

A CONTENT ANALYSIS OF THE DALLAS FARMERS MARKET INSTAGRAM

A Thesis

by

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ABSTRACT

The local food movement, consumers' desire to be connected to food and its origin, and emergence of Instagram as a source for creating B2C relationships through visual imagery contribute to the need of determining image content that connects with consumers. A quantitative and qualitative content analysis of 144 images from the Dallas Farmers Market (DFM) Instagram account were conducted to determine images with highest and lowest engagement. In this study the variables that made up engagement were likes and comments. Images with natural fresh-food products made up 34% of all images and had higher consumer engagement. Low engagement categories included farm photo and user-generated content. Qualitative analysis showed no relationship between likes and comments, but users' opinions and engagement influenced each other.

Therefore, future research recommendations from this study include exploring purchase intention and approach behavior as a result of positive consumer engagement. Recommendations for education are to use Instagram as a means to educate students about agricultural products and practices without leaving the classroom. Consumer engagement was highest with natural-fresh food product images on the Dallas Farmers Market Instagram, suggesting that farmers markets should incorporate these images into their social media strategies to generate consumer engagement. This study offered insights to what type of images on Instagram generate consumer engagement for farmers markets. Conclusions are that farmers markets should incorporate natural-fresh food products into their social media strategies to generate consumer engagement.

DEDICATION

I dedicate this work to my parents who have been there for me throughout my entire experience at Texas A&M University. Their constant love, support, and encouragement have meant the world to me.

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Last, but not least, a special thank you to my family for supporting my dreams and goals no matter how crazy they seemed. I could not have accomplished this without your love. I cannot wait to continue to make you proud.

NOMENCLATURE

DFM	Dallas Farmers Market
TE	Total Engagement
USDA	United States Department of Agriculture

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CHAPTER I

INTRODUCTION

Local food movements have emerged, especially in the Dallas/Fort Worth metro area (Aucoin & Fry, 2015), as people look to fill their kitchens with local and fresh-food products. The local food movement is known as the motion in which consumers have shifted to purchasing higher-quality products often labeled locally grown, organic, and more environmentally sustainable than what can be purchased at supermarkets (Aucoin & Fry, 2015). Along with the desire for healthier food options consumers want to know how their food made it to their tables, where and how it was raised, and how it was transported (Schindler, 2014; U.S. Department of Agriculture, 2013).

The term “local food” has no definite meaning but includes a variety of definitions such as geographical location, background information pertaining to the product and the farmer, and production methods (Martinez et al., 2010). Farmers markets are common venues for local food purchasing and have been growing in popularity since the beginning of the 21st century (Martinez et al., 2010; Gao, Swisher, Zhao, 2012). Farmers markets have the ability to boost local economies, give consumers access to fresh-local foods, and help small to medium size farms build and develop businesses (U.S. Department of Agriculture, n.d.). The National Agricultural Statistics Service (2012) reported that the total earnings from direct to consumer sales was \$1.3 billion in fresh food products, making them a reliable source of revenue for small scale farms who accounted for a majority of those sales.

Farmers markets are often perceived by consumers as having fresh and local produce making them a prime location for direct interaction between producers and consumers (Gao et al., 2012; Conner, Colasanti, Ross, & Smalley, 2010). According to Mount (2012), local food systems should connect the consumer and the producer during a direct exchange of product. “Direct agricultural markets promise human connection at the place where production and consumption of food converge, an experience not available either to consumers shopping at ‘superstores’ or ‘hypermarkets’ or to farmers selling through conventional wholesale commodity markets”(Hinrichs, 2000, p. 295). Direct interaction between producers and consumers includes, but is not limited to, purchasing local and fresh-food products, educating consumers about the origin of their food, and informing them how it came to market. Because of the direct interaction between farmers and consumers hosted by farmers markets, consumers have the opportunity to make the desired connection to how their food came to market. Consumers can also make connections with local food producers online through social media. There has been an increase in professional use social media to reach and engage with consumers by brands, and marketing through social media can improve brand awareness and impact profitability (Kumar, Bezawada, Rishika, Janakiraman, & Kannan, 2016).

Social Media

Social media has the capability of transforming consumers from “passive information recipients” (p. 107) to active and engaging players when it comes to food-related education (Shan, et al., 2015). Many agriculturalists have yet to see the advantages of using social media and how it can be used to educate consumers about agriculture, market products and build relationships through engagement (Meyers, Irlbeck, Graybill-Leonard, & Doerfert, 2011; Edman, 2010).

According to Meyers et al. (2011), “social media tools are a farming revolution that can be used to make farming more profitable and depict agriculture in a positive manner” (p. 7). The 2014 Media Channel Study conducted by the Association of Business Information Companies found that only 12 percent of agriculturalists use social media on a weekly basis. This supports that agriculture has a weak online presence when it comes to social media, putting them at a disadvantage (Topp, Stebner, Barkman, & Baker, 2014).

The Power of Visuals through Instagram

An important feature of social media is the ability to upload visual imagery to multiple platforms that can be viewed by targeted audiences. Visuals are powerful in influencing emotions and reinforce textual messages and information (Edgar & Rutherford, 2014). If social media is the doorway to engage with consumers to create meaningful relationships illustrate the production of fresh and local food through visual imagery can be a positive way to educate consumers about their food, market products, and engage with consumers to create meaningful relationships.

Instagram is a relatively new platform devoted to the art of visual story-telling, and the story is the brand (Diamond, 2013). By posting only visual content, accompanied by a caption, brands are forced to portray their messages and values through images to connect with their audiences.

On Instagram users interact with brands and other consumers through two types of engagement: likes and comments. Likes and comments can be influential in determining the whether a user had a positive or negative emotional reaction to an image (Khobzi & Teimourpour, 2014). In order to create positive engagement and create meaningful relationships through imagery, it is important that brands understand what kind of images emotionally connect with consumers when using Instagram to communicate and market products.

Statement of the Problem

Agriculture does not have a prominent presence on social media and changing consumer's demands, such as the local food movement, contribute to the need for agricultural producers and consumers to form new connections (White, Meyers, Doerfert, & Irlbeck, 2014). According to Edgar and Rutherford (2011), there is a need for research that is focused on images that are associated with marketing agriculture. Farmers markets are hosts for direct interaction between producers and consumers, so understanding how to emotionally connect and engage with audiences online is crucial to business success (Diamond, 2013).

If visuals are a powerful tool when emotionally connecting with an audience then brands using social media, specifically Instagram, need to understand what types of

images to post that will yield the most engagement. Generating engagement increases brand awareness and has the potential to affect consumer response behavior, such as purchase intention (Sashi, 2012).

There has been little research on social media for smaller businesses, such as farmers markets, and their usage of Instagram is significantly less than other platforms such as Facebook (Cui, 2014). A recent shift to online communication practices from consumers has businesses more interested in marketing online (Latiff & Safiee, 2015), regardless that there has been little research and literature to support Instagram's effectiveness in online marketing. According to Latiff and Safiee (2015), consumers prefer to trust their online peers more than the brand itself when shopping online. A review of literature also revealed the lack of research involving Instagram for marketing purposes, particularly within the agricultural industry.

Purpose

The purpose of this study was to analyze the Dallas Farmers Market Instagram account (@dallasfarmersmarket) and determine the types of images present and that generate the most engagement for local farmers markets.

Objectives

This study was based on three objectives:

1. Quantify image engagement on the Dallas Farmers Market Instagram account from March 1, 2015–July 31, 2015 using a modified version of Ginsberg's (2015) categories.

2. Compare images that contain fresh produce and images that do not contain fresh produce to identify highest and lowest total engagement.
3. Describe the polarity relationship between the number of comments and comment content of the highest and lowest engagement categories of images identified in research objective one.

Scope of the Study

The scope for this study will be the Dallas Farmers Market Instagram account because of its large social media following and large amount of media on Instagram. Images analyzed were posted from March 1–July 31, 2015.

Definition of Terms

The following terms are defined for purpose and use of this study:

1. Fresh-food products: Products that are unprocessed and in their raw state, includes fresh meat, seafood, vegetables, fruits, herbs and eggs (Unnevr, 2000; Martinez et al., 2010).
2. Fresh Produce: Raw/unprocessed fruits, vegetables or herbs (Go Texan, n.d.).
3. Engagement: Consists of likes and/or comments on Instagram; gives insight into audience activity (Simply Measured, 2015).
4. Processed food: Making food from one or more ingredients, or synthesizing, preparing, treating, modifying or manipulating food, including food crops or ingredients, includes baking, boiling, bottling, canning, cooking, cooling, cutting, drying, evaporating, extracting, freezing, pasteurizing, peeling, and trimming (U.S. Food and Drug Administration, 2015).

Limitations

The following limitations were identified for this study:

1. Instagram is a dynamic environment because its users have the ability to delete/add comments or likes at any given time. Therefore the amount of comments and/or likes recorded at the time of data collection may have been altered at any point during or after the study.
2. The Dallas Farmers Market Instagram account is a publicly accessed account. A user does not have to be a follower to engage with photos. The calculated total engagement values may have included users who were not shoppers of the DFM or local to the Dallas/ Fort Worth metro area. This is an important limitation because it cannot be assumed that all engagement came from a local shopper or follower.
3. Images can be classified in more than one category. This caused some differences between coders due to multiple types of content within images.
4. Emoji vary by mobile device and software. There are slight differences between software versions and devices that may have resulted in users not being able to express emotions with the use of Emoji in the same way as others.

Significance of the Study

Instagram is a mobile application that illustrates a story through images (“Instagram for Business,” 2016) “enabling brands to build an emotional engagement and most likely a profitable relationship with customers” (Gong, 2014, p. 5). This study identified and provided the Dallas Farmers Market, as well as other fresh produce

vendors, insight as to what types of images users engage and emotionally connect with on Instagram. Understanding what types of images consumers connect allows brands to adjust their social media strategies accordingly to maximize positive consumer engagement, resulting in the satisfaction of customer needs and affecting response behavior (Sashi, 2012). This study focused on the determination of what type of images will yield the most consumer engagement for farmers markets.

Summary

Social media has become increasingly popular in B2C marketing, and it is important to understand how to effectively engage with consumers. To generate consumer engagement brands need to understand types of images consumers emotionally connect with, which can influence response behavior. The local food movement suggests consumers put an emphasis on understanding the origin of food and farmers markets provide a place of direct interaction for farmers and consumers to connect the dots. Farmers markets who use social media, especially Instagram, need to understand the visuals that consumers engage with the most in order to execute effective social media strategies for brand exposure and positive consumer response behavior.

