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Richard Blake Bowen
Clemson University, rbbowen@g.clemson.edu

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DEVELOPMENT OF DYNAMIC TESTING METHODS USING FACIAL EXPRESSION ANALYSIS TO EVALUATE PACKAGING DESIGN IN A REALISTIC SHOPPING ENVIRONMENT

A Thesis
Presented to
the Graduate School of
Clemson University

In Partial Fulfillment
of the Requirements for the Degree
Master of Science
Packaging Science

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by
Richard Blake Bowen
August 2016

Accepted by:
Dr. R. Andrew Hurley, Committee Chair
Dr. Elliot Jesch
Dr. Jennifer Bisson

ABSTRACT

80 to 95 percent of all new product launches fail (Dillon, 2011; Copernicus Marketing, Consulting, and Research, 2013). However, businesses can increase the chances of a successful product launch by better understanding consumer preferences and wants. Research done by McKinsey and Company shows that “more than 80 percent of top performers periodically tested and validated customer preferences during the development process, compared to 43 percent of bottom performers” (Gordon et al., 2010). With most purchasing decisions being made at the point of purchase, packaging is the last opportunity for businesses to influence the consumers decision to purchase their product. Packaging evaluation research helps businesses accomplish this goal by assessing packaging design, developing an understanding of the consumer’s perception of the packaged product, and identifying key factors of package design that are underperforming.

Biometric devices such as eye tracking, galvanic skin response (GSR), and electroencephalography (EEG), are popular methods that are often used in the packaging industry to quantitatively evaluate the effectiveness of packaging design. However, with the exception of eye tracking, applications for these instruments are limited when it comes too dynamic testing in a shopping environment.

Facial expression analysis is another method that has traditionally been limited to static testing environments due to limitations in technology and a lack of methodology developments. This research solves that problem by creating dynamic testing methods that allow for researchers to evaluate packaging design using facial expression analysis in shopping environments.

This thesis outlines the step-by-step process of developing dynamic packaging evaluation research methods using facial expression analysis as an analytical tool. The researchers show how to develop the necessary equipment, create a package performance shelf study, integrate software to combine facial expression analysis and eye tracking, and how to statistically analyze and draw conclusions. An example of a shelf performance study is executed that future researchers can use as a reference to develop their own studies using facial expression analysis as a dynamic testing method.

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CHAPTER ONE

INTRODUCTION

Product packaging is often the last opportunity for businesses to influence the purchase decision of consumers. With 55% of in-store purchases being unplanned (POPAI, 2012) and increases in pricing competition; businesses are increasingly applying more emphasis to their packaging design as a brand extension and marketing tool. Successful businesses are turning to quantitative and qualitative research methods in order to gain insight into their package's appeal and their consumer's preferences. Research shows that over 80 percent of top performing businesses tested and validated their customer's preferences during the product development process (McKinsey & Company, 2010). This investment into packaging research is helping businesses generate new loyal customers as well as saving businesses money on the production of untested packaging designs that may not appeal to consumers.

The uses of biometric devices such as electroencephalography (EEG) and galvanic skin response (GSR) have been popular quantitative methods used by the packaging industry to evaluate packaging design. However, the uses of these devices are generally limited to static research methods that lack any realistic consumer-shopping context. In order to gain any real insight into the decision-making process and preferences of consumers, dynamic testing methods that can be applied to realistic shopping environments must be developed in order to produce quantitative data that reflects actual consumer behavior.

This thesis focuses on the development of dynamic testing methods of packaging design using facial expression analysis as the quantitative evaluation technique. Facial expression analysis has become increasingly popular, as the tedious process of human facial coding is being replaced with algorithm-based software. With most emotional biometric devices being limited to measuring the emotional dimensions of valence or arousal, facial expression analysis is unique due its ability to gather quantitative data on valence and specific emotions (joy, surprise, sadness, anger, fear, disgust, contempt).

Using this analytical tool to evaluate packaging design has the possibility to provide immense benefits for businesses wanting to optimize their product packaging by giving insight into the packages effect on the consumer's emotional process during the shopping experience. Research shows that brands who use packaging design as a brand extension to create emotionally positive associations are more likely to be considered at the point of purchase (Underwood, 2003), more likely to be purchased (Crilly et al., 2004), and more likely to be evaluated at a higher price value (Belen del Rio et al., 2001).

This thesis provides a step-by-step guide of how to develop dynamic testing methods using facial expression analysis for researchers interested in using this analysis technique to evaluate packaging design. The researchers provide detailed methodology that explains how to develop the equipment necessary to accurately analyze facial expressions, create a shelf performance study in a shopping environment, statistically analyze facial expression analysis data, and integrate eye tracking software and methods to be used in conjunction with facial expression analysis.

CHAPTER TWO

LITERATURE REVIEW

Using Packaging to Create an Emotional Impact on Consumers

Packaging is used to protect, contain, preserve, and display information concerning the product (Lee & Lye, 2003). In addition, packaging is used as a marketing tool by differentiating products, ensuring brand recognition, and increasing the consumer's willingness to purchase the product (Hinz & Weller, 2011). Most purchasing decisions are made at the point of purchase (Prone, 1993) and packaging has a large effect on that decision (Silayoi & Spence, 2004). Connecting with consumers is becoming more difficult as shelf competition increases (Munzinger & Musiol, 2009) and product differentiation decreases (Hinz & Weller, 2011). Since emotions can be manipulated to influence purchasing decisions (Mograbi & Mograbi, 2012), it is important to design packaging that creates an emotional impact on consumers (Duchowski, 2007).

Packages evoke an emotional response from their design, graphics, and structural design such as shape, size, and materials (Duchowski, 2007; Kamil & Jaafar, 2011). These elements all contribute to the consumers' overall perception of the product (Hurley et al., 2012). If used correctly, they can attract the consumer and guide attention to the package (Munzinger & Musiol, 2009) as well as influence information processing (Wedel & Pieters, 2006).

Structural design can be constructed to form a better connection with the target consumer by manipulating the shape of the package, the material, or how the consumer perceives the product. Clear material packages that show the product over a graphical representation have a higher likelihood of being purchased (Hurley et al., 2012). Structural shape can be altered to influence the consumers judgment of the amount of product contained in the package. Differentiating package shape from others in the same product category can have this effect since consumers are unfamiliar with the contents of the new shape. There is evidence that shows packages that are short and wide are perceived to contain more product than elongated packages (Folkes & Matta, 2004). Perception is everything as consumers want to purchase products they perceive are in line with their wants and desires (Crilly et al., 2004).

Graphic design is used in packaging to display information in the form of images and words. Using colors and pictures over other informational elements have a greater effect on keeping consumer attention (Underwood et al, 2001). Graphics also aid the consumer in identifying specific products (Kamil & Jaafar, 2011). This is important for businesses that want consumers to easily identify their brand on a shelf. Consumers are shown to make decisions more quickly from a selection of brands that contain a brand they are familiar with (Macdonald & Sharp, 2000). Even minor details such as inserting an emotional word like ‘love’, stylizing a logo, or flags that represent nationality can influence viewing strategies and create an emotional impact (Nikolaus & Lipfert, 2012).

Effective use of these design elements can evoke emotional responses as well as trigger physiological responses associated with emotion. This makes making an emotional connection through package design crucial in influencing consumers as many purchases involving low risk decisions are made upon pure liking (Silayoi & Speece, 2004). Likewise, ineffective packaging is less likely to be considered at the point of purchase (Underwood 2003).

The main takeaway is creating an emotional impact can greatly alter the consumer perception of the product. Consumers relate with the attributes of the product, package, and brand (Crilly et al., 2004). For example, packages that market that the brand donates to charity could connect with consumers that empathize with particular charities. Creating the right expectations and associations that consumers identify with through packaging will influence consumers to purchase your product (Hurley et al., 2013).

Defining and Categorizing Emotions

Emotions are forces that influence our behavior, actions, and thoughts. Everyday, humans make decisions that defy their traditional logic based upon their current emotional state. While that nature of emotion has long been debated, most psychologists agree that an emotion is a psychological state that consists of a subjective experience, physiological response, and a behavioral response (Hockenbury & Hockenbury 2010).

Emotions should not be confused with feelings or moods, which are differentiated in affective neuroscience. Feelings happen as the emotion is integrated it into our psychological state and we our cognitively aware of it (Fox, 2008). Moods lack a stimulus, are obscure, and are derived from a compilation of inputs such as physiology, environment, thinking patterns, and current emotions (Hume, 2012).

In order to better understand the large variety of human emotions, psychologists have attempted to classify emotions into categories. Ekman & Friesen (1971) classified six basic emotions: happiness, surprise, anger, disgust, fear, and sadness. The basic emotions are unique because the facial expressions are universally recognized despite differences in culture, location, or race (Ekman, 1972). Other studies show contempt is also universally recognized (Matsumoto, 1992; Ekman, 1999).

