we Instagram: A first analysis of Instagram photo content and user types. In *Proceedings of AAAI International* Conference on Web and Social Media
- Huet, E. (2017). These Are the 50 Most Promising Startups You've Never Heard Of. In Bloomberg. Retrieved from http://www.bloomberg.com/graphics/2017-fifty-best-startups/
- Hum, N., Chamberlin, P., Hambright, B., Portwood, A., Schat, A., & Bevan, J. (2011). A picture is worth a thousand words: A content analysis of Facebook profile photographs.Computers in Human Behavior, 27(5), 1828 1833
- Kietzmann, J., Hermkens, K., McCarthy, I., & Silvestre, B. (2011). Social media? Get serious!

 Understanding the functional building blocks of social media. *Business Horizons*, *54*, 241-251.

- McNely, B. (2012, October). Shaping organizational image-power through images: Case histories of Instagram. In *2012 IEEE International Professional Communication Conference*, 1-8.
- Messaris, P., & Abraham, L. (2001). The role of images in framing news stories. In S. D. Reese, O. H. Gandy, Jr., & A. E. Grant (Eds.), *Framing public life* (pp. 215–226). Mahwah, NJ: Erlbaum.
- Munar, A., & Jacobsen, J. (2014), Motivations for sharing tourism experiences through social media. *Tourism Management*, 43, 46–54.
- Phua, J., Jin, S., Kim, J. (2017). Gratifications of using Facebook, Twitter, Instagram, or Snapchat to follow brands: The moderating effect of social comparison, trust, tie strength, and network homophily on brand identification, brand engagement, brand commitment, and membership intention. *Telematics and Informatics*, *34*(1), 412-424.
- Perry, D., Taylor, M., & Doerfel, M. (2003). Internet-based communication in crisis management. *Management Communication Quarterly*, 17(2), 206-232.
- Peters, A. & Salazar, D. (2010). Globalization in marketing: An empirical analysis of business adoption and use of social network sites. *Paper No. 570, AMCIS 2010 Proceedings*, Lima, Peru. August 12-15.
- Peters, K., Chen, Y., Kaplan, A., Ognibeni, B., & Pauwels, K. (2013). Social media metrics A framework and guidelines for managing social media. *Journal of Interactive Marketing*, 47(4), 281-298.
- Pittman, M. (2015). Creating, consuming, and connecting: Examining the relationship between social media engagement and loneliness. *The Journal of Social Media in Society*, *4*(1), 66-98.

- Pittman, M., & Reich, B. (2016). Social media and loneliness: Why an Instagram picture may be worth more than a thousand Twitter words. *Computers in Human Behavior*, 62, 155-167.
- Porter, L. & Golan, G. (2006). From subservient chickens to brawny men: A comparison of viral advertising to television advertising. *Journal of Interactive Advertising*, 6(2). 30-38.
- Qualman, E., (2013). Socialnomics: How social media transforms the way we live and do business. Hoboken, NJ: John Wiley & Sons, Inc.
- Rapp, A., Beitelspacher, L., Grewal, D., & Hughes, D. (2013). Understanding social media effects across seller, retailer, and consumer interactions. *Journal of Interactive Marketing*, 27(4), 281-298.
- Robehmed, N. (2013). What is a Startup? In *Forbes*. Retrieved from https://www.forbes.com/sites/natalierobehmed/2013/12/16/what-is-a-startup/
- Rodriguez, L., Dimitrova, D. (2011). The levels of visual framing. *Journal of Visual Literacy*, 30(1), 48–65
- Scheufele, D. (1999). Framing as a theory of media effects. *Journal of Communication*, 49(1), 103–122
- Schnotz, W. (2005). An integrated model of text and picture comprehension. In R. E. Mayer (Ed.), *The Cambridge handbook of multimedia learning* (pp. 49–69). Cambridge: Cambridge University Press.
- Smith, A. (2015). U.S. Smartphone use in 2015. In *Pew Research Center*. Retrieved from http://www.pewinternet.org/files/2015/03/PI_Smartphones_0401151.pdf
- Sontag, S. (2003). Regarding the Pain of Others. New York, NY: Picador
- Start-up. (n.d.). Retrieved December 5, 2017, from https://www.merriam-webster.com/dictionary/start-up

- Sundar, S. (2008). The MAIN model: A heuristic approach to understanding technology effects on credibility. In M. J. Metzger and A. J. Flanagin (Eds.), *Digital Media, Youth, and Credibility* (pp. 73-100). Cambridge, MA: The MIT Press
- Taylor, R. E. (1999). A six-segment message strategy wheel. *Journal of Advertising Research*, 39(6), 7-17.
- Thayer, S., & Ray, S. (2006). Online communication preferences across age, gender, and duration of Internet use. *CyberPsychology & Behavior*, 9(4), 432-440.
- van Oosten, J., Peter, J., & Boot, I. (2015). Exploring associations between exposure to sexy online self-presentations and adolescents' sexual attitudes and behavior. *Journal of Youth and Adolescence*, 44(5), 1078-1091.
- Wischmann, L. (1987). Dying on the front page: Kent state and the Pulitzer Prize. *Journal of Mass Media Ethics*, 2(2), 67-74