CHAPTER II

LITERATURE REVIEW

Business to Consumer Marketing

Business-to-consumer (B2C) marketing is a transaction in which a business sells a product or service directly to the consumer (Hom, 2011). Since the emergence of the Internet as a communication tool, growth in B2C electronic commerce (e-commerce) has occurred (Ranganathan & Ganapathy, 2002) because businesses can directly promote or advertise their products, on company websites and/or social media outlets. As of February 2015, Internet sales for B2C products were projected to account for 13.2 percent of company sales over the next 12 months (Mooreman, 2015). Additionally, the 2014 social media marketing industry reported B2C marketers were more likely to use Facebook, Instagram, Pinterest, and YouTube to market products directly to customers.

Along with an increasing trend of businesses using Internet marketing, a steady incline in popularity of consumers shopping online has emerged (Ranganathan & Ganapathy, 2002). Pew Research Center (2008) reported two-thirds of online users have shopped online because it saves time and is convenient that 81percent use the Internet to research products and services. According to Lamb, Hair, and McDaniel (2015), social media in B2C marketing has “been the most pervasive marketing trend in the past five years” (p. 124). According to Kumar et al. (2016), as businesses put more effort into social media marketing consumer connections continue to strengthen and higher levels of social media engagement drive sales.

Social Media

The emergence of social media has been steadily increasing since 2005 changing the way the world communicates and connects personally and professionally, “challenging marketers into the next generation of marketing” (Carlson & Lee, 2015, p. 81). Pew Research Center (2013) found that 67% of Internet users were social media users. Two years later, in September of 2014, Pew Research Center updated that 74% of Internet users were using social networking sites. The seven percent increase in users supports a shift in communication and an increase in popularity of adopting social media across multiple generations (Pew Research, 2015).

Social media tends to engage a variety of target audiences and creates an online community through which the world can communicate (Smith, 2009). According to Lamb, Hair, and McDaniel (2015) social media has also become a gathering place for the online discussion of brands and a host to researching products and services for consumers supporting that social media is used for more than informalities. For businesses, social media plays an important role in marketing products and services, and increasing brand awareness through the targeting of consumer audiences (Thackeray, Neigar, Hanson, & McKenzie, 2008; Kumar & Mirchandani, 2012).

Agriculture and Social Media

Consumers’ changing communication preferences and advancements in technology creates a need for the agricultural industry to effectively convey news and issues to the public (Graybill- Leonard, Meyers, Doerfert, & Irlbeck, 2011). According to Topp, Stebner, Barkman, and Baker (2014), the agricultural industry been a laggard

when it comes to social media presence. The Association of Business Information Companies (2014) conducted a media channel study with 1,029 participants classified as owners, operators, and/or farm or ranch managers. Only 12% of participants used social media on a weekly basis and 18% used it monthly. Even though the percentages are small, there was a 3% usage increase from 2010 to 2014. In addition, 47% of digital users indicated that accessing digital media was an essential activity when running a farm or ranch (Association of Business Information Companies, 2014). As society continues to shift from traditional media outlets, such as magazines and newspapers, to digital media and mobile technology, it's important for younger generations to use social media to advocate and circulate information about products and practices (Topp et al, 2014).

There also is a need to identify social media strategies in agriculture for advocating, building relationships with the community, and maximizing marketing efforts so producers can effectively advertise their products and services (Meyers, Irlbeck, Graybill-Leonard, & Doerfert, 2011). As suggested by Edgar and Rutherford in 2011, "there is a need to complete research focused on images associated with marketing agriculture" (p.17). If utilized efficiently, social media platforms provide producers with a source of free marketing with the use of original visuals of products and their brands.

Social Media Marketing

Consumer driven changes in communication have forced brands to shift from traditional marketing mediums such as television, radio, newspapers, magazines, and billboards to online marketing through the use of social media (Jadhav, Kamble, & Patil,

2013). Brands are “looking for more innovative and cost effective ways to market their products or services and are paying more attention to social media as a powerful survival tool and shifting from traditional to social media” (Kirtis & Karahan, 2011, p. 265). Social media helps businesses create more meaningful relationships with customers, (Hoffman & Fodor, 2010; Khobzi & Teimourpour, 2015) in turn, increasing revenue and decreasing costs (Khobzi & Teimourpour, 2015). In 2014, Social Media Examiner published a report describing 2,800 marketer’s use of social media to grow and promote business. The findings showed that 83% of marketers included social media in marketing activities, and 92% believed social media was important for business growth and increased brand awareness (Stelzner, 2014). According to Thackeray et al. (2008), social media contributes to three aspects of promotional marketing strategies: brand or product awareness, persuasion to purchase products, and serves as a reminder of products and services provided by a brand.

Businesses have reported the overall impact of social media to be positive, yet a large percentage of businesses are concerned with measuring return on investments (Kumar et al., 2016). Stelzner (2014), reported that 50% of participating businesses had no way of knowing if social media increased sales because of the lack of analysis and tracking tools. Measuring return on investment (ROI) on social media has become an obstacle for businesses because it requires “tracking consumer investments and analyzing social media interactions” (Geho & Dangelo, 2012, p. 63). Many managers and companies calculate ROI in terms of dollars (Hoffman & Fodor, 2010); however, with social media, ROI may not just be monetary. Because social media sites such as

Facebook, Twitter, Instagram, and Pinterest offer the basic use of their sites at no charge, it makes sense to measure engagement rather than dollars. According to Hoffman and Fodor (2010),

Instead of emphasizing their own marketing investments and calculating the returns in terms of customer response, managers should begin by considering consumer motivations to use social media and then measure the social media *investments* customers make as they engage with the marketers' brands. (p. 42)

For businesses, determining whether marketing strategies resulted in connecting with consumers is important (Kumar & Mirchandani, 2012). To determine the effectiveness of marketing on social media, measuring interaction and considering consumer motivations and investments as they engage with brands would be much more efficient (Hoffman & Fodor, 2010). For social media platforms such as Facebook, Twitter and Instagram these "social media investments," otherwise referred to as engagement features in this study, are likes and comments (Khobzi & Teimourpour, 2015).

In 2014, Khobzi and Teimourpour found a correlation between likes and users' comments on Facebook. The popularity of a post was determined by the number of likes, which reflected the polarity of the comments under the post. For example, a post with a higher number of likes was found to have a higher polarity score. It was also observed that users' comments influenced each other in terms of polarity contributing to potential engagement from others (Khobzi & Teimourpour, 2014).

This study suggested that measuring the impact of likes and comments is crucial to determining the ROI of social media (Khobzi & Teimourpour, 2014). If a post has more likes and positive comments, it gains popularity which in turn, generates positive more positive engagement with that brand. The same conclusion was made if a post has a low amount of comments accompanied by negative comments then a post is considered unpopular and could potentially be harmful to the image that brand portrays (Khobzi & Teimourpour, 2014). As a result of obtaining data based on consumer engagement, businesses should have a clearer understanding of how to create and execute marketing strategies in the future that are more effective.

Another study looked at brand post popularity in relation to the type of social media marketing strategy implemented. De Vries, Gensler, and Leeflang (2012) used six categories of brand posts to describe brand post popularity. The findings of this study were similar to Khobzi and Teimourpour's (2014) study in that the number of likes was related to the number of positive comments of a brand post (De Vries, Gensler, & Leeflang, 2012). However, De Vries et al. (2012), determined that their study confirmed that negative comments contributed to brand post popularity just as much as positive comments. This supports that comments, whether positive or negative, potentially motivate other users to express their opinions in the form of likes or comments, which increases engagement. One of most popular type of social media brand posts in this study was pictorial images (De Vries et al., 2012), which have the capability of also affecting consumer engagement by creating relationships, influencing consumer preferences, and enhancing communication (Gong, 2014; Diamond, 2013). The

emergence of Instagram, created in 2010, is a unique social media platform that conveys messages through the sharing of visual images to connect with other users (Lee, Lee, BS, Moon, & Sung, 2015).

Instagram

Instagram a free, photo-sharing platform, focuses on visual rather than textual content. According to Pew Research Center (2014), 26% of Internet users are active on Instagram, which is up 9% from 2013. Since its creation in 2010 Instagram has been recognized for its visual marketing potential (Bergstrom & Backman, 2013). In 2015 Instagram tallied more than 300 million active users, had more than 30 billion photos shared, received 2.5 billion likes daily further, on average users shared 70 million photos a day (Lee et al., 2015). Instagram is installed as an application on a mobile device used by Apple and Android users and is unique due to its ability to edit photos before posting (Hempel, 2014). The editing features include size, color, lighting, position, brightness, contrast, saturation as well as the ability to apply a filter or create collages.

The adoption of this new platform is spreading rapidly while becoming new territory for Internet marketing (Bergstrom & Backman, 2013; Hempel, 2014). Bui (2014) said, “Instagram’s growing popularity makes it an ideal platform of choice for communicators because it provides a versatile stage that can host a number of strategic initiatives to market a business, brand, or specific product” (p. 5). The 2014 social media marketing industry report indicated that marketers who invested more than 40 hours a week to social media were focused more on Instagram and 42% of marketers planned on increasing their use of Instagram (Stelzner, 2014). Because Instagram is a relatively new

social media platform, little research was found to support its effectiveness with visual marketing to support return on investment for professional use of the platform.

Communications research has previously explored Facebook, Twitter, and blogs, but Instagram is absent.

Fresh Produce and Farmers Markets

In 2005 Wolf, Spittler, and Ahern concluded that consumers believe farmer's market produce is fresher than produce from supermarkets, tastes better, and is a higher-quality product grown locally. "The momentum behind the local food movement has grown in recent years with rising support for, and awareness of, local farmers markets, making them increasingly popular destinations among food shoppers" (Cui, 2014, p. 88). Farmers markets continue to rise in popularity as a source for high-quality fresh produce products along with the consumer demand for fresh produce (compared to grocery stores). These markets have become a major player in urban-farm linkage, connecting consumers to the origin of their food (Wolf, Spittler & Ahern, 2005; Hearn, Collie, Lyle, Choi, & Foth, 2014).

Most people associate farmers markets to be providers of local and regional farm products. According to the United States Department of Agriculture (2012), "farmers markets are often the first point of entry into the marketplace for small to medium sized producers" (p. 1). New farmers, both small and mid-sized, are finding reasons to sell closer to home and market their products to local communities (U.S. Department of Agriculture, 2012). The types of products found at farmers markets varies due to

vendors, season and other environmental factors. Farmers markets typically sell a variety of products ranging from fresh-food products to non-food products.