Ekman (1999) distinguishes the basic emotions from other emotions and from other affective phenomena through the following unique characteristics, "distinctive universal signals, distinctive physiology, automatic appraisal, distinctive universals in antecedent events, distinctive appearance developmentally, presence in other primates, quick onset, brief duration, unbidden occurrence, distinctive thoughts, distinctive subjective experience [p.56]."

Robert Plutchik (2001) further classified emotions by developing the 'wheel of emotions' (Figure 1); a diagram that demonstrates how primary emotions can be mixed together to form more complex emotions. Plutchik configured the wheel by pairing the following eight different emotions across the wheel from its bipolar counterpart: anger and fear, trust and disgust, surprise and anticipation, sadness and joy. The wheel operates similar to a color wheel where two different emotions can combine to form a unique emotion much like red and blue can combine to form purple. Also depicted by the wheel is the ability for emotions to change with varying degrees of intensity similar to how colors become lighter or darker shades.

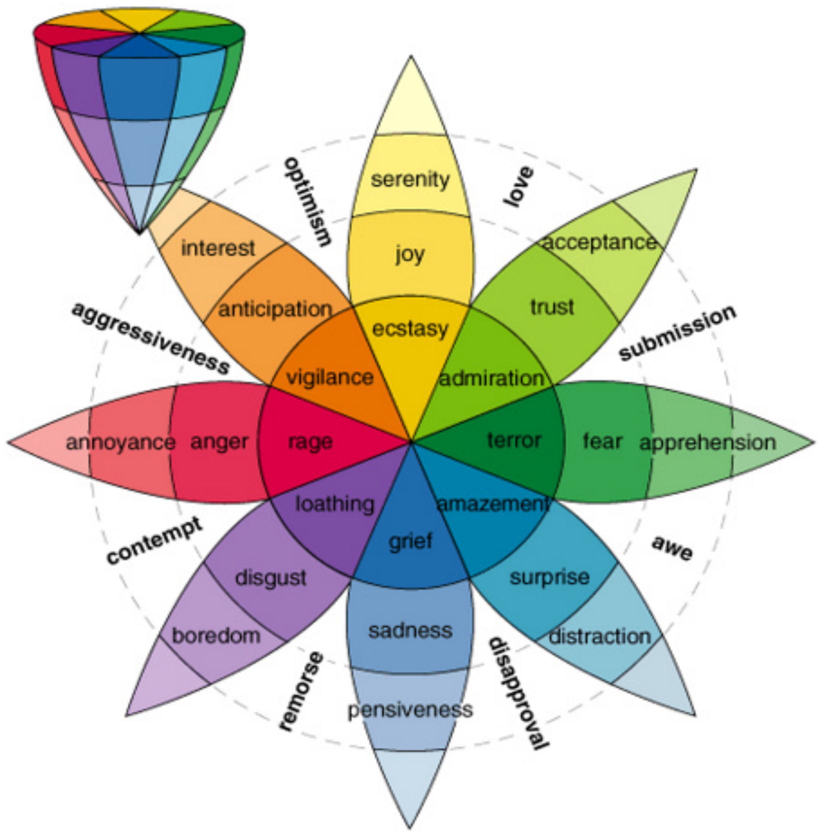


Figure 1: Plutchik's (1980) Wheel of Emotion

In order to better understand how people conceptualize emotions, Russell (1989) proposed that emotions could be categorized based on two dimensions of valence and arousal. Valence ranges from positive to negative (or pleasant to unpleasant) and arousal ranging from low to high activation. Emotional states can be plotted and represented on a circumplex model of emotion as seen in Figure 2. The model can be effectively used to plot emotions that are evoked by certain stimuli or elementary feelings that may be occurring naturally (Russell & Barrett, 1999).

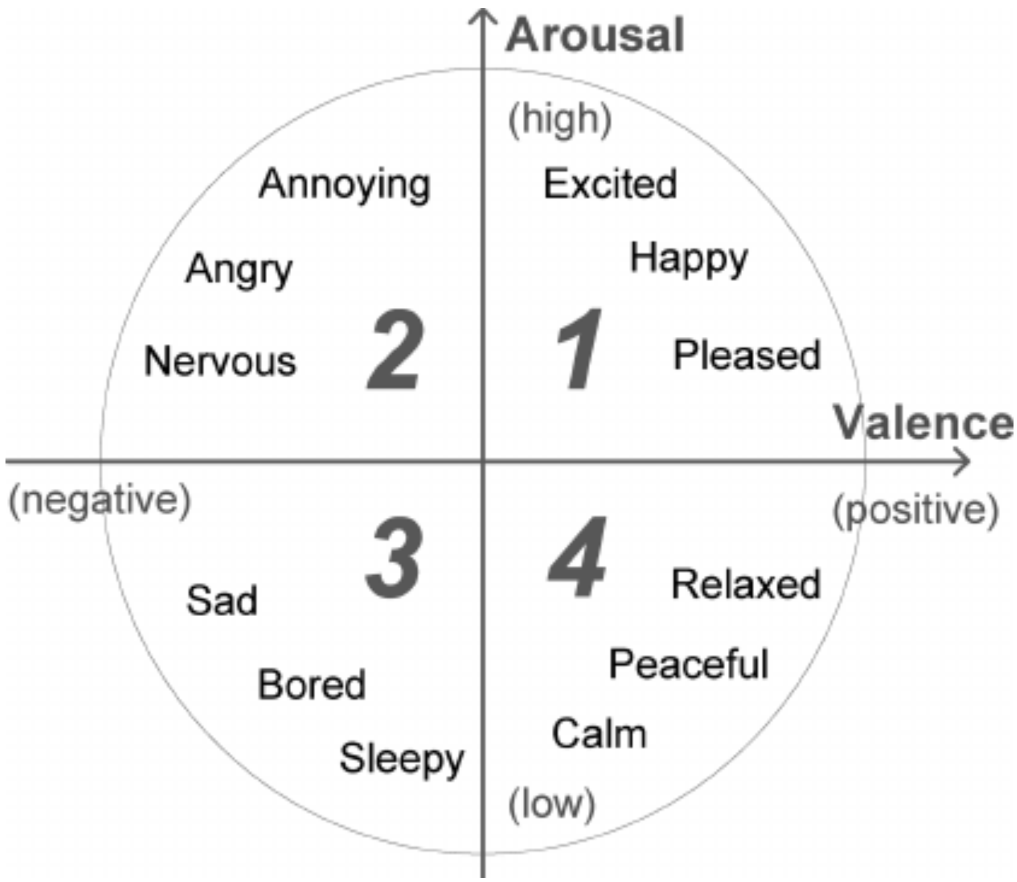


Figure 2: Circumplex model featuring valence and arousal dimensions

When emotions are experienced, the body rapidly responses psychologically and physiologically based upon the type of emotion and the level of intensity. Psychologically, memory networks are activated that are associated with the emotion, behaviors that are associated with the emotion are shifted upwards in response hierarchies, and attention is altered. Physiologically, facial expressions, muscles, voice tone, endocrine activity, and autonomic nervous system activity reacts to produce a response that is appropriate for the emotion being experienced (Levenson, 1994). Examples include changes in blood pressure, heart rate, alertness, and skin temperature.

From an evolutionary point of view, physiological responses as a result of emotional activation provide the organism the ability to handle problems that are critical to survival such as defending territory and possessions, avoiding harm, signaling distress, and attracting potential mates (Tooby & Cosmides, 1990).

The behavioral component of emotions consists of communicating and expressing emotions through muscle movements, mainly facial expressions. Paul Ekman (1980) estimates that humans are able to make over 7,000 different expressions using the 80 muscles in the human face. This large amount of versatility allows humans to express many different emotions of varying intensities. Due to the biological need of facial expressions, it is accepted that facial expressions for the six basic emotions are universally recognized despite differences in facial muscles across cultures (Waller & others, 2008; Ekman, 1972).

How does Emotion Shape Behavior?

Research shows that emotion has a profound influence on human behavior. There are two psychological theories that describe how emotion guides behavior. The first states that a major purpose of emotion is to activate necessary behavior for survival. The second involves a more complex argument suggesting that emotion functions as a feedback system and indirectly influences behavior.

The underlying assumption of the first theory is that emotion is a strong and direct cause of behavior, and so identifying someone's emotional state explains why the person acted in a certain way. Everyday, people will attribute someone's actions as having been performed "because she was angry," or sad, or worried, or afraid (Baumeister et al., 2007).

Loewenstein, Weber, Hsee, and Welch (2001) proposed a model that highlights the role of anticipatory emotions or immediate visceral reactions (e.g., fear, anxiety, dread) to risks and uncertainties that arise at the time of decision-making (Figure 3). The model shows how anticipatory emotional reactions can come from cognitive evaluations and influence on behavior. The authors suggest that gut feelings experienced at the moment of making a decision, which are often independent of the consequences of the decision, play an important role in the decision that is made and are not unique to decisions involving immediate risk.