Appendix A

Coding Sheet for Content Analysis

Image	Features (F	R ₁):				
	Single perso	on 🗆	Mul	tiple people	Food	Object
	Text	Pet		Activity	Fashion	
	Destination		Gra	phic		
Image	Function (I	\mathbf{R}_2): What	t is the	e purpose of the	image in the po	ost?
	Branding		Call	ing for action	Informing	-
	Humanizing	9				
	~				•	resence of the viral advertising ne appeal is present.
	Humor:	0	1			
	Sexuality	0	1			
	Violence:	0	1			
	Children:	0	1			
	Animals:	0	1			
		_		Determine which is the se		ments are present in the image.
Transn	nission: Rati	on:	0	1		
	Acu	te need:	0	1		
	Rou	tine:	0	1		
Ritual.	Ego	:	0	1		

	Sensory:	0	1
presence o but not acu present, en	f each segment ar	in for TView.	the totals for each view, transmission and ritual, based on the them below. For example, if ration and routine are present Transmission View. If ego but not social or sensory are
Post Enga	gement: Record	the num	aber of likes and comments the image post received.
Post Likes	:		
Post Comm	ments:		

Social:

Appendix B

Qualtrics Survey: Digital Coding Sheet

Instagram Image Coding Sample

Q1 Select coder
▼ Coder 1 (1) Coder 2 (2)
Q2 Name of startup
▼ Hudl (1) Look App (10)
Q3 Post number

Q4 Select all	image features that apply
	Single person (1)
	Multiple people (2)
	Food (3)
	Object(s) (11)
	Text (5)
	Pet (6)
	Activity (7)
	Fashion (8)
	Location (9)
	Graphic (10)
Q5 Image Fur	nction: What is the purpose of the image in the post? Select one.
O Brand	ing (1)
O Call-to	p-action (2)
O Inform	ning (3)
O Huma	nizing (4)

Q6 Ac	lvertising	Appeals: Select all appeals that apply (only if they are present)
		Humor (1)
		Sexuality (2)
		Violence (3)
		Children (young children) (4)
		Animals (5)
Q7 Cr	Ration	Weed (2)
C) Ego (4)	
C	Social (
	Sensory	· (6)
Q8 Po —	st Likes:	

Q7 Post Comments:			

Appendix C

Code Book for Coder Training

Image Features (R₁): Mark the box for the feature if it is present, as it is either present or not. Multiple elements can be present. For example, an image showing two people eating food looking out over the city would be coded by marking "Multiple people," "Food," "Activity," and "Destination."

Single person: Is a single person present in the image? Can include selfies or even images where only parts of someone's body is shown (e.g.: only a hand in the frame). Both real or animated people qualify.

Multiple people: Are two or more people present in any form?

Food: Is any edible food or beverage in any state present? Ingredients, spices and herbs, and food packaging qualify.

Man made objects: Is technology present in any form? Includes mechanical or electrical devices or objects such as phones, watches, cars, planes, appliances, and tools.

Text: Is text either prominently displayed or superimposed on the image? In other words, is there text on or in the image that is clearly meant to be legible?

Pet: Is there an animal or multiple animals in the picture, especially pets such as dogs and/or dogs? Pets can also include farm animals such as horses, cows, pigs, etc.

Activity: Is a person or are people performing some type of activity, or are there obvious indications that an activity is or was performed? Simply posing for a picture does not qualify, but rather he, she, or they must be involved in some activity such hiking, camping playing a sport, using a product, getting a massage, watching a movie, painting, etc. Conversations with other people, whether directly or through mediated means (i.e., phone) count. Can be indoors or outdoors. A mess, instruments, or tools displayed in such a way as to indicate

Fashion: Is the emphasis of the picture fashion, whether clothing items being worn by a person or displayed in a box or on a hanger? Someone wearing clothes in an image does not qualify as fashion. Elements of the picture, from framing to positioning, must emphasize the fashion aspect of the clothing.

Location: Is the picture clearly highlighting or displaying a location? This includes the office, cityscapes, landscapes, landmarks (i.e., Eiffel Tower or Golden Gate bridge), and signs indicating a specific location. These destinations may be recognizable to you, the coder, but do not have to be to qualify.

Graphic: Not every image posted to Instagram is a photograph. Is the image created or constructed as a graphic, or is their a graphic superimposed over a photo? This could include cartoon characters, logos, animated representations of a product, etc.