For small to medium size farms and local producers in urban areas, the financial difficulties of marketing and selling foods can be problematic (U.S. Department of Agriculture, 2012). Some producers have begun to use social media as a means of improving business-to-consumer marketing, which has the potential to generate financial impact (Graybill-Leonard et al., 2011). According to Know Your Farmer, Know Your Food Compass (2012), generating financial impact is only a portion of the local food system.

Local and regional food systems also include providing education about their products so that consumers can feel connected to where their food comes from ((U.S. Department of Agriculture, 2012). “Consumers now put more emphasis on wanting food that is convenient, ethically raised, and healthy; they want to know where their food is coming from, how it was raised, and how it got to their plate” (White et al., 2014, p. 73). Producers are able to tell their stories directly through branding and the way they merchandise their products both in person and on the Internet. The shift in B2C e-commerce and local food movements creates a need for agriculturalists to understand how to effectively market their products supporting the need for research on types of images that influence consumers to engage in their brands as suggested by Edgar and Rutherford (2011).

Visual Communications

Marketers are becoming increasingly interested in learning more about creating original visuals to accompany their posts on social media (Stelzner, 2014). Imagery effects consumer engagement by through an intellectual or emotional connection. The relationship between visual material and its power to be memorable, arouse emotion and persuade target audiences to change their attitudes and behavior makes it influential (Joffe, 2008).

Visuals are thought to send people down along emotive pathways whereas textual material leaves them in a rational and linear pathway of thought. Visuals are readily absorbed in an unmediated manner because viewers are not generally provoked to reflect on or deconstruct them in the way that occurs in relation to textual material.”(Joffe, 2008, p. 85)

According to Lester (2006), “photography has become the most popular medium for creating visuals” (p.241). “Photographs influence viewer’s emotions more often than words and can also strengthen a message beyond what words can describe” (Edgar & Rutherford, 2011, p. 17). Textual materials supersede visual marketing suggesting that information alone isn’t enough to capture attention, instead visual materials must use to stimulate emotions and connections between the viewer and the content (Joffe, 2008).

When creating high-quality images for online content, one must understand humans react and connect with visuals based on technical characteristics such as light, edges, shapes, color variation, motion, and patterns (Lurie & Mason, 2007).

Photographs, ads and other forms of imagery have the capability of encouraging people

to interpret an entity differently as well as stimulate different responses in regards to what they see (“Instagram for Business,” 2016). Not everyone sees the same thing when viewing images, different experiences shape an individual’s interpretation of an image (Diamond, 2013). This is an important factor to consider as brand or marketer, not all audiences and consumers can be reached with the same visuals because they all have different perceptions shaped by different experiences.

Understanding the way consumers visually communicate with brands is just as important as marketers visually communicating to consumers. On social media users have the option to “comment” under posts where they can express their thoughts and feelings textually. Shigetaka Kurita created “emoji’s,” small digital icons used to express ideas, emotions, and represent objects from the physical environment via electronic communication (Kelly & Watts, 2015; Oxford English Dictionary online, n.d.). The word “emoji” comes from the Japanese language combining *e* meaning picture, and *moji* meaning letter or character (Oxford English Dictionary online, n.d.). These are not to be confused with emoticons, which are representations of facial expressions using keyboard characters (Stark & Crawford, 2015; Oxford English Dictionary online, n.d.).

According to Kelly and Watts (2015), emojis extend beyond the capabilities of emoticons and include a number of other symbols besides facial expressions that convey emotions such as hearts and hand gestures. Emojis have given social media users a new way to visually express their emotions outside of text, and can be evaluated by sentiment analysis (Novak, Smailović, Sluban, & Mozetič, 2015). Defined by Wilson, Weibe, and Hoffman (2005), sentiment analysis is the “task of identifying positive and negative

opinions, emotions, and evaluations” (p. 347). Emojis can be used in-text to enhance visually represent the reaction of a user and used to analyze consumer emotions by sentiment analysis.

Theoretical Framework

This study applied the stimulus (S), organism (O), and response (R) paradigm (Mehrabian & Russell, 1974a; Mehrabian & Russell, 1974b) to identify the type of Instagram visuals used to market fresh produce and the characteristics that engage consumers and create emotional and intellectual connections. Mehrabian and Russell (1974b) proposed the SOR paradigm to explain the effects of an environment on behavior. The “stimulus” refers to physical stimuli, or everyday things of the physical environment. These physical stimuli relate to any of the five senses and include visual cues, smells, textures, and temperature. The stimuli (S) contains cues that in turn affect an individual’s, or the organism’s (O), emotions, influencing them to engage or not engage. The engagement then invokes a response (R) of approach or avoidance of the stimuli (Spangenberg, Crowley & Henderson, 1996).

According to Mehrabian and Russell (1974b), SOR has three essential emotional dimensions that address internal states caused by physical stimuli: pleasure, arousal, and dominance. Pleasure, referred to as pleasure-displeasure, is often associated with smiles, laughter, and general positive versus negative facial expressions (Mehrabian and Russell, 1974b). Arousal is a unitary emotional response that measures responsiveness and most often includes vocal activity, facial activity, speech rate, and volume (Mehrabian and Russell, 1974b). For the purpose of this study dominance was

eliminated since previous research has indicated it has had little to no effect on consumer behavior (Ha & Lennon, 2010).

Effects on consumer behavior previously studied include satisfaction, purchase intention, and approach behavior. Ridgway, Dawson, and Bloch (1989) used the SOR model to gain a better understanding of consumers approach responses in a physical retail environment using a survey. In order to measure emotions the study was conducted in an outdoor, unmediated shopping center. Results from Ridgway et al. (1989) were that pleasure had a significant impact on satisfaction and purchase intention while arousal impacted approach-avoidance behavior. Fister, Ti, and Burns (2010) analyzed consumer responses in retail environments using different visual displays and background music to invoke emotional states that lead to approach behavior. The two emotional states tested were aesthetic responses and mental imagery arousal (Fister, Ti, & Burns, 2010). Overall findings concluded that shopping displays that invoked mental imagery arousal responded with approach behavior.

The SOR model has also been used by researchers to measure a brand's image in an online shopping environment. Park and Lennon (2009) looked at store image and brand awareness, revealing that well-known brands lead to positive cognitive state which resulted in a higher probability of purchase intention compared to brands without established online presence. A Korean study compared "visual, vocal and celebrity effects in motion pictures" (p. 377) to determine if tourism motivation was affected (Rajaguru, 2013). Results showed that visual affects played a major part in customer decisions to visit tourism locations (Rajaguru, 2013).

Following Mehrabian and Russell's (1974b) framework, the emotional reactions of Instagram followers can be explored. Instead of placing potential consumers in a physical environment with many different stimuli, Instagram photos represented the physical environment. In 2015, Ginsberg used 11 categories to analyze photo elements in the top five food brands on Instagram at the time. Quantitative content analysis was conducted based on previous studies of using Instagram for brand awareness in order to determine the type of marketing visuals used (Ginsberg, 2015). Ginsberg combined Goor's study (2012) based on the theory that brands are categorized by function (persuasion, sales response, symbolism, relational self-efficacy, and emotion) with Bui's study (2014) that focused on social-integrative content suggesting that a brand's photo content should include products as well as be entertaining and connect with consumers with diverse content (Ginsberg, 2015). Results of Ginsberg's (2015) study were that a variety of images were used across all five brands, it was noted that product promotion images were most common and that pictures with people were identified as inviting and created more meaningful relationships with consumers.

In 2012, Goor used a content analysis of current social media strategies using Instagram for marketing. He based his study on the theoretical frameworks related to brand typology and traditional marketing strategies. Every photo was analyzed for possible strategy characteristics and coded appropriately. Goor (2012) found that "product representation brands mainly use persuasion, relational and emotion strategies, by applying branding, making the emotional connectedness with the brand most important, and using slice-of-life scenarios in their photos" (p. 31). In 2014, Bui showed

how Instagram was helpful to mobile food vendors and looked at the motivations of users to engage in social media. Bui concluded that “social-integration and tension release components present in Instagram posts were more likely to activate engagement from users” (p. 25). This study used 12 image categories to categorize images determine which categories had the highest engagement from users.

The SOR model was applied to show the correspondence between stimuli and emotional reactions. Instagram represented the physical environment and individual images contained specific content or stimuli that invoked consumer emotions. The cues within the image stimulate the organism (consumer) causing them to engage or not engage. Pleasure is represented by “liking” an image posted on Instagram and arousal is represented by “commenting” on an Instagram photo. Pleasure or arousal will then determine the consumer response such as avoidance, approach, purchase intention or satisfaction. A conceptual model is illustrated in Figure 1.

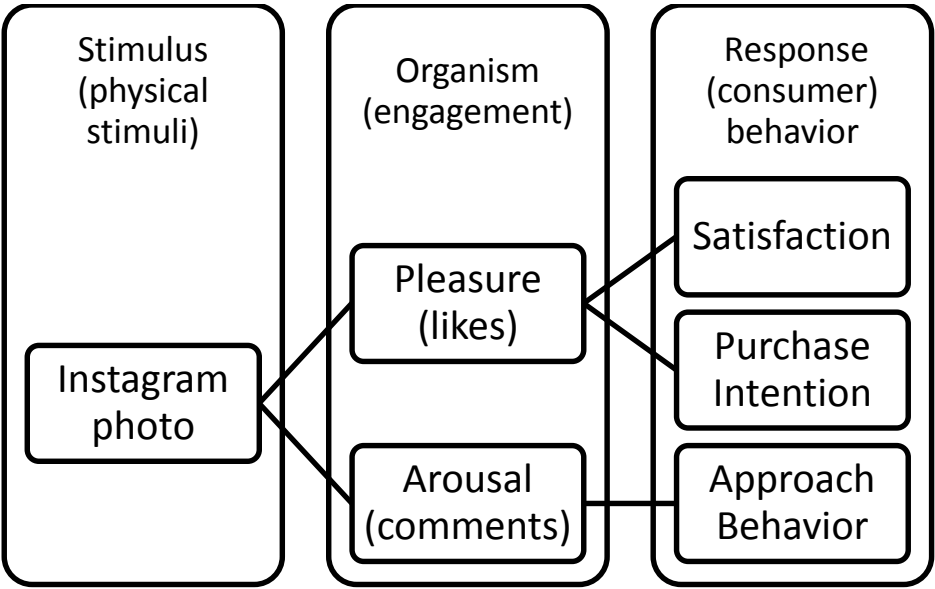


Figure 1. SOR Model Applied to Visual Images on Instagram

Purpose and Objectives

The purpose of this study was to analyze the Dallas Farmers Market Instagram account (@dallasfarmersmarket) and determine what types of images are present and generate the most engagement for local farmers markets. The following research objectives guided this study:

1. Quantify image engagement on the Dallas Farmers Market Instagram account from March 1, 2015- July 31, 2015 using a modified version of Ginsberg's (2015) categories.
2. Compare images that contain fresh produce and images that do not contain fresh produce to identify highest and lowest total engagement.
3. Describe the polarity relationship between number of comments and comment content of the highest and lowest engagement categories of images identified in research objective one.