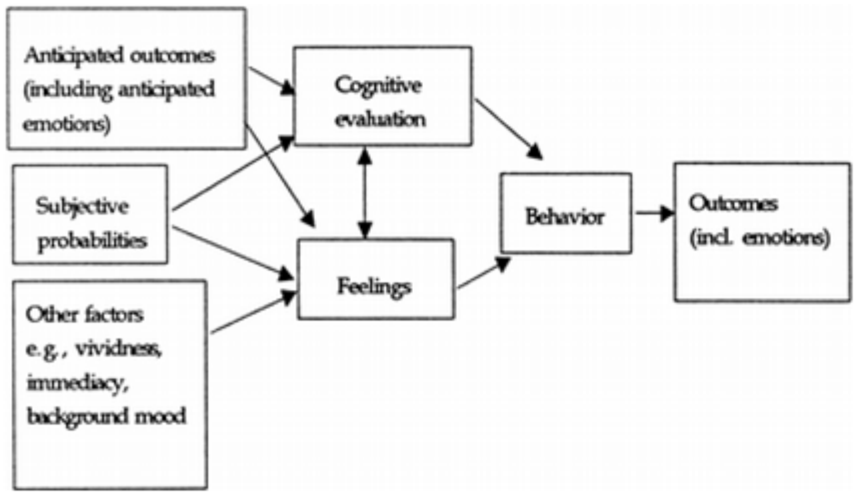


*Figure **3**: Emotion directly influences behavior*

In contrast, the second theory suggests that emotion works as a feedback system (Figure 4) that conditions the person based on the valence of the emotion being experienced. The brain references past emotions relating to present behavior. If the emotional outcome was positive, the behavior will most likely be repeated. On the other hand, the individual will modify behavior if past outcomes resulted in negative emotional experiences. Human behavior is then determined by anticipated emotions (Baumeister et al., 2009).

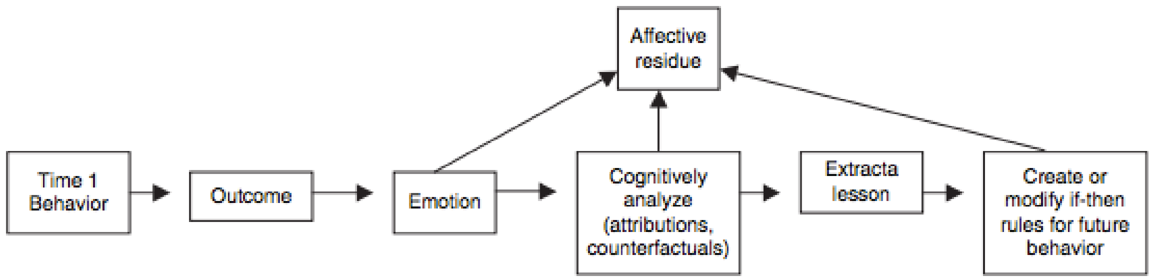


Figure 4: Emotion indirectly guides behavior

Methods to Measure Emotion

Subjective Reporting

Self-reporting is a popular method of analyzing emotions and is the only method to analyze the subjective experience of an individual. The emotion being experienced is reported by the individual through the use of verbal protocols or rating scales. Rating scales can be assembled to represent any mixture of emotion and any set of emotion. However, there is not always a 'straight' translation for many emotional words. This causes problems when evaluating between cultures (Desmet, 2003).

Physiology Testing

Analyzing the autonomic nervous system (ANS) can provide insight to the emotion of the individual. The most common activities measured are based on electrodermal or cardiovascular responses such as skin conductance level, skin conductance responses, heart rate, blood pressure, and total peripheral resistance (Mauss & Robinson, 2009). However, these activities are not exclusively a function of emotional responding and it is often unclear if the activity observed reflects emotional processes or other ANS functions (Bernston & Cacioppo, 2000; Stemmler, 2004).

Researchers also use electroencephalography (EEG) and neuroimaging methods to detect physiological changes in the brain triggered from discrete emotions. The assumption is that an emotional trigger will increase blood flow to a particular region of the brain. However, research that attributes a specific emotion to activity in a corresponding area of the brain is inconsistent and inconclusive. For example, disgust stimuli tend to be associated with insula activation. However, Phan et al. (2002) found that a wide variety of negative emotions also activated the insula. Also, in some studies, fear stimuli and amygdala activation are connected (Phan et al., 2002), but other research shows that other negative emotions as well as reward processing and positive emotional states can be attributed to amygdala activation (Cahill et al., 1996; Canli, 2004).

Facial Expression Analysis

The use of facial expressions can be used to measure emotion due to the correlation between expressions and emotion. Ekman and Friesen (1971) showed that there are six basic emotions (fear, sadness, disgust, joy, surprise, and anger) that are universally associated with facial expressions. Ekman and Friesen (1978) later created the Facial Action Coding System (FACS), a coding system that allows a coder to trace facial muscle movements. FACS measures all possible combinations of movements by analyzing 44 different muscle movements named ‘action units’.

Facial expression analysis is an increasingly interesting method to collect quantitative data pertaining to emotion. However, it is important to note that humans can regulate expressions, as pure expressions of emotion would be chaotic in social situations (Matsumoto et al, 2008). The connection between facial expressions and emotion is explained more thoroughly in the next section of the review.

Introduction to Facial Expressions

Facial expressions are the movements of the muscles in the human face. Charles Darwin (1872) theorized that the use of facial expressions was an unlearned and habitual trait that was connected with emotional processes and communication. Since that time, studies have confirmed and expanded on the research done by Darwin. Matsumoto, Keltner, Shiota, O'Sullivan, and Frank (2008) summarize five traits of facial expressions, "(1) discrete facial expressions of emotion occur universally in emotionally arousing situations, (2) judged universally and discretely, (3) linked with subjective experience, (4) part of a coherent package of emotional responses, and (5) have important social functions (p.2)".

From an evolutionary point of view, the use of facial expressions evolved from the need to solve problems pertaining to social living. Expressions can signal danger, attraction to the opposite sex, or hostility. Due to this implication, expressions should be universal to all humans regardless of gender, race, or culture (Matusomoto et al. (2008).

Ekman and Friesen (1971) provided further evidence to this claim by classifying the six universal emotions and their facial expressions.

Ekman (1972) also suggests that facial expressions of emotion are universally recognizable despite different influences in culture. Even though expressions are similar across cultures, the display rules and elicitors may be different. Display rules refer to mechanisms humans use in order to regulate their facial expressions. This allows humans to restrain from constantly expressing aroused emotions. Ekman and Friesen (1969) found seven ways humans regulate expressions: "(1) expressed as is, (2) deamplified, showing less than what is felt, (3) neutralized, expressing nothing, (4) qualified, shown with other emotions, (5) masked, concealed by mixing emotions, (6) amplified, express more intensely than what is felt, (7) simulated, expressing when not felt" (p.22).

The subjective experience of emotion is largely considered one of the three components of emotion along with behavioral and physiological responses (Hockenbury & Hockenbury, 2010). This is even more evident in situations where individuals are not socially pressured to change or adjust their expression (Matsumoto et al, 2008). Many studies show a positive correlation between facial expression and subjective experiences (Ekman et al., 1980; Ekman et al., 1990; Keltner & Bonanso, 1997).

Darwin (1872) hypothesized that facial expressions are a part of a much larger behavioral response system that lead to certain actions which are useful for survival. Therefore, facial expressions must be connected to emotional experience as well as autonomic changes that enable humans to respond adaptively (Matsumoto et al., 2008). Levenson (2003) showed this by recording physiological changes of subjects who were experiencing a specified emotion. Evidence shows that facial expressions of emotion correlate with changes in autonomic activity, physiological responses, and specific behavior.

Due to the correlation between emotion, physiology, and behavior, psychologists have developed methods in order to predict emotion based on these components. Advances in technology have developed facial expression analysis from a time intensive process that requires an expert coder, to an easy process available to anyone via software. The next section will review methods used to predict behavior from facial expressions.

Using Facial Expressions as a Method to Evaluate Behavior

Facial expressions are a part of the behavioral response that make up the three components of emotion along with subjective experiences and physiological responses (Hockenbury & Hockenbury, 2010). The relationship between facial expressions, emotion, and physiological responses allow predictions to be made about human behavior. Analyzing facial expressions has proven to be a useful tool in neuromarketing, media testing, psychological research, clinical research, medical applications, and website design. Current methodology being used to analyze facial expressions include facial electromyography (fEMG), facial action coding system (FACS), and software-based facial expression analysis.

fEMG uses electrodes connected to facial muscles around the eyebrows, mouth, and cheekbones to detect electrical impulses generated from facial activity. fEMG has been used in advertising research such as the emotional effectiveness of television commercials (Hazlett & Hazlett, 1999). This method provides precise results and can detect very subtle changes in facial activity. However, using fEMG requires an extensive amount of equipment and is intrusive due to the sensors being placed on the subjects face. Expert biosensor processing skills are also necessary to conduct this type of analysis (iMotions, 2016).