Image Function (R_2): What is the primary purpose of the image in the post?

Branding: Does the image highlight key landmarks, destinations, or artifacts that invite the viewer to make a connection to the startup? For example, a product or spokesperson in the woods or outdoors invites the viewer to connect the company to outdoor recreation, conservation, and natural beginnings. This can often be seen in images of trucks where the truck is at a construction site or driving up a mountain. In either instance, the location and/or other artifacts (piles of rocks in the truck bed, for example), help brand the company as rugged and durable.

Call-to-action: Does the image elicit a response from the viewer, such as including text that asks for comments, invites viewers to enter a giveaway or do something specific like buy or shop? Refer to the caption if necessary.

Provide information: Does the image showcase the product or service in a way as to convey its specifications, use, availability, or other information?

Humanize: Does the image attempt to humanize the startup by featuring a spokesperson or employees, or by showing an aspect of the startup in a human-like setting? Think of how the image gives a face or personality to the startup or shows it on the human scale: everyday life, relationships, etc.

Advertising appeal (R₃): Note that two or more appeals may be present in a post. You may refer to the caption to help understand the intent of the image.

Humor: Does the image make a conspicuous attempt at humor? This can be any type of humor, including situational, based on pop culture, or otherwise. The most important thing to note is whether the image makes an attempt at humor or not and not if it is successful or funny to you, the coder.

Sexuality: Is a sexualized situation or person, such as a beautiful women in a suggestive pose and/or clothes or an attractive, physically fit man without his shirt on, prominent? Or is the image clearly attempting to evoke a sexual response from the viewer?

Violence: Is a violent action or emotion (i.e., excessive anger) demonstrated or displayed in the image? This can be someone or something acting out on another person or thing. Hitting, punching, kicking, yelling angrily, wrestling, tackling, shooting, stabbing, pushing, and even pointing a gun all suggest violence.

Children: Are children, especially young children such as infants or toddlers, the focus of the image? Anyone who seems to be 18 or older does not qualify.

Animals: Are animals prominent in the image? These animals can range from pets, such as dogs and cats to farm animals (horses, cows, chickens) to exotic or wild animals (tigers, lions, monkeys, etc.)

Transmission View: Visual messages targeting the cognition or logic of the user. This view focuses on objective information surrounding the product, service, or brand. Specifications of a product, size of a company, capabilities, convenience, and other feature-based content indicate a transmission view. Bear in mind that the transmission view can appeal to the viewer's wants and/or needs, but it does so by informing the viewer. If one of the following three segments is prominent in an image, than the image can be categorized under the transmission view.

Ration: Messages that appeal to a consumer's need for information. The information does not only inform, however, but also persuades, as consumers are to be considered "rational, conscious, calculating, deliberative individuals" (Taylor, 1999). Examples of products commonly advertised with ration are cars (MPG, seating capacity, handling, etc), phones (camera ability, screen size, durability, etc) and computers (processing ability, memory, display sharpness, etc).

Acute Need: Messages that appeal to the immediate situations of a consumer and the subsequent needs: e.g., guests stop by unannounced for dinner and you need to order food. In this segment, the role of messages is to create brand recognition so that when consumers are limited by time and information and in immediate need of a product or service, they will choose the one with which they are the most familiar (Taylor, 1999). A product or service's accessibility or reliability in time of need indicates implementation of the acute need segment. Think of replacement parts or disposable goods that people might need not so on a regular basis, but a case-by-case basis. Think of batteries, tires, food delivery, party snacks, etc.

Routine: Messages that appeal to the consumers' habitual needs by emphasizing how a certain product or service fits in with his or her routine, especially in relation to frequently used products or services or even problems that arise on a regular basis (having problems sleeping?). Messages often focus on convenience, ease of use, and product efficacy on a daily or regular basis. Once a consumer is using that product and service as part of his or her routine, messages are designed to reinforce and perpetuate the behavior. Think of cleaning supplies or other household items like clothes, toilet paper, kitty litter, paper towels, coffee, and other common foods such as cereal or dog food.

Ritual view: Visual messages appealing to the emotional, mental, and/or physical wants or needs of the user. This view focuses on such things such as hunger, need for social interaction, bolstering self-esteem, sensory pleasure, status, relationships, etc. If one of the following three segments is prominent in an image, than the image can be categorized under the ritual view.

Ego: The ego segment is characterized by messages that tie the brand and product/service to the viewer's identity. Messages are constructed around the idea of how the product or service, or more importantly, the brand, makes them look. In other words, the messages reinforce the relationship of the brand with the consumer's identity. (Taylor, 1999). Luxury items such as expensive watches and cars are commonly advertised with egoladen messages, as are "brand-name" clothes: e.g., Rolex, Mercedes, or Polo. Note: this segment focuses on how a person uses the brand and/or product/service to reinforce who they are. In other words, the consumer buys the product for him or herself.