CHAPTER III

METHODS

The research method for this study will be mixed-method approach to content analysis. Content analysis is defined by Krippendorff (2004) as “a research technique for making replicable and valid inferences from meaningful matter, such as texts, symbols and images, to the contexts of their use” (p. 18). As defined by Frankel, Wallen, and Hyun (2012), a mixed-methods approach uses both qualitative and quantitative approaches to content analysis. The use of both methods delivers a more in-depth and complete understanding of the research objectives. The quantitative phase allowed variables to be quantified and the qualitative phase will identify the relationships between independent variables. According to Kolbe and Burnett (1991), content analysis allows for the analysis of environmental variables and the effects of message content, such as cognitive and behavioral, on consumer responses. Content analysis is also appropriate when access to data is limited to documentary evidence (Kassarjian, 1977), such as public records on the internet. This supports that content analysis is appropriate for this study when applied to the SOR model because it accounts for environmental stimuli, analysis of emotions and measure of response behaviors.

Phase 1: Quantitative Content Analysis

Kassarjian (1977) defined a quantitative content analysis is a “research technique for the objective, systematic, and quantitative description of the manifest content of communication” (p. 8). Content analysis is an important part of social science research

that explores texts and images in order to yield a better understanding of communication data (Krippendorff, 2004). With the Internet becoming a major player in B2C marketing and communication, a large amount of data is generated that businesses have trouble analyzing, this data is often referred to as big data (“Big Data,” 2016). Krippendorff (2004) data being generated from the Internet, including social media, is “mostly unmined content analysis data” (p. 43). If businesses are unsure of how to analyze and use data to determine the impacts of social media, then using content analysis to give the data meaning makes sense. According to Kolbe and Burnett (1991), content analysis has a place in consumer/marketing research and has ability to describe communication content such as image content within media and content characteristics (Kassarjian, 1977).

To first objective quantified image engagement on the Dallas Farmers Market (DFM) Instagram account by quantitative content analysis for the months of March, April, May, June, and July 2015 and compare total engagement values between categories. DFM is a large farmers market located in Dallas, Texas, with more than 11,800 followers on Instagram. The DFM Instagram account is updated by organization employees. However, content consultation is provided by DMA Solutions in Dallas, Texas. The DFM Instagram account was chosen for this study because of its established presence on Instagram. Of all farmers markets considered for this study, DFM had the largest number of followers and posted media which provided more data.

One-hundred and forty-four posted images were coded into twelve categories for analysis. According to *Go Texan*, 45 types of produce are available at Texas farmers

markets during a calendar year (“Texas Produce Availability Chart,” n.d.). Of the 45, 42 are available from the beginning of March through the end of July, which expands beyond the limitations of seasons. This provides a variety of content for analysis.

Data Collection

Using a content analysis, data are reported in units, which serve as the independent variables within a study. Because users engage with images on Instagram by “liking” and “commenting,” likes and comments will serve as the unit of analysis in this study and be quantified and recorded independent of each other. Variable definitions are sourced from Simply Measured, a website dedicated to generating analytics for social networking sites (SNS). Simply Measured has generated analytics from many established brands such as Adidas, Microsoft, Samsung, and KIA. A like on Instagram is recorded when a user selects the heart shaped icon under posted content. Likes signify an image has connected with a user (Simply Measured, 2015). A comment is left separately under an image by selecting the callout bubble. Comments can contain words, symbols, emoticons and/or Emoji generated by computers, phones, and tablets.

According to Simply Measured (2015), one to the top three metrics to consider when evaluating engagement on Instagram is the total engagement (TE). TE is defined as the sum of likes and comments. “Total engagement gives insight into how active an audience is and how well a strategy is working” (Simply Measured, 2015, p. 4). This study looked specifically at calculating the total engagement per post. Calculating total engagement per post versus tallying likes and comments individually gives strategic insight as to what specific images are receiving the most engagement (Simply Measured,

2015). Most often, analytics sum the number of engagements in a given time period then divide it by the sum of posts to find the engagement-per-post value according to Simply Measured analytics (2015). Because this calculation uses the sum of posts, it calculates an average per post. This investigated engagement individually by image rather than calculating average engagement for a number of images grouped together.

I created a Microsoft Excel spreadsheet to record and organize likes, comments, and total engagement. To view and generate the number of likes and comments for each image I used Iconosquare, a web-based Instagram viewer. After all likes and comments per image were recorded and the total engagement per image was calculated I coded images into categories.

Instrumentation

Once the total engagement values were calculated each image was classified into at least one of the 12 categories according to a codebook with corresponding descriptions of each category. Images were allowed to be count in more than one category depending on the nature of the photo. For example, an image would potentially have more than one category of content if were a collage or a brand intended to capture more than one idea. Six image categories originated from previously reviewed studies and six categories were added based on consumer behavior related to fresh food products, or added to contrast another category. The 12 categories are identified and defined in Table 1 followed by examples of images from each category in Figure 2.

Table 1

Coding Manual with Descriptions of Image Categories

Image Category	Definition
User-Generated Content	Reposted by DFM, originally created by another user, customer or vendor.
Natural Fresh-Food Product	Fresh-food products in their natural or raw states (regardless of packaging) that have not been processed.
Recipe	An illustration of the process to create dishes or other food products with more than one ingredient.
Person with Fresh-Food Product	An individual interacting or posing with a fresh food product.
Holiday/Celebration	Content that relates directly to a “special day of celebration”, such as American Holidays or world events
Campaign with Fresh-Food Product	Direct promotion of the DFM to create a particular outcome and includes a fresh food product. May include brand logos, advertisements for brand-hosted events (including time and place), and brand products.
Lifestyle	Content indirectly promoting products or relating to the DFM, such as aerial shots.
Farm	Photo taken at the origin of fresh food products, may include producers interacting with the product.
Campaign without Fresh-Food Product	Direct promotion of the DFM to create a particular outcome with no fresh food product shown.
Processed Food	Any food product altered from its natural form including canned goods, pizza, breads, pickles, bbq and bottled liquids.
Non-Food	Products not edible or for human consumption, including non-food products include soaps, clothing, flowers and plants, and dog food.
Person with Non-Food Product	An individual interacting or posing with a non-food product.

Note. DFM = Dallas Farmers Market

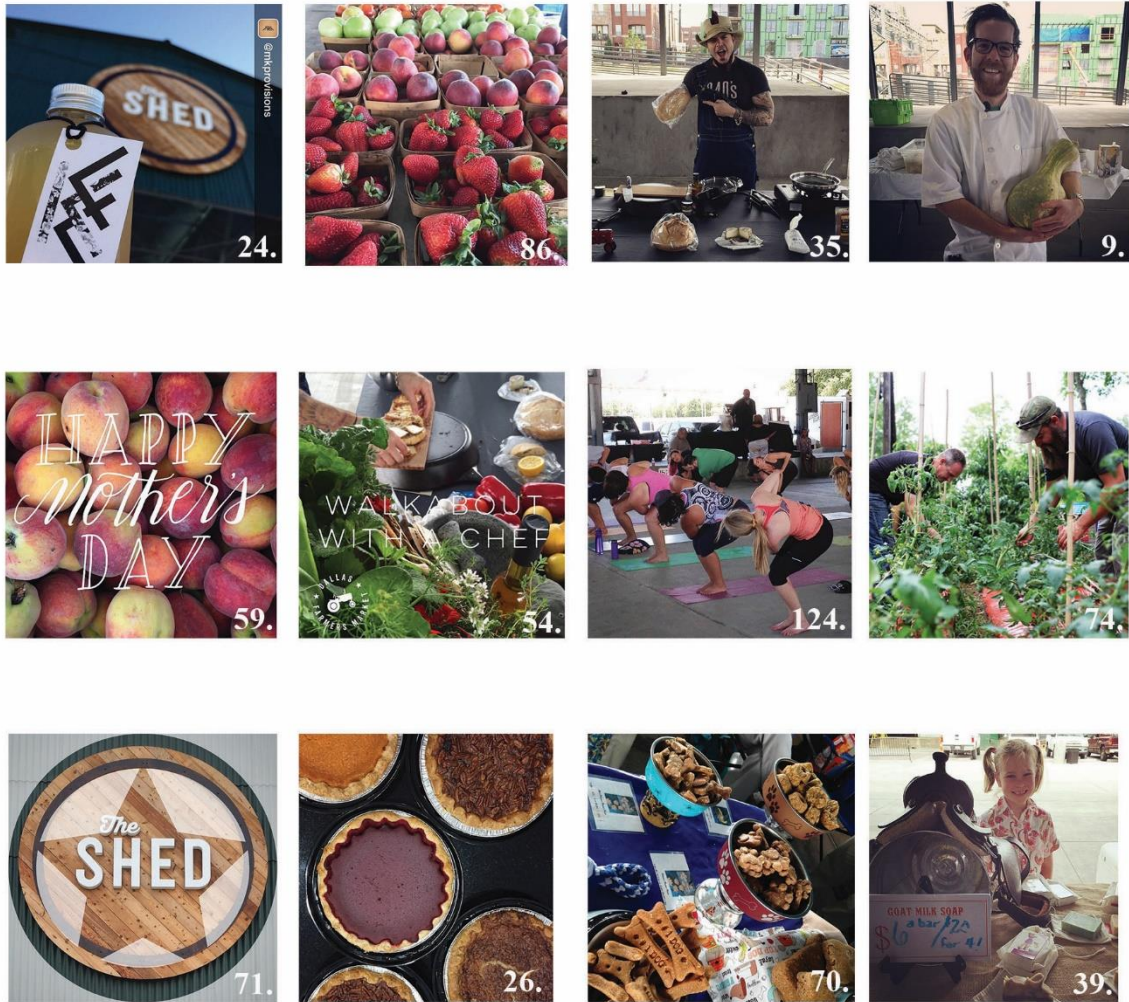


Figure 2. Examples of Image Content from Categories; 24 = User-Generated Content; 86 = Natural Fresh-Food Product; 35 = Recipe; 9 = Person with Fresh-Food; 59 = Holiday/Celebration; 54 = Campaign with Fresh-Food Product; 124 = Lifestyle; 74 = Farm; 71 = Campaign without Fresh-Food Product; 26 = Processed Food; 70 = Non-Food Product; 39 = Person with Non-Food Product

In 2015, Ginsberg looked at 11 different photo element categories that the leading food brands on Instagram used based previous research by Goor (2012) and Bui (2014). Ginsberg’s photo categories reflect the content components identified in Goor and Bui’s studies. The six categories pulled from Ginsberg’s (2015) study of photo

elements were user-generated content, recipes, person with product, current events, campaign without fresh-food product, and lifestyle.