FACS is a system created by Ekman and Friesen (1978) that gives experts the tools to decompose facial expressions into action units (AUs). Action units are considered the smallest facial movements that can be visually singled out by a human. Other systems that are comparable to FACS are not as thorough, cannot differentiate many facial movements, consider some facial movements that are not unique to be separable, and connect facial expression directly to emotion (Cohn et al., 2007). FACS is also a reliable, non-intrusive, and accurate method to analyze facial expressions (iMotions, 2016). FACS is only used to measure facial expressions and any inferences made connecting expression to an emotional state are done extrinsically (Cohn et al., 2007). FACS has been used mostly in experimental psychology but has been used in other applications such as evaluating expressions of children receiving immunizations (Breau et al., 2001). The major disadvantage of FACS is it is a time intensive process. Analyzing one minute of video data can take a well trained coder up to 100 minutes to completely process (iMotions, 2016.)

The last method is through automatic facial expression analysis, a software based approach to facial coding. Automatic analysis operates by detecting the face of the subject, identifies facial features such as the nose, eyebrows, and mouth, and finally processes the facial movements through an algorithm that outputs emotional and AU data. It is a non-intrusive and precise method, which does not require substantial equipment, compared to fEMG and FACS. This method has been applied to a wide variety of analysis applications including video (Yeasin & Sharma, 2006), audio (Hamzy & Dutta, 2000), advertising (iMotions, 2016), and packaging. However, automatic facial expression analysis has faced criticism for categorizing all facial movements into emotions. Due to limits in technological capabilities, current software is unable to decipher differences between mental, physiological, emotional, and non-emotional facial movements (Fassel & Luettin, 2003).

Role of Emotions in Decision-Making

Traditionally economic theory and consumer decision-making operates under the assumption that humans make rational decisions based upon defined preferences (Bettman, Luce, & Payne, 1998). Herbet Simon (1967, 1983) introduced the idea of bounded rationality, stating that human rationality is limited in the decision-making process by the time available, cognitive limitations, tractability of the problem, and the available information. The proposed model of rational choice theory is therefore incomplete until the influences of emotion and motive on cognitive behavior are accounted for (Simon, 1967). Further research shows evidence that the traditional model of decision-making is incomplete (Camerer, Loewenstein, & Prelec, 2004; Tversky & Kahneman, 1981).

Research evaluating the role of emotion in decision-making has grown exponentially since the introduction of the idea by Simon (1967). Scholarly papers on the topic of emotion in the decision-making process "doubled from 2004 to 2007 and again from 2007 to 2011, and increased by an order of magnitude as a percentage of all scholarly publications on "decision making" from 2001 to 2013 (Lerner et al., 2015)".

Large amounts of evidence suggest that emotions are more dominant than cognitive functions when making important life decisions (Scherer, 1984; Keltner et al. 2014; Ekman, 2007). Emotion guides the decision-making process subconsciously by the desire to increase positive feelings and to avoid negative feelings (Loewenstein & Lerner, 2003; Keltner & Lerner, 2010). Humans then experience new emotions after the decision materializes (Mellers, 2000; Coughlan & Connolly, 2001).

There has been a continuous debate concerning how cognitive and emotional systems function together to find answers to decisions. Most theories suggest that there are two systems the human brain uses to make decisions. Stanovich and West (2000) introduced the idea of the two-system approach with *system 1* being the brain's "fast, automatic, intuitive approach" and *system 2* being the brain's "slower, analytical mode, where reason dominates (Kahneman, 2011)". *System 1* constantly influences the beliefs and choices of *system 2* by relaying feelings, impressions, and emotions from similar experiences (Kahneman, 2011). Mood affects the functions of *system 1* depending on the valence of the emotions being experienced. Positive moods loosen the control by *system*

2 and humans become more creative and intuitive but are more likely to make logical mistakes. Negative moods will have the opposite effect; individuals will use logic to make the correct decision in order to increase their chances of reverting their emotional state back to being positive (Kahneman, 2011).

Paul Slovic (2007) developed a theoretical framework describing how emotions guide decisions and judgments. Slovic suggests that the choices people make express their emotions generally without the persons knowing. This affect heuristic allows individuals to make rational decisions in many important decisions but affect is also a major factor. The emotional evaluation of the result, current emotional state, and the approach avoidance tendencies identified with them, are factors that guide decision-making (Damasio, 1994).

Lerner (2014) sums up emotion and decision-making with eight major themes. (1) Integral emotions, (2) incidental emotions, and (3) specific emotions influence decision-making; (4) emotions shape decisions via the content of thought, (5) the depth of thought, and (6) via goal activation; (7) emotions influence interpersonal decision-making, and (8) unwanted effects of emotion on decision-making can be reduced.

It is clear that emotion and cognition work together to produce answers to decisions. The decision-making process is not completely rational as once thought (Bettman, Luce, & Payne, 1998) but is influenced by the role emotions, feelings, and moods. Understanding the influence of emotions is vital to the study of consumer psychology and understanding how emotions affect the consumer purchasing process.

Effect of Emotions on Consumer Behavior

Under the understanding that humans do not behave rationally, consumers psychologically experience opposing emotions when faced with a purchase decision: the satisfaction of purchasing a product and the discontent in spending money. Exposure to emotion stimuli can greatly affect this process by altering consumer judgment and behavior (Mograbi & Mograbi, 2012). Consumers often do not have well-defined preferences and use available information during the purchasing decision to construct them (Bettman et al., 1998). Triggered emotions are constantly relaying information to the conscience brain that reflects past outcomes of that emotion (Kahneman, 2011). Therefore, it is possible to influence consumer decision to a desired outcome by manipulating factors that will affect emotions (Mograbi & Mograbi, 2012).

Many studies involving the emotion of consumers have concentrated on the emotional response to advertising (Hill, 2010; Derbaix, 1995), consumer behavior (Laros & Steenkamp, 2005), and product evaluation (Chakrabarti & Gupta, 2007; Howard & Gengler, 2001). There is also a large body of work showing the role of emotions concerning customer satisfaction (Phillips & Baumgartner, 2002), service failures (Zeelenberg & Pieters, 1999), and consumer complaint behavior (Stephens & Gwinner, 1998). With the importance of the effect of emotion in the decision-making process being discussed, this section of the review looks to demonstrate different emotional factors that ultimately affect the purchasing decision of consumers.

Businesses understand the importance of the emotional state of the consumer and use the store environment to influence it before, during, and after the purchasing process.

Effective stores give consumers a positive mindset by using lighting, sound, promotions, customer service, and the number of customers (Baker, 1996). Environments that manage to arouse positive emotions will find that their consumers are more likely to pay higher for services, customer loyalty, and spread positive words about the experience (White & Yi-Ting, 2005; Kotri, 2011).

Due to the objectives of this study, it is important to understand how the basic emotions influence consumer behavior. When consumers experience *happiness*, they are more likely to experience pre-purchase satisfaction (Watson & Spence, 2007) and will be more satisfied with their purchase (Westbrook & Oliver, 1991). *Anger* leads to higher levels of complaining and individuals are more likely to speak negatively about the experience and *fear* causes consumers to judge pessimistically due to uncertainty (Watson & Spence, 2007). *Sad* consumers experience dissatisfaction to a smaller degree than angry consumers and are willing to buy items at a higher price (Westbrook & Oliver, 1991).

CHAPTER THREE

PILOT STUDY

Objectives

The objective of the pilot study was to evaluate the developed dynamic testing methodology of facial expression analysis as well as techniques used in the data analysis phase. Before the development of this study, the use of facial expression analysis has been limited to static testing methods that do not fully represent realistic consumer behavior. In order for dynamic testing of facial expression analysis to occur, new equipment was created and effectively tested in the pilot study. In addition, the researchers used facial expression analysis in the pilot study to evaluate the emotional process of participants opening and discarding home delivery packages. Different protective packaging materials cushioning the delivery packages were examined to gain an understanding if different materials evoke different emotions from the participants.

After the pilot study, improvements were made to the final experiment design as well as the methods used to video record facial expressions. The final experiment (Chapter IV) utilizes a consumer retail environment, consumer shopping objectives, and eye-tracking technology; three factors that are not featured in the pilot study. The remainder of the chapter will show a brief overview of the equipment and methods used in this experiment. More details pertaining to the development of equipment and methods will be explained in full in the next chapter (Chapter IV).

Participants

Surveys used to screen potential participants were distributed using the SurveyMonkey® platform. In order to participate in the study, participants had to meet the following criteria:

1) Be the primary shopper or share the shopping role in the household
2) Order items online for home delivery in the last two months

125 participants were analyzed over a four-day period. The sample consisted of 34% male and 66% female. The age of the participants ranged from 18 to 65 with 61% being between the ages of 21-39. Most of the sample group was single (52%) and did not have any children at the time (61%). A majority of the participants were college educated and earned a bachelor, master, or doctorate degree (66%). The income range was between less than $20,000 to above $200,000 with 22% reported earning an income between the range of $50,000 and $74,999 (Appendix D).