Social: Characterized by messages that target a consumer's emotional needs, but only as it pertains to that consumer's need to gain social approval or operate within a collective setting. The brand and/or product must be framed in a social context: "The role of advertising is to create the appropriate social situation within the advertising that motivates the consumer and thus transforms the product into the appropriate emotion such as love, affection, affiliation, noticing, or admiration" (Taylor, 1999). Think of items commonly given as gifts such as jewelry. In this segment, consumers are forced to think how the brand and/or product must be bought by the consumer for others.

Sensory: Characterized by messages that attempt to communicate how a product, service, and/or relationship with a brand create immediate sensory pleasure. These message appeal to any or all of consumers' fives senses: taste, sight, hearing, touch, and smell (Taylor, 1999). Think of up-close shots of delicious food or drinks, beautiful artwork, cute crafts, or stunning landscapes. In essence, the sensory segment includes all types of portrayals of the brand and/or product that evoke emotional responses. Since this study focuses on images, appealing visual graphics or "artsy" photos fall into this category.

Appendix D

Schema Related to Low and High Engagement for Likes and Comments

Segment 1

Top 10 percent of posts that received high levels of like engagement

Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	stal followe	Percent Likes	Percent comments
Coder 2	NewStore	394	Location	Humanizing		Social	75	12	231	0.324675325	0.051948052
Coder 2	NewStore		Multiple people	Humanizing		Social	64	4	231	0.277056277	0.017316017
Coder 2	NewStore	391	Object	Informing		Ration	61	4	231	0.264069264	0.017316017
Coder 2	NewStore		Multiple people	Humanizing		Social	55	0	231	0.238095238	0
Coder 2	NewStore	393	Multiple people, Activity	Humanizing		Social	51	1	231	0.220779221	0.004329004
Coder 2	NewStore	401	Single person	Humanizing		Ego	51	0	231	0.220779221	0
Coder 2	NewStore	404	Multiple people	Humanizing		Social	49	0	231	0.212121212	0
Coder 2	Look App	430	Text (overlaid on image), Graphic	Informing		Acute Need	187	4	970	0.192783505	0.004123711
Coder 2	Look App	438	Single person,Location,Graphic	Humanizing		Ego	179	4	970	0.184536082	0.004123711
Coder 2	Look App	424	Text (overlaid on image), Location, Graphic	Call for action		Ego	160	6	970	0.164948454	0.006185567
Coder 2	NewStore	398	Multiple people, Activity, Location	Branding		Routine	34	2	231	0.147186147	0.008658009
Coder 2	Look App	432	Object	Branding		Acute Need	138	2	970	0.142268041	0.002061856
Coder 2	Look App	436	Graphic	Branding		Sensory	135	6	970	0.139175258	0.006185567
Coder 1	Starry	35	Text (overlaid on image)	Informing		Ration	106	6	762	0.139107612	0.007874016