A total of six categories were added to the original six from Ginsberg's study. Two categories were added based on how "local food systems convey information to consumers so that they may feel connected to where their food comes from" (U.S Department of Agriculture, 2013, p. 7). If consumers are more interested in the origin of their food, then illustrating origin of products and how they came to market are necessary. The two additional categories based on previous research regarding consumer preferences included fresh-food product in its natural state (raw state) and farm photos. Four categories were added in order to make sure all content was accounted for during analysis and to contrast other categories. These four categories include processed food, non-food products, campaign with fresh-food, and non-food products with a person. Categories were coded by an assigned number of one through twelve for sorting purposes and are shown in Table 2.

Table 2

Image Category Coding

Image Category	Identifier
User-Generated Content	1
Natural Fresh-Food Product	2
Recipe	3
Person with Fresh-Food Product	4
Holiday/Celebration	5
Campaign with Fresh-Food Product	6
Lifestyle	7
Farm	8
Campaign without Fresh-Food Product	9
Processed Food	10
Non-Food Product	11
Person with Non-Food Product	12

The category assignment for each image was added in a column on the same Excel spreadsheet as total engagement. Images were then sorted based on the value from highest to lowest. Sorting the data based on categories the images were assigned helped me view each image category separately and calculate total engagement values for each image category individually.

After assigning each image to a category, I sorted the images according to whether each image actually contained fresh produce products or did not contain fresh

produce products. For this study, fresh produce was defined as fruits, vegetables, and herbs based on the “Texas Produce Availability Chart” provided by *Go Texan* (APPENDIX C). If an image contained fresh-produce anywhere within its content, it was noted with a “P” for fresh produce. Similarly, if an image contained no fresh-produce content, it received an “N” for no fresh produce. After coding all images for visible fresh-produce content, the number of images with and without fresh produce were summed and recorded for each image category. Figure 3 shows one image with fresh-produce content and one with non-fresh produce content.



Figure 3: Fresh-Produce and Non-Fresh Produce Example Images; Fresh Produce is included in image 106; No fresh produce is included in image 103

Phase 2: Qualitative Content Analysis

The second phase of this study used a qualitative content analysis approach to describe the polarity relationship between the number of comments and comment content for the highest and lowest engagement categories. According to Krippendorff (2004), “content analysis has evolved into a repertoire of methods for research that yield inferences from all types of verbal, pictorial, symbolic and communication data” (p.17). Using a qualitative content analysis, themes and reoccurring patterns of meaning are

identified and coded (Merriam, 2009). Comments were described as positive, negative or neutral based on phrase-level sentiment analysis, including the presence of emotion words, emoji and overall context of the comment. Sentiment analysis has been used previously, especially on Facebook and Twitter, to evaluate consumer reviews (Khobzi & Teimourpour, 2014).

One of the most common applications of sentiment analysis is to track attitudes and feelings on the Web, especially for tracking products, services, brands or even people. The main idea is to determine whether they are viewed positively or negatively by a given audience (Khobzi & Teimourpour, 2014, p. 257).

The sample for the qualitative approach to analyzing the Dallas Farmers Market Instagram account is an accumulation of all comments posted under the images within the highest and lowest engagement categories. To collect comment content of the highest and lowest engagement category, the DFM Instagram account was viewed again using Iconosquare. The sample of comments for the highest engagement category were copied onto a Microsoft Word document by image, in order of the earliest post to latest post. Comments were viewed by date of posting and independently of the actual image they were posted under.

Instrumentation

I grouped comments by the date of the image posted. To avoid bias images did not accompany comments. Each comment was analyzed in a systematic approach using a codebook and heuristic tools. Before any coding was done, a reinforcement of the basic understanding and definitions of positive and negative emotions were reviewed.

According to Fredrickson (2001), experiences and feelings such as “joy, contentment, love and the like” (p. 218). characterize positive emotions. Negative emotions contrast with positive emotions and reflect on such feelings of anxiety, sadness, anger and despair (Fredrickson, 2001). Thus, neutral comments can neither be determined as positive or negative.

A wide variety of comment content can be found on social media and may include text, Emoji, emoticons and/or user handles. Because different types of content can occur in any combination, comments were evaluated based on three characteristics: emotion words, Emoji definitions and phrase-level context. First, I identified emotion words using McLaren’s emotional vocabulary list (n.d.) that gives example of positive and negative emotions. Coders then identified Emoji that expressed emotions according to the Emojipedia dictionary (Emojipedia, n.d.). The last characteristic to consider before describing the individual comment’s polarity was the overall context of the comment. The possibility no emotion words or Emojis being present in the content of comments makes phrase-level analysis necessary in order to determine overall polarity. The codebook contains McLaren’s Emotional Vocabulary list and a list of Emoji found on the Dallas Farmers Market Instagram (Appendix D).

The amount of positive, negative and neutral comments were tallied per image and recorded in separate columns by coder. Coders interpreted comments based on the overall tone of the comment in relation to the comments posted prior or the tone and context the comment individually. Comments could be analyzed in reference to earlier posted content under their respective images. The method of determining polarity of

comment content by images rather than individual comments was used because the researcher was looking to compare the polarity of comment content overall between categories as a whole. Some comments indicated that thoughts were identical to previously posted comments about the image or idea portrayed by the image.

Interrater Reliability

To determine if the study was reproducible, interrater reliability (IRR) was calculated (Krippendorff, 2004). To ensure reliability of the results, the findings should be replicated, yielding the same results. Thus, another researcher must be able to obtain the same results by applying the same technique when analyzing data (Krippendorff, 2004). Two coders (master's students majoring in agricultural leadership, education and communications) used the same existing documents as the researcher. This idea is referred to as reproducibility and arguably one the most practical and strongest types of reliability to use (Krippendorff, 2004; Hayes & Krippendorff, 2007).

If the researcher and coder agreed 100 percent a (1) was assigned. If coding resulted in a disagreement a (0) was assigned. The reliability of objective one was 74%. Because multiple photos could be classified in more than one category, and if coders agreed on at least one category, agreement was set to 1. The reliability for objective two, determining the presence versus the absence of fresh-produce in images, was calculated to be 89%. If the number of positive, negative and neutral comments were equal between coders a 1 was assigned. If differences existed the image earned a coefficient of 0. Even though polarity was tallied by image, the number of comments overall was considered into to calculate IRR. Additionally, to have the correct number of matches, the

differences from disagreements must be totaled. For example if one coder recorded one positive, one negative and one neutral comment and the other coder recorded two positive and one negative then the difference between coders is 1. The total number of comments summed up to be 237 and the match total summed up to 214. Reliability for objective three was 90%. All calculations were above 70%, so the methods of coding images and comment content was systematic and reliable.

CHAPTER IV

RESULTS

RO1: Image Categories and Quantifying Engagement

The first objective of this study was to quantify total engagement and categorize images using a modified version of Ginsberg's (2015) image categories to determine the highest and lowest total engagement categories. Using quantitative content analysis, a total of 144 images were coded and categorized and 22 images classified in more than one category. Seventy-three of the images coded into one Ginsburg's original six categories. Examples of images classified in multiple categories were collages and images with more than one type of content. The overall total engagement (TE) value for the Dallas Farmers Market (DFM) Instagram was 20,864 between March and July 2015. This sum includes all pictures included in the study. After all coding was completed images were ranked from highest TE value to the lowest TE value.

The highest engagement category (TE = 7,678) was the natural/raw fresh-food product category, which accounted for a 34% of all images analyzed and 37% of total engagement. This category also had the greatest amount of likes, comments and, images. The lowest total engagement image category (TE = 83) was the farm photo category, which only had one image to code. It included 82 likes and one comment. Image categories had three main sections (because of the two significant breaks within the TE column). The first and largest break occurred between the highest and second-highest total engagement category (Lifestyle TE = 3,201) separating the highest engagement

category significantly from the rest of the data. Rankings two through nine are close in TE value with a range of 2,462, followed by ranks 10 through 12 ranging from 81 to 405.

As the total engagement values decreased, so did the number of likes per category decreased. Such was true for the number of comments as well, except for the holiday/celebration and processed food categories (rankings three and four). Even though processed foods had a higher TE value than holiday/celebration images, the number of comments for processed food was lower (comments = 109). Holiday/celebration images received 62 more comments than processed foods even though the image category itself had less images. The number of images in each category also descended along with TE except for between rankings two to three and seven to eight. The results from research objective one are displayed in Table 3.

Table 3

Image Content Categories Ranked by Total Engagement Values

Rank	Image Category	Likes	Comments	TE	<i>n</i>	%
1	Natural/Raw FFP	7,453	243	7,678	57	34
2	Lifestyle	2,979	222	3,201	22	13
3	Processed	2,437	109	2,546	23	14
4	Holiday/Celebration	1,435	167	1,602	14	8
5	Non-Food Product	1,277	44	1,321	10	6
6	Campaign Without FFP	1,084	109	1,193	10	6
7	Recipe	1,082	40	1,122	11	7
8	Person with Product	764	20	784	7	4
9	Non-Food Product with Person	703	36	739	5	3
10	Campaign with FFP	405	15	420	4	2
11	User-Generated Content	173	2	175	2	1
12	Farm	82	1	83	1	1
	Totals	19,856	1,008	20,864	166	100

Note. Fresh-Produce Product is referred to as FFP; TE = Total Engagement; *n* = number of photos in sample set;

RO2: Images Containing Fresh-Produce Content vs. Non-Fresh-Produce Content

The second objective was to compare the number of images containing fresh produce and to the number of those not containing fresh produce using Ginsberg's categories to identify highest and lowest engagement. Findings were consistent and descended in the same sequence as research objective one. Using the same data set as research objective one, images were re-sorted and ranked highest to lowest by the number of images that containing and not containing fresh produce. One-hundred and one images had fresh-produce content, and 67 images did not have fresh-produce content. Some images contained both fresh produce content and non-fresh produce content. Twenty-nine of the images contained fresh produce and were coded into one of Ginsburg's original six categories.