Apparatus and Stimuli

GoPro HERO4 Session Action Camera

The device used to record facial expressions throughout the process was the GoPro HERO4 Session action camera (Figure 5). This camera was chosen due to its lightweight (74g) and the ability to control the camera via the GoPro application (Figure 6) available on smartphone devices. An SD card is located in the camera, which allowed data to be transfer to a computer database easily. Videos were recorded at a 720p resolution but the camera can record up to 1440p. Two cameras were used in this pilot study to accommodate for the long research hours and the battery life of the cameras (1–2 hours).

Figure 5: GoPro HERO4 Session action camera

Figure 6: GoPro mobile application

Facial Expression Recording Helmet

The biggest challenge of recording the face of a mobile participant is accounting for the side-to-side and up-and-down movement of the head. In order for facial expression analysis to occur, video recordings must contain the entire face. If the entire face is not in the video frame, the data will be incomplete and absent for the time frame where the face is not present.

In order for the analysis to be accurate, the camera must be placed parallel to the face. Analysis of facial expressions from a face recorded from a camera that is not parallel will confuse the software and will define facial expressions inaccurately. This is due to the software not being able to detect facial features such as eyes, brows, and mouth corners from that angle of view.

Figure 7: GoPro camera view

Figure 8: Prototype of facial expression analysis helmet

The solution used was to mount the camera onto a helmet that was attached to the participant's head. This allowed the camera to constantly record the face of the participant despite head movements (Figure 7). A prototype was built to test the method in the pilot study and is shown in Figure 8. For sanitary reasons, the inside of the helmet was cleaned with a disinfectant spray after each use.

Protective Packaging Materials

Understanding if protective packaging materials have an effect on the emotion of the consumer can help businesses choose a material that accomplishes the goals of (1) protecting the contents of the package and (2) emotionally impacts the consumer in a neutral or positive way. Using materials that consumers create negative associations with could create additional negative associations with the business or sender as well.

Experimental Design

The objective of the pilot study was to evaluate the developed dynamic testing methodology of facial expression analysis as well as techniques used in the data analysis phase. In order to accomplish the objectives, an experiment was developed to evaluate the emotional impact of protective packaging materials contained in home-delivery packages. To best simulate this scenario, a realistic home environment (Figure 9) at Clemson University was chosen as the setting.

Figure 9: Ruby Craven Room

To simulate a delivery package, items were packaged and sealed into a 12 x 12 x 12 brown shipping box. Due to the home environment, the items contained in the shipping box simulated an online order made by someone hosting a dinner party. Box cutters and scissors were placed beside the package in order for the participant to have tools to open the package that might be found in their own home. Trash and recycling receptacles were placed in close proximity to the participant to give them disposing options that they may have at their own home.

The researchers chose to examine two actions of interest in this pilot study: the opening process and the disposal process. Facial expressions for each material during both processes were analyzed separately in order to understand if the emotions expressed during the opening process differed from discarding process. 'Opening time' was defined as the moment the participant began opening the package to the moment all of the items had been removed. 'Discarding time' was defined as the moment all of the items had been removed until the disposal process was complete.

Procedure

Before the experiment, participants had to sign and agree an Institutional Review Board (IRB) form in order to be video recorded. Once the form was signed, the helmet containing the mounted camera was secured on the top of the participant's head. The GoPro mobile application was used to ensure the camera was positioned parallel to the participant's face.

The experiment began by instructing the participant to “open the package, remove and unpack the items, and discard of the packaging”. At this moment, the recording of the camera began via control from the GoPro mobile application. Next, the participant was brought to the kitchen table where the delivery package was waiting for them. Following instructions, the participant removed the packages contents as they would in their own home.

Once the items were removed, the participant chose to discard the protective material in either a recycling or trash receptacle located next to the table. In contrast, some participants took the initiative to dispose of the protective material throughout the opening process. After the delivery package was completely disposed of, the researcher entered the room and removed the equipment from the participant. The participant then completed a post-survey that gathered additional qualitative data.

After 30 participants, the protective packaging used to cushion the delivered items was changed.

Facial Expression Analysis

Emotient Analytics was used to decode facial expressions into quantitative data. The software uses algorithms to translate facial features (brows, mouth corner, nose tip, etc.) into defined action units (AUs), fundamental movements of individual muscles, which are coded into facial expressions using the Facial Action Coding System (FACS) (Ekman & Friesen, 1978). FACS allows coders to define facial expressions into the universal emotions of joy, surprise, disgust, contempt, anger, sadness, frustration, confusion, and fear. Emotient Analytics works similarly by generating values for each of the universal emotions. The value ranges from a scale between -5 and 5 and represents the odds in a logarithmic (base 10) scale of a target expression being present, versus it not being present. For example, a negative value for joy means the likelihood that joy is present is less than the likelihood that joy is absent. A visual explanation is given in Table 1.

Table 1: Facial expression analysis explanation

Value	Channel	Description of Expression
2	Joy	The expression is 100 times more likely to be categorized by an expert human coder as joyful than not joyful.
1	Joy	The expression is 10 times more likely to be categorized by an expert human coder as joyful than not joyful.
0	Joy	There is equal chance that the expression is to be categorized by an expert human coder as joyful or not joyful.
-1	Joy	The expression is 10 times more likely to be categorized by an expert human coder as *not* joyful than joyful.
-2	Joy	The expression is 100 times more likely to be categorized by an expert human coder as *not* joyful than joyful.

The output generated from Emotient Analytics comes in Microsoft Excel file format containing many values that include time, emotion, valence, and action unit (Figure 10). For each material, the emotion values were separated and averaged for ‘opening’ and ‘discarding’.

	timestamp	baseline	anger	confusion	contempt	disgust	fear	frustration	joy	sadness	surprise
OPEN	0.033	0.00877196	-2.95211	-2.34634	0.644292	-3.04989	-1.78164	-1.82992	-0.27242	0.0422187	-1.59421
OPEN	0.066	0.0392962	-2.90332	-2.32754	0.624738	-2.96412	-1.82172	-1.80039	-0.18367	-0.0712077	-1.52698
OPEN	0.1	0.0233304	-2.76496	-2.35623	0.580227	-2.77139	-1.77129	-1.80812	0.0303771	-0.309708	-1.35416
OPEN	0.133	0.044445	-2.78653	-2.39351	0.518435	-2.71061	-1.70371	-1.91878	0.0623268	-0.385995	-1.18434
OPEN	0.166	0.159046	-3.00329	-2.38225	0.430327	-2.81395	-1.58986	-2.15228	-0.206897	-0.181455	-0.98972
OPEN	0.2	0.207205	-3.16838	-2.38404	0.356357	-2.85304	-1.52507	-2.36997	-0.391538	-0.0440496	-0.82877
OPEN	0.233	0.208049	-3.18233	-2.32557	0.330045	-2.75154	-1.54856	-2.45625	-0.468968	0.0914833	-0.770415
OPEN	0.266	0.229781	-3.18543	-2.27067	0.23244	-2.65344	-1.5281	-2.54658	-0.58309	0.218957	-0.665073
OPEN	0.3	0.295851	-3.22485	-2.25779	0.0671435	-2.58249	-1.52254	-2.70416	-0.784817	0.289538	-0.505926

Figure 10: Example of Emotient facial expression analysis Microsoft Excel output

Results and Discussion

Table 2: Likelihood of facial expression occurring when opening package

	Anger	Confusion	Contempt	Disgust	Fear	Frustration	Joy	Sadness	Surprise
Peanut	-2.8	-3.2	-0.82	-1.6	-2.9	0.99	-0.99	-1.9	-2.9
Paper	-2.6	-2.0	-0.37	-1.88	-2.2	-1.9	-0.98	-0.87	-3.0
Bubble	-3.0	-3.0	-0.53	-2.0	-2.8	-2.5	-0.10	-1.8	-3.7
Air Brick	-2.6	-2.6	-0.39	-1.4	-1.8	-2.4	-0.11	-1.4	-2.8