Coder 2	NewStore	399	Food,Object,Text (overlaid on image)	Branding		Ego	31	1	231	0.134199134	0.004329004
Coder 2	NewStore	400	Multiple people, Activity	Humanizing		Social	31	1	231	0.134199134	0.004329004
Coder 2	NewStore	410	Multiple people, Text (overlaid on image), Graphic	Humanizing		Social	31	1	231	0.134199134	0.004329004
Coder 2	NewStore	407	Multiple people, Activity	Humanizing		Social	31	0	231	0.134199134	0
Coder 2	NewStore	411	Single person, Object, Activity	Humanizing		Ration	31	0	231	0.134199134	0
Coder 2	Look App	425	Text (overlaid on image), Graphic	Branding		Ration	130	6	970	0.134020619	0.006185567
Coder 2	Look App	421	Object	Branding		Sensory	129	5	970	0.132989691	0.005154639
Coder 2	Look App	434	Multiple people, Food, Object, Text (overlaid on image), Activity, Gra	Informing		Acute Need	126	5	970	0.129896907	0.005154639
Coder 2	Look App		Text (overlaid on image), Graphic	Call for action		Acute Need	126	2	970	0.129896907	0.002061856
Coder 2	Look App	431	Text (overlaid on image), Graphic	Informing		Acute Need	125	3	970	0.128865979	0.003092784
Coder 2	Look App	417	Text (overlaid on image), Location, Graphic	Call for action		Social	124	8	970	0.127835052	0.008247423
Coder 2	NewStore	405	Text (overlaid on image), Graphic	Informing	Humor	Routine	29	3	231	0.125541126	0.012987013
Coder 2	NewStore	408	Multiple people, Fashion	Humanizing		Social	27	0	231	0.116883117	0
Coder 2	Look App	420	Multiple people, Activity, Location, Graphic	Humanizing		Social	113	4	970	0.116494845	0.004123711
Coder 1	Nowait	38	Object, Fashion	Branding		Ego	63	5	542	0.116236162	0.009225092
Coder 2	NewStore	412	Text (overlaid on image), Graphic	Call for action		Ration	26	1	231	0.112554113	0.004329004
Coder 2	NewStore	397	Object	Branding		Acute Need	26	0	231	0.112554113	0
Coder 2	Look App	416	Text (overlaid on image), Location, Graphic	Call for action		Ego	109	4	970	0.112371134	0.004123711
Coder 2	Look App		Text (overlaid on image), Graphic	Branding		Ration	109	4	970	0.112371134	0.004123711
Coder 2	Look App		Multiple people, Object, Activity	Humanizing		Social	109	0	970	0.112371134	0
Coder 2	NewStore	395	Object, Location	Branding		Sensory	24	0	231	0.103896104	0
Coder 2	Look App	436	Single person	Humanizing	2	Sensory	100	2	970	0.103092784	0.002061856
Coder 2	Look App		Object,Text (overlaid on image),Graphic	Call for action		Ego	97	2		0.1	0.002061856
Coder 2	NewStore		Object, Location	Branding		Ego	23	0	231	0.0995671	0
Coder 2	Look App		Text (overlaid on image), Activity, Graphic	Branding		Ration	94	10		0.096907216	0.010309278
Coder 2	Look App		Text (overlaid on image), Location, Graphic	Call for action	1	Sensory	87	6		0.089690722	0.006185567
Coder 2	NewStore		Location	Branding	1	Ration	20	0		0.086580087	0
Coder 2	Look App		Text (overlaid on image), Graphic	Informing		Acute Need	82	0		0.084536082	0
Coder 2	Simple		Multiple people,Object	Humanizing		Sensory	1141	8	13,700	0.083284672	0.000583942