The highest total engagement (TE) category for images containing fresh produce was the natural fresh-food product category. Out of 54 images within this category 52 contained fresh produce content and accounted for 58% of total engagement for images containing fresh produce. The natural fresh produce category also contained the largest amount of fresh-produce images. This category had 55 images of the 57 determined to have fresh produce content, significantly higher than any other image category. The next TE category for fresh-produce content had a TE of 1,547, and accounted for only 12% of images containing fresh-produce content. The difference between first and second rankings marked a clear break within the data. When looking at the numbers of images containing fresh produce, processed food, recipe and lifestyle categories all tied for second place with each having nine.

User-generated content and campaigns without fresh food content were the lowest engagement categories for fresh-produce content images. Their TE values were both zero because they had no images containing fresh produce categories. The non-food product category placed third from last and had a total engagement value of 74. This category had one image with fresh produce content in the background, close to the subject of the picture. Results for fresh produce content are displayed in Table 4.

Table 4

Image Categories Ranked by Total Engagement of Fresh-Produce Content

Rank	Image Category	TE	<i>n</i>
1	Natural/Raw FFP	7,522	54
2	Lifestyle	1,547	9
3	Processed	1,208	10
4	Recipe	940	9
5	Person with Product	692	6
6	Holiday/Celebration	573	5
7	Campaign with FFP	420	4
8	Non-Food Product	148	0
9	Farm	83	1
10	Non-Food Product With Person	74	1
11	Campaign Without FFP	0	0
12	User-Generated Content	0	0

Note. A “P” was assigned by coders to signify the presence of fresh-produce content; TE = Total Engagement; *n* = number of photos in sample set

The lifestyle category had a total engagement value of 1,654, the highest for images containing non-fresh produce. Even though the lifestyle and processed food categories had the same number of non-fresh produce images, processed food had a lower TE value of 1,338 than lifestyle. Unlike the fresh-produce content data, non-produce content data did not have any significant breaks, and the total engagement values descended. The processed and non-food images had the highest number of non-fresh produce images. The lowest engagement category for non-produce comments were the categories for campaigns with fresh-food products and farm photos. Neither of these categories had any engagement because all of their photos contained fresh produce. The total engagement values for non-fresh produce content from categories is shown in Table 5.

Table 5

Image Categories Ranked by Total Engagement of Non- Fresh-Produce Content

Rank	Image Category	TE	<i>n</i>
1	Lifestyle	1,654	13
2	Processed	1,338	13
3	Non-Food Product	1,321	9
4	Campaign Without FFP	1,193	10
5	Holiday/Celebration	1,029	9
6	Non-Food Product with Person	665	4
7	Natural/Raw Product	304	2
8	Recipe	182	2
9	User-generated Content	175	2
10	Person with Product	92	1
11	Campaign With FFP	0	0
12	Farm Photo	0	0

Note. An “N” was assigned by coders to signify the presence of non- fresh-produce content

RO3: Comment Polarity Relationships

The third research objective was to describe the polarity relationship between the number of comments and comment content of highest and lowest engagement category.

A total of 50 images were included in the qualitative content analysis to determine a polarity of positive, negative, or neutral comment content. The highest engagement category had 57 images; however, six did not have any comments at the time of data collection. A total of 238 comments were analyzed by: 237 natural fresh-food product images and one farm content image. Even though 243 comments were recorded during only 237 were visible to viewers for the fresh-food product category. Comments can be deleted by the account or by Instagram users, which was a limitation of the study. As mentioned previously, polarity was determined by phrase-level analysis which incorporated textually expressed emotions, Emoji, and overall context of the comment.

Few identified emotional words were included in the codebook as supplements to determining polarity. A total of 75 Emojis expressed emotions by facial expression or hand gestures, and nine emoticons were included in comments from the highest engagement category. Exactly half of the fresh-food product images contained comments with Emoji. Thirty-four of the comments consisted of only a handle (@) or social mention without other comment content. Those comments were coded as positive. For this study, mentioning another user's handle as a comment is viewed as positive because it causes awareness of the brand to another user.

For fresh-food product images overall comment polarity was 44 positive images, three negative images and three neutral images. Therefore, the overall comment polarity was determined as positive. The images were 91% percent positive, followed by 5% negative and 3% neutral. The farm photo category, lowest TE category, received only one comment which was positive.

By determining the polarity of comment content and engagement values for individual images of the highest engagement category, the type of comment content did not vary systematically. Specifically, an image's overall polarity did not reflect number of likes or comments. Within the highest engagement category, image 86 had the most negative comments (comments = 11), and the second highest number of likes (likes = 211). Image 82 had both the most positive comments (comments = 21) and highest number of comments. Image 82 also received 171 likes which was 38 less than the average of the natural product category (mean = 133). Therefore, it can be concluded for

this study that the number of comments does not predict or show a direct relationship with any one type of comment polarity.

The data showed a pattern between the first comment and the overall comment polarity of a single image. The polarity of the first comment most often determined the polarity of the comment content that followed. Even though the number of likes for image 86 was high compared to the rest of the category, comments were negative. The first comment posted under this image had negative polarity and all but two comments received the same polarity score. The same pattern was viewed for images that were determined to be positive in polarity. Image 82 received 21 visible comments from users and the first comment was positive, which set the trend for polarity of following comments. The four negative comments that accompanied image 82 did not refer to the actual image. Instead, users were using the image to connect and communicate with other users rather than discuss image itself.

CHAPTER V

CONCLUSIONS

This study addressed three objectives and revealed the relationship image comment content and to total engagement values. The category with the highest engagement value was the category that represented a fresh-food product in its natural (or raw) state. The category with the lowest engagement category was the farm photo category, illustrating the origin of fresh-food products. Additionally, the overall comment content polarity was positive. Analyzing individual image comments and comparing those comments to other image comments within the highest engagement category, the overall polarity of comment content was not directly related to the number of comments per image. However, the polarity was influenced by the first comment posted. This supports that users are influenced by other users' comments and that brands should pay close attention to consumer comments. Last, the number of images objective led to the conclusion that the amount of images and total engagement values associated with fresh-produce content was significantly higher in the natural fresh-food category than any other category.

The Dallas Farmers Market Instagram account primarily posts images with content of natural-fresh-food products, specifically fresh produce. With this image category having the highest total engagement (TE) value, the data suggested users engaged with this type of photo are more focused on what a fresh-food product looks like at the point of purchase. Knowing users engage more with natural fresh-food

product and fresh produce images DFM should continue to post these types of images to build brand awareness and engage users with content (De Vries et al., 2012; Sashi, 2012). As previously stated within the literature review, understanding the relationship between image content and engagement could potentially increase sales (De Vries et al., 2012; Geho & Deangelo, 2012). Posts that receive higher engagement increases the probability of connecting with users. According to the SOR model (Mehrabian & Russell, 1974), once a consumer engages and connects with a brand a response behavior is exhibited. This study focused on the second step of the SOR model, once an organism has engaged with content there is a possibility of increasing purchase intention and approach behavior.

The quantitative content analysis showed more types of fresh-food products are available at farmers markets. Processed food and non-food products, such as dog food, crafts, and homemade soaps, were included in the imagery posted. Farmers markets are most often associated with having “fresh food,” so it was interesting to see processed foods ranked as the third highest engagement category. According to a study on consumer perceptions at farmers markets in Florida, a majority of respondents believed that more than 80% of vendors sold local food and believed that a majority of products had been harvested a few days or less before sales (Gao, Swisher, & Zhao, 2012).

According to Harrison (2013), the social aspect of farmers markets has also become important, supporting the use of image content campaigning for local events hosted by the brand. Multiple images advertised or visualized yoga classes at the Dallas

Farmers Market, indicating farmers markets support not only local producers but also healthy lifestyles.

Instagram can tell a story with a variety of image content (“Instagram for Business,” 2016), and is not only a voice for reactions to imagery but a medium for agriculture to communicate its stories visually. For the agricultural industry, this could include many steps, involved in moving products from field to table. “With less than two percent of the U.S. population involved in farming, we have to take our stories directly to the consumer.” (Lohr, 2011, p. 2) However, not all stages of the growing process are present within images of fresh-food products. Only one farm photo, which showed producers tending to plants in the field, was included out of 144 images analyzed. Review of literature revealed that consumers do place an interest in knowing and understanding where food originates, but the low engagement of this photo compared to those of the natural fresh-food product category was significantly lower.

If consumers are truly interested in the story line of the products they purchase from local farmers and producers, engagement would give some indication. The image content category with the lowest total engagement (TE) was the farm photo category. This category had one image, putting it at a disadvantage against other image categories, but opening discussion. Consumers are engaging in local food movements that include wanting to know where their food comes from (White et al., 2014), yet there weren’t enough farm photos to generate enough engagement for comparison. This section of data raises the question of whether brands are interested in advocating for the agricultural industry or just focused on sales. Brands that were focused on the educating consumers

through social media would post images that illustrate the path from farm to table. Over half of the images posted to the Dallas Farmers Market Instagram (DFM) were product in a raw or natural state ready to purchase, this suggests that they may have a single focus on sales.

The local food movement and the desire for fresh-food products is on the rise (Aucoin & Fry, 2015). Some Instagram users referred to the images on DFM as “fresh” and “healthy.” Supporting Aucoin and Fry’s (2015) findings that local foods offered at farmers markets are perceived as “healthy and of higher quality than conventional foods” (p. 63). Additionally, a number of users expressed interest in visiting the DFM because they asked questions pertaining to hours of operation and said that they wanted to attend. This information supports, again, the last phase of the SOR model, because addressing engagement can have a direct effect on approach behavior.