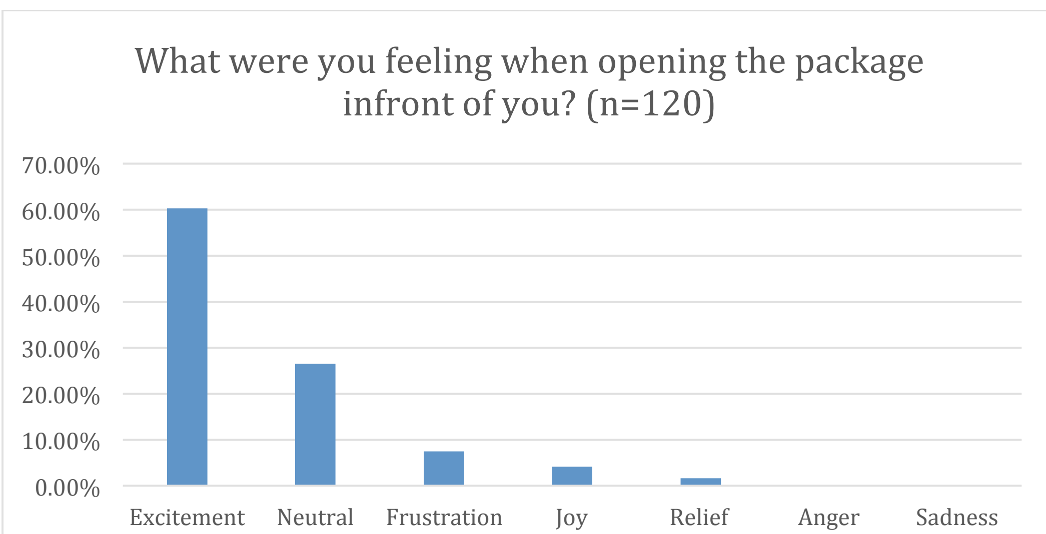


Figure 11: Survey data of participant emotions during the opening process

Statistical testing was not conducted between the protective packaging stimuli in this pilot study to look for significance. Examining the quantitative data in Table 2 shows that facial expressions of emotion were not likely to have occurred during the opening process of the delivery package. However, the expression of frustration was likely to have occurred for participants that opened packages containing peanut material. This aligns with the hypothesis that peanuts would most likely cause frustration compared to the other materials tested.

Survey data shows participants experienced a great amount of excitement while opening the delivery package. This can be attributed to the surprise of finding out what is inside the package. It is interesting to note that survey results showing the experience of excitement do not correlate with the quantitative data. To conclude, it is assumed that emotions experienced are not necessarily going to be expressed through facial expressions.

Table 3: Likelihood of facial expression occurring when discarding package

	Anger	Confusion	Contempt	Disgust	Fear	Frustration	Joy	Sadness	Surprise
Peanut	-2.8	-3.2	-0.91	-1.6	-1.6	-1.2	0.03	-1.8	-2.8
Paper	-2.3	-1.9	-0.23	-1.9	-2.0	-1.7	-1.2	-0.81	-2.8
Bubble	-3.1	-3.4	-0.75	-2.2	-2.6	-2.8	-0.14	-1.9	-3.58
Air Brick	-2.6	-2.8	-0.72	-1.5	-1.6	-2.5	-0.20	-1.5	-2.7

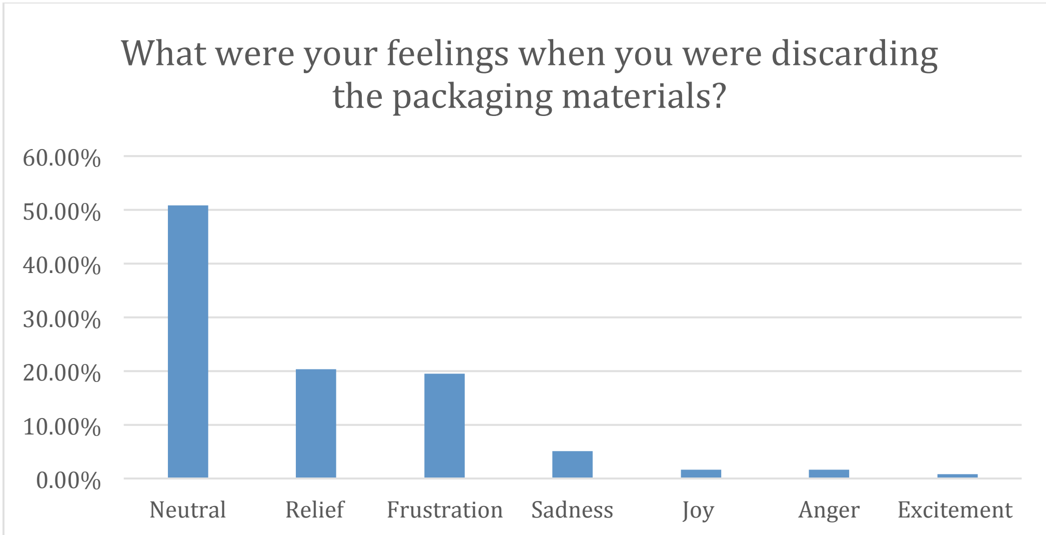


Figure 12: Survey data of participant emotions during the closing process

Statistical testing was not conducted between the protective packaging stimuli in this pilot study to look for significance. Examining the quantitative data in Table 3 shows that facial expressions of emotion were not likely to have occurred during the discarding process. Participants discarding peanut material may have expressed a small amount of joy throughout the process, but the likelihood is very small.

A higher percentage of participants reported experiencing a neutral valence throughout the discarding process. Figure 12 shows that the emotion of excitement was absent compared to the large amount of participant reporting the emotion during the opening process. Higher levels of frustration were reported during the opening process but were not expressed through facial expressions.

Conclusions

The pilot study provided an opportunity to develop and test the methodology created in order to evaluate the facial expressions of mobile research participants. The facial expression analysis helmet was able to successfully record video despite head movements by the participants. Unique insights on emotional impacts of protective materials of delivery packages were found by evaluating the qualitative and quantitative data.

When opening the package, the facial expression of frustration was likely to have occurred when the package was protected with peanuts. The value of 0.99 means the expression is 10 times more likely to be categorized by an expert human coder as frustrated than not frustrated. This aligned with the survey data with 46.63% of participants (n=30) reporting the feeling of frustration when opening packages containing peanuts. When discarding the package, the emotion of joy was more likely to have occurred when the package was protected with peanuts.

The results for peanuts were expected as most consumers view peanuts as an undesirable protective packaging material due to the difficulty of disposing the material as well as the difficulty of finding the shipped items contained in the delivery package. The results strengthen the validity of the dynamic testing methodology and supports reasoning to add complexity to the methodology such as the addition of eye tracking equipment. There is evidence to support that dynamic testing using facial expression analysis will also be effective in a shopping scenario occurring in a realistic shopping environment.

CHAPTER FOUR

MATERIALS & METHODS

Objectives

Can facial expression analysis be used as an effective dynamic testing method to evaluate consumer emotional responses to packaging design in a realistic shopping environment? If so, how can this type of analysis be used to gain insight into the packaging appeal of products? Up until this point, dynamic testing using facial expression analysis has been limited to static testing procedures due to software and technology limitations. In order to correct this problem, additional equipment and methods were created that allowed for the transformation of facial expression analysis from a static testing method into a dynamic testing method.

This thesis looks to test the methodology that was developed in order to use facial expression analysis as a dynamic testing method in conjunction with other devices in the packaging evaluation workflow. The methodology will be effective if the followings objectives are completed:

1. Successfully gather facial expression analysis and eye tracking data using the proposed methodology.
2. Statistically analyze differences in facial expression analysis data between a control and stimulus package.
3. Find improvements that can be made to enhance future studies.

Stimulus

The fictitious brand, Zapotec, of single-serve coffee pod packages was used as the packaging stimuli of interest in this study. In order to differentiate the stimulus from the control, a bright red foil stamp was applied to the branding symbol on the front of the package (Figure 13). The design of the control package included the same symbol without the application of the foil stamp (Figure 14). Previous case studies have proven that packages containing foil stamps perform better on the shelf and are more likely to be purchased (Foil and Specialty Effects Association, 2013). The stimulus was designed to perform better than the control. Brand name products were also on the shelf with the control and stimuli in order to simulate a shelf performance research study.

Figure 13: Stimulus Zapotec package

Figure 14: Control Zapotec package

This stimulus was chosen due to the large differentiation in preference recorded from qualitative data between the two packages. Survey data from the participant pool (n=162) shows that 67.28% of participants preferred the packaging appeal of the stimulus to 13.58% of participants who preferred the packaging appeal of the control. 18.51% did not have a preference between the two packages (Figure 15). Therefore, the researchers are hypothesizing that the facial expression analysis data for the stimulus package will outperform the control package.