Note. Percentages are in shown in decimal form: e.g., 0.016 = 1.6%

Segment 2

Bottom 10 percent of posts that received low levels of like engagement

Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	stal followe	Percent Likes	Percent comments
Coder 2	OfferUp	205	Object	Informing		Ration	334	11	628,000	0.000531847	1.75159E-05
Coder 1	OfferUp	145	Object	Informing		Ration	332	4	628,000	0.000528662	6.36943E-06
Coder 1	OfferUp	181	Object	Informing		Ration	324	10	628,000	0.000515924	1.59236E-05
Coder 2	OfferUp	251	Object	Informing		Ration	320	9	628,000	0.000509554	1.43312E-05
Coder 1	OfferUp	169	Object	Informing		Ration	314	13	628,000	0.0005	2.07006E-05
Coder 1	OfferUp	177	Object	Informing		Ration	313	7	628,000	0.000498408	1.11465E-05
Coder 1	OfferUp	130	Object	Informing		Ration	310	15	628,000	0.000493631	2.38854E-05
Coder 1	OfferUp	118	Object	Informing		Ration	309	6	628,000	0.000492038	
Coder 1	OfferUp	158	Object	Informing		Ration	309	1	628,000	0.000492038	1.59236E-06
Coder 2	OfferUp	208	Object	Informing		Ration	306	2	628,000	0.000487261	3.18471E-06
Coder 1	OfferUp	168	Object	Informing		Ration	304	3	628,000	0.000484076	4.77707E-06
Coder 1	OfferUp	192	Object, Fashion	Informing		Routine	298	6	628,000	0.000474522	9.55414E-06
Coder 1	OfferUp	138	Single person,Object	Humanizing	Children (yo	Sensory	293	5	628,000	0.000466561	7.96178E-06
Coder 1	OfferUp	122	Single person, Object	Informing		Ration	291	4	628,000	0.000463376	6.36943E-06
Coder 1	OfferUp	154	Object	Informing		Ration	287	3	628,000	0.000457006	4.77707E-06
Coder 1	OfferUp	115	Multiple people, Food, Activity	Humanizing		Social	274	4	628,000	0.000436306	6.36943E-06
Coder 2	OfferUp	235	Object, Text (overlaid on image), Graphic	Informing		Ration	269	34	628,000	0.000428344	5.41401E-05
Coder 1	OfferUp	186	Object	Informing		Ration	262	1	628,000	0.000417197	1.59236E-06
Coder 2	OfferUp	239	Object, Text (overlaid on image), Graphic	Informing	Humor	Ration	260	7	628,000	0.000414013	1.11465E-05
Coder 2	OfferUp	247	Object, Text (overlaid on image), Graphic	Informing	Humor	Ration	260	4	628,000	0.000414013	6.36943E-06
Coder 2	OfferUp	222	Object	Informing		Ration	259	6	628,000	0.00041242	9.55414E-06
Coder 2	OfferUp	242	Food, Object, Text (overlaid on image), Graphic	Informing	Humor	Ration	257	7	628,000	0.000409236	1.11465E-05
Coder 2	OfferUp	252	Object	Informing		Ration	252	8	628,000	0.000401274	1.27389E-05
Coder 2	OfferUp	241	Object, Text (overlaid on image), Graphic	Informing	Humor	Ration	251	15	628,000	0.000399682	2.38854E-05
Coder 1	OfferUp	183	Object	Informing		Ration	247	3	628,000	0.000393312	4.77707E-06
Coder 1	OfferUp		Object	Informing		Ration	242	6	628,000	0.00038535	9.55414E-06
Coder 2	OfferUp	230	Object, Text (overlaid on image), Graphic	Informing	Humor	Ration	231	4	628,000	0.000367834	6.36943E-06
Coder 2	OfferUp	225	Multiple people, Object, Text (overlaid on image), Graphic	Informing	Humor	Ration	230	1	628,000	0.000366242	1.59236E-06
Coder 2	OfferUp	228	Object, Text (overlaid on image), Graphic	Informing		Ration	220	11	628,000	0.000350318	1.75159E-05
Coder 2	OfferUp	232	Object, Text (overlaid on image), Graphic	Informing	Humor	Ration	218	14	628.000	0.000347134	2.2293E-05
Coder 2	OfferUp	246	Object, Text (overlaid on image), Graphic	Informing		Ration	211	2	628,000	0.000335987	3.18471E-06
Coder 2	OfferUp	231	Object, Text (overlaid on image), Graphic	Informing		Ration	208	16	628,000	0.00033121	2.54777E-05
Coder 2	OfferUp		Object, Text (overlaid on image), Graphic	Informing	Humor	Ration	207	7		0.000329618	1.11465E-05
Coder 2	OfferUp		Object	Informing	Humor	Ration	205	1		0.000326433	1.59236E-06
Coder 2	OfferUp	236	Object, Text (overlaid on image), Graphic	Informing	Humor	Ration	204	14		0.000324841	2.2293E-05
Coder 2	OfferUp		Food, Text (overlaid on image), Graphic	Informing	Humor	Ration	197	5		0.000313694	
Coder 2	OfferUp		Single person, Object, Text (overlaid on image)	Informing	Humor	Ration	195	2	628,000	0.00031051	3.18471E-06
Coder 2	OfferUp		Object, Text (overlaid on image), Graphic	Informing	1	Ration	192	10		0.000305732	
Coder 2	OfferUp		Object,Text (overlaid on image),Graphic	Informing	Humor	Ration	189	2		0.000300955	
Coder 2	OfferUp		Object,Text (overlaid on image),Graphic	Informing	Humor	Ration	182	14		0.000289809	
Coder 2	OfferUp		Object,Text (overlaid on image),Graphic	Informing	Humor	Ration	180	8		0.000286624	
Coder 2	OfferUp		Object,Text (overlaid on image),Graphic	Informing		Ration	180	6		0.000286624	9.55414E-06
Coder 2	OfferUp		Object, Text (overlaid on image), Graphic	Informing		Ration	144	2		0.000229299	
Coder 2	OfferUp		Single person, Object, Text (overlaid on image), Graphic	Informing	Humor	Ration	136	4		0.000216561	