The overall comment polarity was positive and influenced consumers and users perceptions of the Dallas Farmers Market Instagram positively, supporting a connection with positive emotions. The negative comments associated with the highest total engagement category (natural fresh-food product) showed users expressed their negative emotions about the absence of local vendors. These comments directly attacked the DFM, not the image. Users use Instagram as a way to not only connect with imagery but also voice their opinions and feelings about a brand. Thus, the image is merely a portal users’ voices. The Dallas Farmers Market audience was more emotionally connected with visuals that have fresh-food product content. This study did not reveal why each

user personally connected with the image itself, only if their emotions were positive, negative or neutral.

Khobzi and Teimourpour (2014) used sentiment analysis on Facebook to explore comment content polarity and related it the overall attractiveness and popularity of posts. They hypothesized that the polarity of comments would have a significant relationship with the number of likes related to the post and polarity would have a significant relationship with number of comments related to the post (Khobzi & Teimourpour, 2014). However, in this study the relationship between the number of comment and polarity of comment content cannot be readily determined based only on quantifying engagement. A post within the highest engagement category with positive polarity did not necessarily mean it would be more popular in terms of likes when compared to a post with negative polarity. However, the first comment posted was more likely to influence the polarity of comments that followed, suggesting that the Dallas Farmers Market should pay close attention to users' comments.

Illustrating the process of how producers bring their foods to market could not only benefit them, but advocate for the agricultural industry by educating consumers. The agricultural industry is far behind using social media effectively (Topp et al., 2014; Lohr, 2011), yet as the younger generations step-up into leadership roles and take over operations, the industry may see an increase in social media usage.

Limitations

One limitation of this study was the dynamic environment of Instagram. The Dallas Farmers Market is a publicly-accessed account that can be viewed by any

Instagram user, which affects this study because the data may not be from current followers of the Dallas Farmers Market (DFM). So while the DFM is posting content intended for their target audience, because of this Instagram characteristic, engagement was not guaranteed to originate from followers only. Engagement can increase and decrease at any given time: users and brands have the ability to add or delete comments as well as like or unlike images. I accounted for this by gathering engagement values one day and only using those values whether they fluctuated at a later date or not.

Another, and possibly the main, limitation of his study was images could be classified in more than one category because the brand posted images using a collage feature incorporating more than one type of content. Also, single images could contain multiple types of content. This is important because some categories had an advantage for total engagement. More images does not necessarily mean more engagement, because engagement is dependent on many variables.

Emojis were also a limitation of this study. Emoji vary by the type of mobile device used to input them. Emoji are included in many different platforms/devices including Apple, Samsung, Facebook, Instagram, and Snapchat. Each of these can have slightly different icons depending on the software of each device. A large percentage of Emoji are shared between platforms but some may include more options than others. Therefore some users may not have the option to incorporate Emoji into their comments, which puts them at a disadvantage for visualizing their emotions with Emoji support.

Recommendations

This study serves as a precursor to future research, practice, and education. Interviews or focus groups should be conducted to investigate exactly what the characteristics or stimuli of the image that triggered an emotional connection. Such research will further support how to effectively use Instagram to market products and services and help brands understand what and why visuals yield more engagement. More specifically conducting interviews or focus groups will help test the first phase of Mehrabian and Russell's SOR model and focus on the stimuli within the environment that triggered emotional connections.

A big question is whether or not marketing efforts are effective. Thus, second opportunity for future research would be to conduct interviews or administer questionnaires to determine if users approached the Dallas Farmers Market with intention to purchase products. This applies to Instagram because it would be an indicator measuring return on investment or return on engagement with the response being purchase behavior or approach behavior. This focuses on the final phase of the SOR model. Determining if engagement with particular images influenced response behavior will help brands start to determine if their Instagram marketing efforts are persuading consumers to buy a product.

Determining if consumers are interested in viewing the life cycle of their food products on Instagram, and if knowing about the production process would compel them to purchase food products would be another recommendation for further research. Previous literature showed consumers want to know the origination of their food.

Because only one farm photo was present in the sample, not enough engagement data was not present to support that consumers want to connect with the origin of their food. Thus, marketer's perceptions of farmers markets may not align with consumers. Both vendors and farmers markets seek to make a profit, but are their values the same? If there is a difference in what each party wants consumers to see, then research on marketer's perceptions of farmers markets would explore if values align the local food movement.

Social media strategists would benefit from reviewing the literature further and then exploring whether consumer preferences are still identical to the local food movement. Social media is a tool to reach mass audiences, including Instagram. Instagram currently has over 400 million active users, one post has the potential to reach 400 million people and educate them on products and services, but only if the needs of consumers and marketer's strategies align. To establish relationships with consumers, marketers must first understand consumer needs to effectively communicate (Sashi, 2012). If consumer needs and preferences change then the marketing strategy must change.

My first recommendation for the Dallas Farmers Market, and other similar entities, would be to continue to incorporate fresh-food products into their visual marketing strategies since they received the most engagement. Additionally, DFM should extend the sample of this study and conduct a full content analysis to better understand Instagram's engagement patterns with consumers. A larger sample may also reveal that more images in certain categories are present, or absent. Analytics services

are unable to categorizing photos to determine if visuals are effective, so continuing content analysis and observation of user engagement can be beneficial to the brand. Keeping up with consumer preferences could potentially increase customer-lifetime values long-term, maintain meaningful relationships, and affect purchase behavior (Lamb, Hair, & McDaniel, 2015; Sashi, 2012).

Incorporating farm photos can assist the brand in telling a story. Visual representations can be educational. Instagram can be used as a virtual classroom for agricultural education purposes. Educators can access real-world images that illustrate the different practices for food producers. Visuals can be a powerful learning tool to help students make connections to places and things they have never seen (Raggl & Schratz, 2004).

Summary

The social media revolution has brought about great change in the way businesses market to consumers. Erik Qualman, said “we don’t have a choice on whether we do social media, the choice is how well we do it.” There are many supplemental online resources that give an abundance of advice and explain that a variety of content is crucial to being successful with social media, especially on Instagram (“Instagram for Business,” 2016). Using the information obtained from social media, researchers can gain valuable insights into the beliefs, values, attitudes, and perceptions of social media users” (Lai & To, 2015, p. 138). The agricultural industry must establish a presence on social media and adapt to change quickly to meet consumer needs.

As stated previously, there is a need for agriculturalists to understand how to effectively market their products (Edgar & Rutherford, 2011; White, Meyers, Doerfert, & Irlbeck, 2014). Instagram focuses on creative context and visual language to inspire consumers and users to engage. By effectively using Instagram, agriculturalists can market to educate customers: both of which raise awareness for local food producers and the agricultural industry. There are many visual characteristics and variables taken into account by consumers when they shop for agricultural products, especially fresh produce products. If products like fresh produce and other fresh food products are picked based on visual characteristics than it is important to understand how to effectively visually market to and communicate with customers to create meaningful relationships and emotions that stimulate responses to engage with brands or affect response behavior.

This study showed that the highest engagement category for a farmers market was the natural fresh-food-product category and the lowest engagement category was the farm photo category. Images that portray and support that a brand is advocating healthy lifestyles is also important in alignment with the local food movement. Understanding and being able to analyze how users and consumers feel about a brand is crucial. This study revealed users' comments are influential when it comes to brand awareness. It is important for agricultural producers to understand they can reap advantages of using social media, specifically Instagram, to visually market their products and draw potential consumers to their products and services. Instagram is an opportunity for agriculturalists to engage, build relationships, advocate, and visually market products and services while educating consumers.

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APPENDIX A

Gmail - Courtney Eberts- Written Consent for TAMU thesis

<https://mail.google.com/mail/u/0/?ui=2&ik=d3f54328f6&view=pt&q=...>



Courtney Eberts <eberts2012@gmail.com>

Courtney Eberts- Written Consent for TAMU thesis

Amanda Vanhoozier <Amanda.Vanhoozier@dallasfarmersmarket.org>

Wed, Nov 4, 2015 at 8:32 AM

To: Courtney Eberts <eberts2012@gmail.com>

Courtney

Good to talk with you just now about your marketing project. I am confirming the use of the DFM Instagram photos and comments for your analysis. Please send an email about the posting of customer focus groups as I would need to also confirm that with the corporation. Thanks
Amanda

Sent from my iPhone

[Quoted text hidden]

Information contained in this e-mail transmission is privileged and confidential. If you are not the intended recipient, do not read, distribute or reproduce this transmission (including any attachments). If you have received this e-mail in error, please notify the sender by e-mail reply.

APPENDIX B

DIVISION OF RESEARCH



DATE: January 05, 2016

MEMORANDUM

TO: Tracy Rutherford
ALRSRCH - Agrilife Research - Ag Leadership, Education & Communication

FROM: Human Research Protection Program
Institutional Review Board

SUBJECT: Exempt Determination

Study Number: IRB2015-0838

Title: A MIXED-METHOD APPROACH TO ANALYZING THE DALLAS FARMERS MARKET INSTAGRAM

Determination Date: 01/05/2016

Continuation Due: 12/01/2020

Expiration Date: 01/01/2021

Comments:

- Research is to be conducted according to the study application approved by the IRB prior to implementation.
- Any future correspondence should include the IRB study number and the study title.