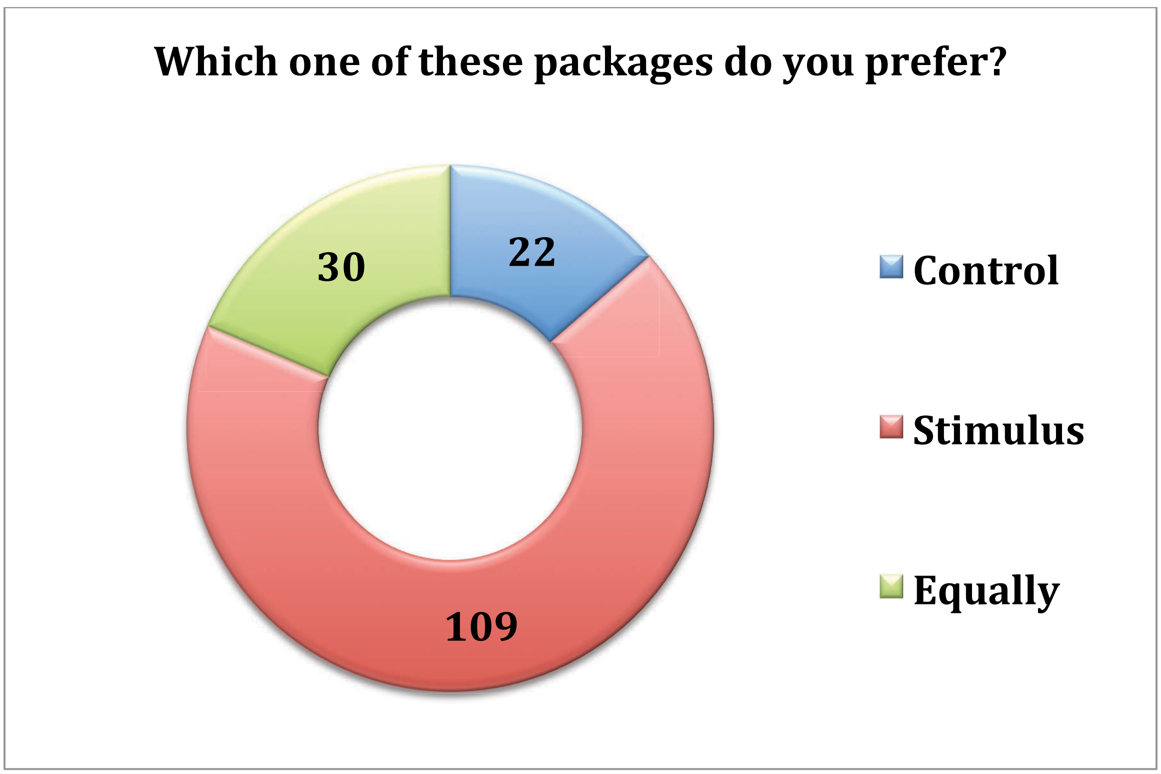


Figure 15: Packaging preference between packages of interest

Apparatus

GoPro HERO4 Session Action Camera

The device used to record facial expressions throughout the process was the GoPro HERO4 Session action camera (Figure 16). This camera was chosen due to its lightweight (74g) and the ability to control the camera via the GoPro available on smartphone devices. An SD card is located in the camera, which allowed data to be transfer to a computer database easily. Videos were recorded at a 720p resolution but the camera can record up to 1440p. Two cameras were used in this methodology experiment to accommodate for the long research hours and the battery life of the cameras (1–2 hours). This is the same device used in the pilot study (Chapter III).

Figure 16: GoPro HERO4 Session action camera and GoPro mobile application

Facial Expression Recording Equipment

Facial expression recording equipment was developed in order to use facial expression analysis as a dynamic testing method in a shopping environment. In a previous study, the helmet allowed for the static testing of facial expression analysis (Holzhauer, 2016). Additional evidence from the pilot study (Chapter III) further shows that the apparatus is an effective tool to record facial expressions using dynamic testing methods. In this methodology experiment, eye-tracking equipment will be used in conjunction with facial expression analysis equipment in order to evaluate the functioning on the two devices being used in conjunction as well as increase the amount of insight developed from additional quantitative data.

There is question to whether there are any significant differences between the facial expression analysis values gathered from static testing experiments and dynamic testing experiments. Since this is the first instance of facial expression analysis being used in a dynamic testing method, there is no research exploring differences in data values between the dynamic and static testing methods of facial expression analysis. However, past research evaluating the differences between eye-tracking metrics gathered from static testing methods and dynamic testing methods showed no significant difference (Stone, 2015). The results from static testing methods and dynamic testing methods are assumed to be similar for facial expression analysis.

In order to improve upon flaws in the pilot study, new helmets were developed to address the problems of the prototype helmet that appeared in the pilot study. The prototype helmet had the following problems:

1) Size could not accommodate the varying sizes of heads.

2) Too much of the participants forehead would be covered up which could cause distortions in the facial expression analysis software.

3) Weight was too heavy and felt obtrusive.

4) Design and overall aesthetic was inappropriate and did not receive a positive response from pilot study participants.

The first mistake was creating an apparatus that was unable to be adjusted and was not compatible between participants with differing head sizes. To address this mistake, two helmets were developed in order to accommodate for the large range of head sizes.

Gaps in the data were also appearing due to the prototype helmet covering a large portion of the forehead. The facial expression analysis software had difficulties analyzing the muscles in the forehead, as the prototype helmet would cover large parts of the forehead. A large portion of the part of the helmet that covers the forehead was removed in order to expose the forehead and part of the hairline (Figure 17).

The camera mount was lightened dramatically by removing the previously wooden mount with multiple metal screws and replacing it with a plastic mount that is half the size and secured by a single screw (Figure 18). These features, along with using a cleaner new helmet as the base, all contributed to giving the apparatus a greater aesthetic appeal (Figure 19).

Figure 17: Prototype (left) compared to forehead cutout of the model (right)

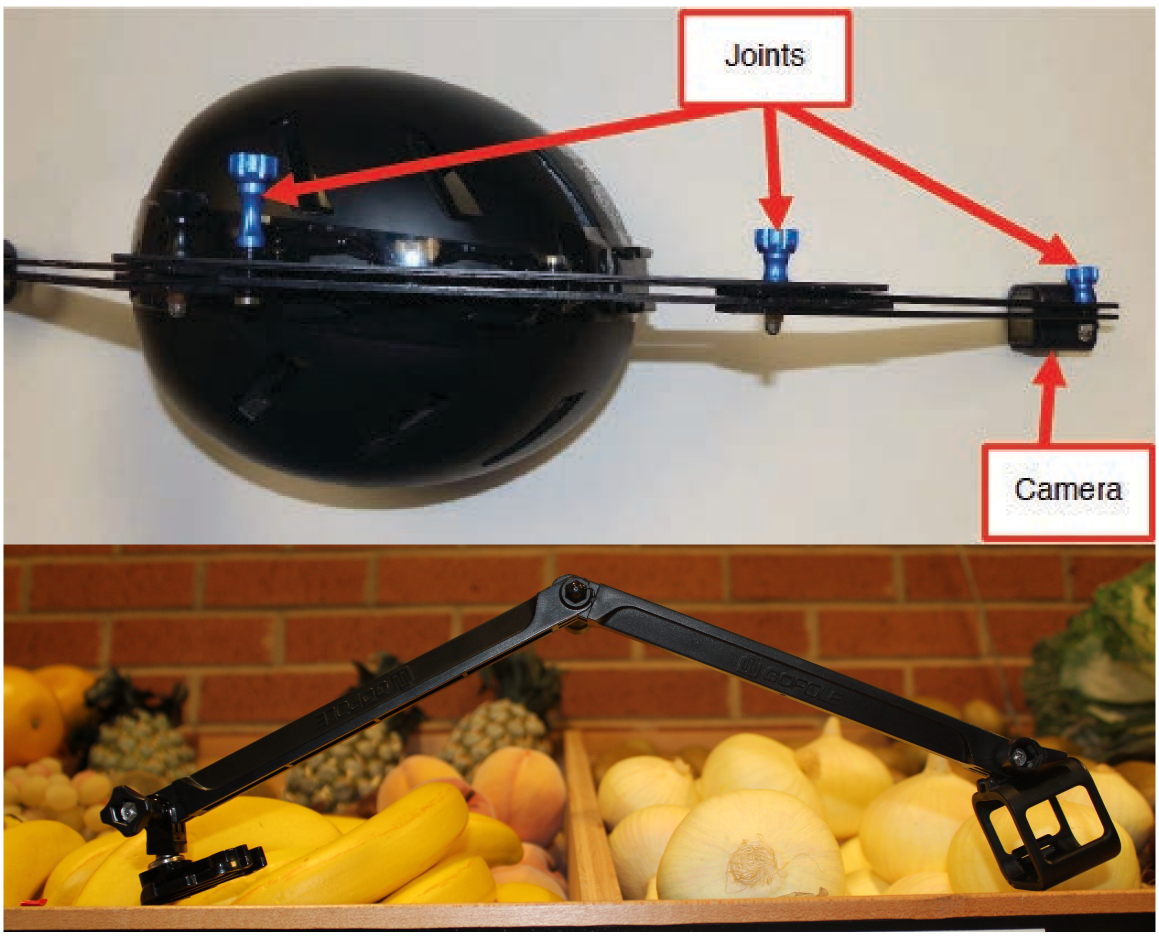


Figure 18: Comparison of the mount used for the prototype (top) and model (bottom)

Figure 19: Comparison of completed prototype (top) versus completed model (bottom)

Tobii Eye-Tracking Pro Glasses 2

Tobii Pro Glasses 2 (Figure 20) were used to record what the participant was looking at while conducting the study. The head unit consists of sensitive sensors that record eye movements at a rate of 50-100 Hz as well as a camera that records the participant's point of view. Eye movement data and video files are transferred to a SD card located in the pocket–sized recording unit.