Segment 3

Top 10 percent of posts that received high levels of comment engagement

Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	stal followe	Percent Likes	Percent comments
Coder 2	NewStore	394	Location	Humanizing		Social	75	12	231	0.324675325	0.051948052
Coder 2	NewStore	392	Multiple people	Humanizing		Social	64	4	231	0.277056277	0.017316017
Coder 2	NewStore	391	Object	Informing		Ration	61	4	231	0.264069264	0.017316017
Coder 2	NewStore	405	Text (overlaid on image), Graphic	Informing	Humor	Routine	29	3	231	0.125541126	0.012987013
Coder 2	Look App	418	Text (overlaid on image), Activity, Graphic	Branding		Ration	94	10	970	0.096907216	0.010309278
Coder 1	Nowait	38	Object, Fashion	Branding	T T	Ego	63	5	542	0.116236162	0.009225092
Coder 2	NewStore	398	Multiple people, Activity, Location	Branding		Routine	34	2	231	0.147186147	0.008658009
Coder 2	Look App	417	Text (overlaid on image), Location, Graphic	Call for action		Social	124	8	970	0.127835052	0.008247423
Coder 1	Starry	35	Text (overlaid on image)	Informing		Ration	106	6	762	0.139107612	0.007874016
Coder 2	Look App	414	Text (overlaid on image), Graphic	Informing		Ration	60	7	970	0.06185567	0.007216495
Coder 1	Bellhops	66	Single person,Pet	Branding	Animals	Sensory	57	23	3,257	0.017500768	0.007061713
Coder 1	Starry	29	Single person, Object, Activity	Humanizing		Acute Need	51	5	762	0.066929134	0.00656168
Coder 2	Instamotor	381	Multiple people, Food, Activity	Humanizing		Social	51	6	967	0.052740434	0.006204757
Coder 2	Look App	424	Text (overlaid on image), Location, Graphic	Call for action		Ego	160	6	970	0.164948454	0.006185567
Coder 2	Look App	436	Graphic	Branding		Sensory	135	6	970	0.139175258	0.006185567
Coder 2	Look App	425	Text (overlaid on image), Graphic	Branding		Ration	130	6	970	0.134020619	0.006185567
Coder 2	Look App	423	Text (overlaid on image), Location, Graphic	Call for action		Sensory	87	6	970	0.089690722	0.006185567
Coder 2	Instamotor	388	Object	Informing		Ration	46	5	967	0.047569804	0.005170631
Coder 2	Instamotor	382	Object,Pet	Branding	Humor, Anin	Sensory	41	5	967	0.042399173	0.005170631
Coder 2	Look App	421	Object	Branding		Sensory	129	5	970	0.132989691	0.005154639
Coder 2	Look App	434	Multiple people, Food, Object, Text (overlaid on image), Activity, Gra	Informing		Acute Need	126	5	970	0.129896907	0.005154639
Coder 2	NewStore	393	Multiple people, Activity	Humanizing		Social	51	1	231	0.220779221	0.004329004
Coder 2	NewStore	399	Food, Object, Text (overlaid on image)	Branding		Ego	31	1	231	0.134199134	0.004329004
Coder 2	NewStore	400	Multiple people, Activity	Humanizing		Social	31	1	231	0.134199134	0.004329004
Coder 2	NewStore	410	Multiple people, Text (overlaid on image), Graphic	Humanizing		Social	31	1	231	0.134199134	0.004329004
Coder 2	NewStore	412	Text (overlaid on image), Graphic	Call for action		Ration	26	1	231	0.112554113	0.004329004
Coder 2	NewStore	396	Single person, Fashion	Branding		Ego	16	1	231	0.069264069	0.004329004
Coder 2	Look App	430	Text (overlaid on image), Graphic	Informing		Acute Need	187	4	970	0.192783505	0.004123711
Coder 2	Look App	438	Single person, Location, Graphic	Humanizing		Ego	179	4	970	0.184536082	0.004123711
Coder 2	Look App	420	Multiple people, Activity, Location, Graphic	Humanizing		Social	113	4	970	0.116494845	0.004123711
Coder 2	Look App	416	Text (overlaid on image),Location,Graphic	Call for action	1	Ego	109	4	970	0.112371134	0.004123711
Coder 2	Look App		Text (overlaid on image), Graphic	Branding		Ration	109	4	970	0.112371134	0.004123711
Coder 2	Look App		Multiple people, Text (overlaid on image), Activity, Location	Call for action		Ego	78	4	970	0.080412371	0.004123711
Coder 2	Look App	427	Multiple people, Activity	Humanizing		Social	72	4	970	0.074226804	0.004123711
Coder 2	Lola	380	Object, Text (overlaid on image), Graphic	Informing	1	Routine	32	2	487	0.065708419	0.004106776
Coder 1	Starry	23	Single person, Object, Activity	Humanizing		Routine	59	3	762	0.077427822	0.003937008
Coder 1	Starry		Single person, Text (overlaid on image), Graphic	Humanizing		Routine	35	3	762	0.045931759	0.003937008
Coder 2	Instamotor	389	Object, Location	Branding		Ration	46	3	967	0.047569804	0.003102378
Coder 2	Instamotor		Text (overlaid on image), Graphic	Informing	1	Routine	29	3	967	0.029989659	0.003102378
Coder 2	Look App		Text (overlaid on image), Graphic	Informing		Acute Need	125	3	970	0.128865979	0.003092784
Coder 2	Simple		Single person, Object	Informing	1	Routine	234	40	13,700	0.017080292	0.002919708
Coder 1	Starry		Object,Text (overlaid on image)	Branding	1	Sensory	54	2		0.070866142	0.002624672
Coder 1	Starry		Object	Informing	1:	Routine	49	2		0.064304462	0.002624672