Investigators assume the following responsibilities:

1. **Exempt Continuation Form:** The study must be renewed by the expiration date in order to continue with the research. An Exempt Continuation Form application along with required documents must be submitted by the continuing review deadline. Failure to do so may result in processing delays, study expiration, and/or loss of funding.
2. **Completion Report:** Upon completion of the research study (including data collection and analysis), a Completion Report must be submitted to the IRB.
3. **Unanticipated Problems and Adverse Events:** Unanticipated problems and adverse events must be reported to the IRB immediately.
4. **Reports of Potential Non-compliance:** Potential non-compliance, including deviations from protocol and violations, must be reported to the IRB office immediately.
5. **Amendments:** Changes to the protocol and/or study documents must be requested by submitting an Amendment to the IRB for review. The Amendment must be approved by the IRB before being implemented.
6. **Consent Forms:** When using a consent form or information sheet, the IRB stamped approved version

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<http://rcb.tamu.edu>

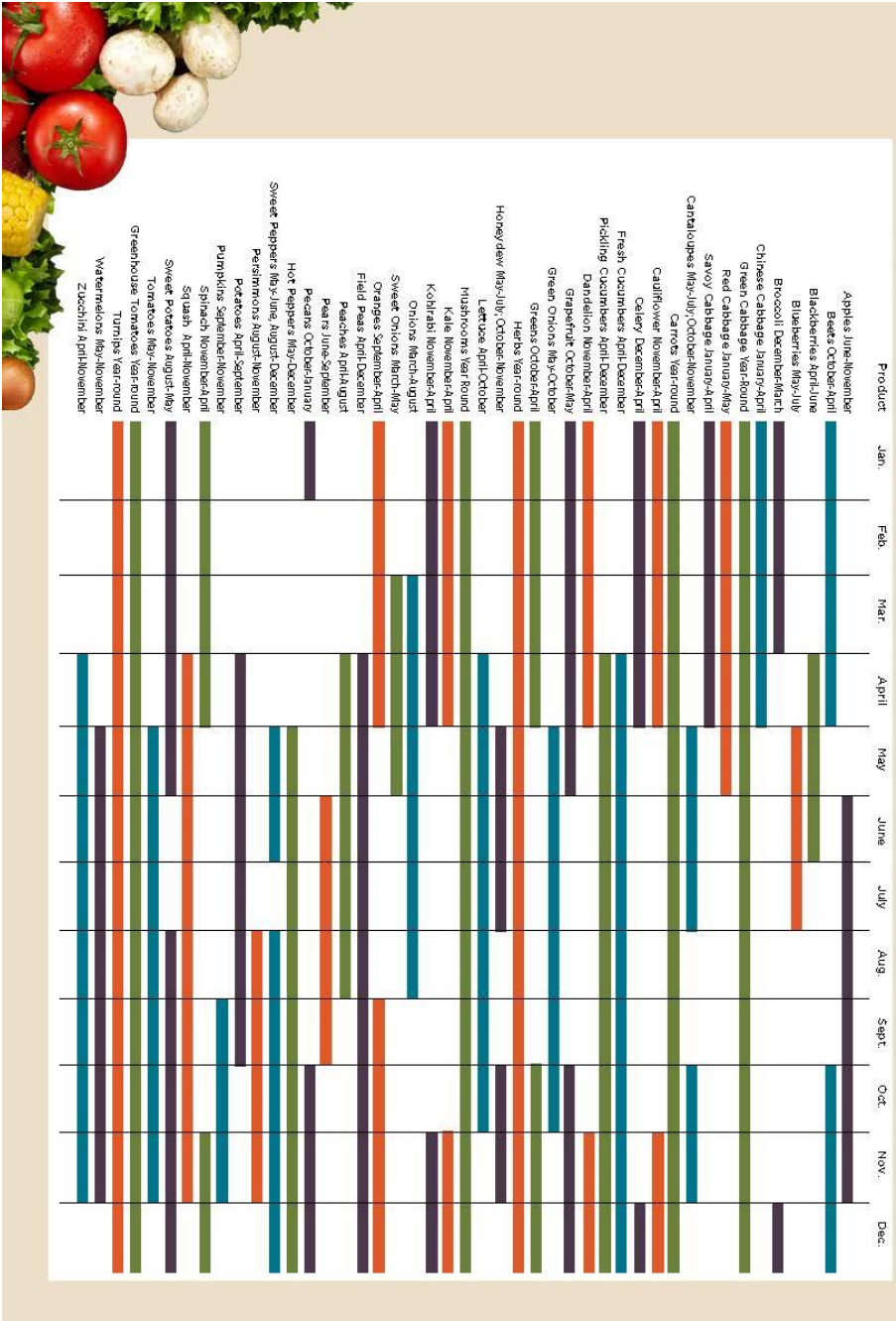
must be used. Please log into iRIS to download the stamped approved version of the consenting instruments. If you are unable to locate the stamped version in iRIS, please contact the iRIS Support Team at 979.845.4969 or the IRB liaison assigned to your area. Human participants are to receive a copy of the consent document, if appropriate.

7. **Post Approval Monitoring:** Expedited and full board studies may be subject to post approval monitoring. During the life of the study, please review and document study progress using the PI self-assessment found on the RCB website as a method of preparation for the potential review. Investigators are responsible for maintaining complete and accurate study records and making them available for post approval monitoring. Investigators are encouraged to request a pre-initiation site visit with the Post Approval Monitor. These visits are designed to help ensure that all necessary documents are approved and in order prior to initiating the study and to help investigators maintain compliance.
8. **Recruitment:** All approved recruitment materials will be stamped electronically by the HRPP staff and available for download from iRIS. These IRB-stamped approved documents from iRIS must be used for recruitment. For materials that are distributed to potential participants electronically and for which you can only feasibly use the approved text rather than the stamped document, the study's IRB Study Number, approval date, and expiration dates must be included in the following format: TAMU IRB#20XX-XXXX Approved: XX/XX/XXXX Expiration Date: XX/XX/XXXX.
9. **FERPA and PPRA:** Investigators conducting research with students must have appropriate approvals from the FERPA administrator at the institution where the research will be conducted in accordance with the Family Education Rights and Privacy Act (FERPA). The Protection of Pupil Rights Amendment (PPRA) protects the rights of parents in students ensuring that written parental consent is required for participation in surveys, analysis, or evaluation that ask questions falling into categories of protected information.
10. **Food:** Any use of food in the conduct of human research must follow Texas A&M University Standard Administrative Procedure 24.01.01.M4.02.
11. **Payments:** Any use of payments to human research participants must follow Texas A&M University Standard Administrative Procedure 21.01.99.M0.03.
12. **Records Retention:** Federal Regulations require records be retained for at least 3 years. Records of a study that collects protected health information are required to be retained for at least 6 years. Some sponsors require extended records retention. Texas A&M University rule 15.99.03.M1.03 Responsible Stewardship of Research Data requires that research records be retained on Texas A&M property.

This electronic document provides notification of the review results by the Institutional Review Board.

APPENDIX C


TEXAS PRODUCE AVAILABILITY CHART



APPENDIX D

Codebook

Image Category Descriptions

1. **User-generated Content** consists of any image reposted by the brand, originally created by another user, customer or vendor; often accompanied by the repost icon 
2. **Natural Fresh Food Product** images consist of fresh food products in their natural or raw states (regardless of packaging) that have not been processed. Examples include berries in cartons and food items being displayed on stands.
3. **Recipe** images are classified as any image that shows food being used to create dishes or other food products. These images may include layouts of ingredients or human interaction with the dish while being made. A finished food product is not classified as a recipe unless the process is shown.
4. **Person with Fresh Food Product** images consist of an individual interacting or posing with a fresh food product.
5. **Holiday/Celebration** images have content that relates directly to a “special day of celebration”, such as American Holidays or world events. Advertisements for the brand are not considered celebratory events.
6. **Campaign with Fresh Food Product** images are categorized as any image with content that directly promotes a brand to create a particular outcome and include a fresh food product. Images may include brand logos, advertisements for brand-hosted events (including time and place), and brand products.
7. **Lifestyle** images contain content that is not directly promoting a specific product but promotes or is related to the brand. Examples of lifestyle images are aerial shots.
8. **Farm** images are taken on the farm, show where a fresh food product came from and can include the producers interacting with the product.
9. **Campaign without Fresh Food Product** images are categorized as any image with content that directly promotes a brand to create a particular outcome and does not include a fresh food product. Images may include brand logos, advertisements for brand-hosted events (including time and place), and brand products.
10. **Processed** food images show any type of processed food regardless of packaging. Examples of processed foods include canned goods, pizza, breads, pickles, bbq and bottled liquids.







11. **Non-Food Product** images contain products that are not edible or for human consumption. Examples of non-food products include soaps, clothing, flowers and plants, and dog food.
12. **Non-food product** with Person images consist of an individual interacting or posing with a non-food product.











Fresh Produce vs Non-Fresh-Produce Images








Fresh-produce images are any images, regardless of category, that contain any type of fresh produce content. These images are assigned and coded by the letter “P.”

Non-fresh-produce images are coded by the letter “N” and classified as not having any fresh-produce content within the image.

Emoji Descriptions

Emoji	Description
	Unamused face- Face with scrunched up and closed eyes, frowning. Used to show helplessness in a situation. May be on the verge of tears.
	A classic red love heart emoji, used to express love. Despite the name “Heavy Black Heart”, this character appears red on all platforms when displayed with emoji presentation
	A face with hearts instead of eyes, or <i>Heart Eyes Emoji</i> as it is generally known. Used as an expression of love, for example: “I love you” or “I love this”
	This face is not amused. This is not a face of sadness, it is more of a grumpy, displeased look. Used to express dissatisfaction.
	A face with a big open (grinning) mouth, showing teeth. Also referred to as happy or smiley face emoji.
	Index finger touching thumb to make an open circle. Represents “I’m okay” or “yes, that’s correct / good.”

Emoji	Description
	A smiling face, with smiling eyes and rosy cheeks. Showing a true sense of happiness.
	Two hands raised in the air, celebrating success or another joyous event.
	Index finger pointing upward, showing the back of the hand while doing so.
	A face smiling and wearing dark sunglasses that is used to denote a sense of cool. The nerd face emoji is a similar face, but with regular glasses.
	A classic winky emoji; winking and smiling. Used to imply humor in written form, or may alternatively be used suggestively, as a form of flirtation
	Two hands clapping emoji, which when used multiple times can be used as a round of applause.
	A friendly, goofy smile with tongue hanging out the side of the mouth. Used to indicate a silly happiness.
	A pink love heart with stars around it, making it look like it is sparkling or shimmering.
	An information desk person, iconically represented in the Apple emoji artwork as a girl holding out her hand as if she were a waitress carrying an invisible tray of drinks. Can be used for a variety of interpretations, such as sassiness or sarcasm.
	Two hands placed firmly together, meaning <i>please</i> or <i>thank you</i> in Japanese culture. Other common uses for this character include prayer/praying hands, or a high-five .

Emoji	Description
	A laughing emoji which at small sizes is often mistaken for being tears of sadness . This emoji is laughing so much that it is crying tears of joy.
	A sad face with tears streaming down both cheeks. This face is distraught and inconsolable. Not to be confused with the tears of joy emoji.
	An exhausted-looking face with an open mouth and tightly closed eyes. On some platforms this emoji is similar in appearance to the Weary Face, and not to be confused with the Sleeping Face which is actually asleep.
	A distraught-looking emoji with an open mouth, and crescent shaped eyes. Appears to have given up
	A thumbs-up gesture indicating approval.
	A pensive, remorseful face. Saddened by life. Quietly considering where things all went wrong.
	A face showing a stuck-out tongue, winking at the same time. Used in an attempt to be wacky, zany, or otherwise joking.

Note. Adapted from <http://emojipedia.org>, Copyright by Emojipedia Pty, LTD.