Segment 4

Bottom 10 percent of posts that received low levels of comment engagement

Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	otal followe	Percent Likes	Percent comments
Coder 1	Starry	10	Single person,Object	Branding		Sensory	40	0	762	0.052493438	0
Coder 2	NewStore	406	Multiple people, Object, Activity	Humanizing		Social	12	0	231	0.051948052	0
Coder 1	Starry	12	Single person	Branding	Humor	Ego	36	0	762	0.047244094	0
Coder 1	Starry	11	Multiple people, Activity	Humanizing	Humor	Social	35	0	762	0.045931759	0
Coder 1	Starry	34	Single person, Text (overlaid on image), Graphic	Call for action	Humor	Social	35	0	762	0.045931759	0
Coder 1	Bellhops	102	Text (overlaid on image),Location	Branding	Humor	Ration	142	0	3,257	0.043598403	0
Coder 1	Starry	22	Object, Graphic	Branding		Sensory	30	0	762	0.039370079	0
Coder 1	Bellhops	44	Multiple people	Humanizing		Social	117	0	3,257	0.035922628	0
Coder 1	Bellhops	43	Object, Text (overlaid on image)	Informing		Ration	116	0	3,257	0.035615597	.0
Coder 1	Bellhops	90	Location, Graphic	Branding		Routine	109	0	3,257	0.03346638	0
Coder 1	Bellhops	60	Single person, Graphic	Branding		Sensory	101	0	3,257	0.031010132	0
Coder 1	Bellhops	49	Multiple people	Humanizing		Social	97	0	3,257	0.029782008	0
Coder 1	Bellhops	82	Single person,Pet	Humanizing	Animals	Sensory	95	0	3,257	0.029167946	
Coder 1	Bellhops	74	Multiple people	Humanizing		Social	94	0	3,257	0.028860915	0
Coder 1	Bellhops	93	Location, Graphic	Branding		Sensory	92	0	3,257	0.028246853	0
Coder 1	Bellhops	59	Pet	Branding	Animals	Sensory	86	0	3,257	0.026404667	0
Coder 1	Bellhops	63	Text (overlaid on image), Graphic	Branding		Routine	82	0	3,257	0.025176543	.0
Coder 1	Bellhops	85	Single person	Humanizing	Humor	Social	82	0	3,257	0.025176543	0
Coder 1	Bellhops	78	Single person,Object	Humanizing		Social	80	.0	3,257	0.024562481	0
Coder 1	Bellhops	50	Multiple people, Activity	Humanizing		Social	68	0	3,257	0.020878109	
Coder 1	Bellhops	73	Multiple people, Activity	Humanizing		Social	68	0	3,257	0.020878109	.0
Coder 1	Bellhops	97	Text (overlaid on image), Graphic	Call for action	i i	Sensory	68	0	3,257	0.020878109	0
Coder 1	Bellhops	84	Multiple people, Activity	Humanizing		Social	66	0	3,257	0.020264047	.0
Coder 1	Bellhops	81	Multiple people	Humanizing	Children (yo	Sensory	63	0	3,257	0.019342954	0
Coder 1	Bellhops	42	Object	Branding		Sensory	61	0	3,257	0.018728892	.0
Coder 1	Bellhops	72	Single person,Object,Activity	Humanizing	Humor	Social	61	0	3,257	0.018728892	0
Coder 2	Instamotor	390	Multiple people	Humanizing		Social	18	.0	967	0.018614271	0
Coder 1	Bellhops	95	Multiple people,Object	Humanizing		Social	59	0	3,257	0.01811483	0
Coder 1	Bellhops	98	Multiple people,Text (overlaid on image)	Branding		Sensory	57	0	3,257	0.017500768	.0
Coder 1	Bellhops	51	Single person	Branding		Sensory	56	0	3,257	0.017193737	0
Coder 1	Bellhops	77	Multiple people, Graphic	Humanizing		Social	52	0	3,257	0.015965613	0
Coder 1	Bellhops	54	Single person	Branding		Sensory	51	0	3,257	0.015658582	0
Coder 1	Bellhops		Multiple people, Activity	Humanizing		Social	46	0	3,257	0.014123426	0
Coder 2	Simple		Multiple people,Location	Branding		Ego	159	0	13,700	0.011605839	0
Coder 1	Bellhops	96	Single person, Object, Activity	Humanizing	1	Social	37	0		0.011360147	0
Coder 1	Bellhops	86	Multiple people	Humanizing		Social	35	0		0.010746085	0
Coder 2	Simple	313	Single person, Fashion	Humanizing		Ego	147	0	13,700	0.010729927	0
Coder 2	Simple	269	Object, Activity	Branding		Ego	143	0	13,700	0.010437956	0
Coder 1	Bellhops	62	Single person,Food	Humanizing	Humor	Sensory	33	0	3,257	0.010132023	0
Coder 2	Simple	326	Location	Branding		Sensory	135	0	13,700	0.009854015	0
Coder 2	Simple		Single person,Object,Activity	Branding		Routine	133	0	13,700	0.009708029	
Coder 2	Simple	337	Object	Branding		Social	115	0	13,700	0.008394161	0
Coder 2	Simple	315	Location	Branding		Sensory	111	0	13,700	0.00810219	0
Coder 1	Hudl	1	Multiple people, Text (overlaid on image), Activity	Informing		Ration	439	0	101,000	0.004346535	0