Eye-tracking glasses are used in consumer behavior research to measure a person's point of gaze, which provides insight into what draws the users attention as well as their cognitive processes. Eye-tracking technology follows the eye movements and identifies where the user looks as they look at an object or area of interest (Figure 21). Eye movements when shopping are many times involuntary, allowing humans to scan thousands of items in a short span. Researchers use this technology to measure that eye movement in order to produce quantitative data that can evaluate the shelf performance of a package. Eye-tracking glasses were used for three purposes in this study:

1) Evaluate if eye-tracking technology can effectively be used in conjunction with the facial expression recording equipment.
2) Show where the participant is looking. This is necessary since the facial expression camera is positioned to record the participant's face.
3) Gather eye-tracking data on the stimulus and control packages.

Figure 20: Participant using Tobii 2 Pro Glasses in shopping environment

Figure 21: Eye tracking heat map data

Tobii 2 Pro Glasses must be modified in order to be completely compatible with facial expression analysis. This is due to the glasses partially covering facial muscles that are used by facial expression analysis software in the classification of expressions. The muscles that are partially covered include the procerus (Figure 22), depressor supercilii (Figure 23), and corrugator supercilii muscles (Figure 24). The best way to minimize this problem is to remove the nose pads from the glasses. Unfortunately, the nose pads were not removed from this methodology experiment.

If the nose pads are not removed from the glasses, the values for the expression 'sadness' and the valence 'negative' may be lower than what would be recorded if the the participant was not wearing Tobii 2 Pro Glasses.

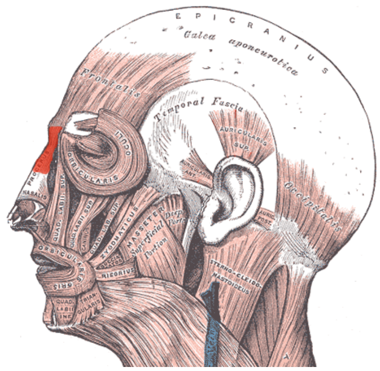


Figure 22: Procerus muscle

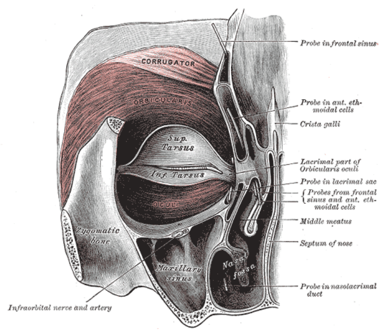


Figure 23: Depressor supercilii

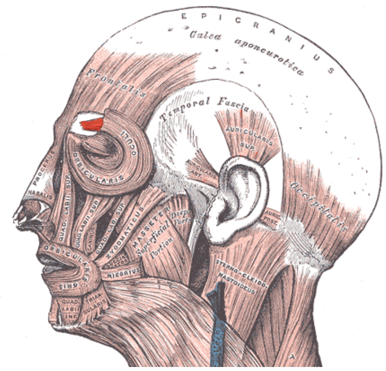


Figure 24: Corrugator supercilii

Calibration

Before an eye-tracking recording can begin, the Tobii 2 Pro Glasses must be calibrated to the participant's eyes in order to account for differences in shapes, light refraction, and reflection properties from participant to participant. During the calibration, the user must stand at a point four feet away from a wall and stare at the designated Tobii calibration card (Figure 25). The calibrator then uses Tobii software to begin the calibration process. Subjects are usually successfully calibrated and given a calibration score of one through five. The higher the calibration score, the more accurate the gaze data will be. Subjects who do not calibrate successfully are usually unable to participate due to inconsistent and inaccurate data.

Figure 25: Calibration process for Tobii 2 eye tracking glasses

Experimental Design

This thesis study took place in CUShop^{TM} (Figure 26, Figure 27), an immersive consumer behavior lab at Clemson University. CUShop^{TM} welcomes participants through automatic sliding glass doors that leads them into a simulated grocery store environment. The shop is equipped with 3 aisles that contain shelving units that span four feet in length six feet in height. The aisles are 7 feet in length to allow shoppers maximum circulation.

Fluorescent lighting is used to mimic that of a typical grocery store including the level of lighting to provide sufficient light to view the products effectively (Stone, 2015).

Figure 26: CUShop™ at Clemson University

Figure 27: Aisles at CUShop™

In order to navigate through CUShop™, participants are given a shopping list (Figure 28) that indicates various items that are of interest. Participants are instructed to shop for the items on the shopping list and make a purchase decision for each product. In order to gather the best data possible, the package of interest is generally placed at the bottom of the list. In this experiment, single-serve coffee pods were the last item participants shopped for in CUShop™. This allows for participants to get acclimated to the shopping environment and begin to behave similarly as they would in an actual store. Pricing options were eliminated in order to isolate the variable of package design and packaging appeal. Instead of a price tag, each package is connected with a corresponding item number that the participant references on their shopping list to indicate their purchase decision (Figure 29).

Package InSight

Shopping List

Instructions: Please do not touch the packages, just write down the number under the package you would purchase. Please shop for the items on the list in order.

Package Number	Product
	Corn Bread Mix
	Crushed Rosemary
	Thyme Leaves
	Minced Garlic
	K-Cups

Participant I.D.

Figure 28: Shopping list used for experiment

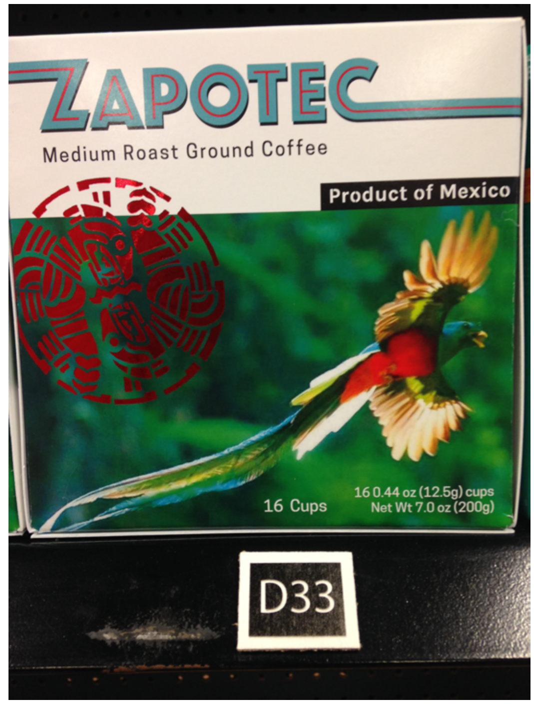


Figure 29: Example of item reference number

The coffee shelf used in this thesis was designed to be a smaller replica of a shelf set-up that would be found in bulk stores such as Costco or Sam's Club (Figure 30). The brands used were Maxwell House, Donut Shop, Eight O'Clock, Gevalia, and Green Mountain Coffee. The stimulus package was placed on the shelf amongst competitive packages for 40 participants (Figure 31). After this amount had completed the study, the stimulus package was removed and replaced by the control package for 40 participants. This limited the amount of choices participants had and increased the likelihood of observing data pertaining to the stimulus and control packages.

Figure 30: Stimulus package placed among competitors on the shelf

Figure 31: Area of analysis with area of interest highlighter

Participants

The dynamic methodology testing consisted of 164 participants (60.25% female and 39.75% male) over a 3-day period. Out of that pool, facial expression analysis was conducted on 80 participants as they shopped for single-serve coffee pods, which contained the packaging stimulus and control. Due to incomplete data, findings for 61 participants were analyzed after the study was completed. Participants were given a $20 gift card as incentive for being a part of the study. Each participant had to meet the following requirements:

1. Be the primary shopper or share the shopping role in their household
2. Be between the ages of 24-54
3. Earn an income of at least $35,000 per year

Subjects who were not screened through the online process were screened at the experiment site.

Participants ranged in age from 25 to 54 years of age. The distribution of incomes was diverse among the participants, ranging from $35,000 to over $200,000 annually. Over 50% obtained a graduate degree or higher and were currently married (69%). 80% of participants claimed to be the primary shopper in their household (Appendix B).

Each participant agreed to be video recorded by signing an IRB regulation form before beginning the study.

Procedure

Upon arriving at the study, the participant was given an ID number and was informed that their face would be video recorded throughout the process. The participant had to sign and date an IRB regulation form to confirm their willingness to be video recorded. After the form was signed, the participant completed a short survey gathering demographic data.

Next, the participant was equipped with Tobii Pro Glasses 2 and the glasses were calibrated to their eyes to ensure data accuracy. Once the calibration process was complete, facial expression recording equipment was securely attached to the head of the participant to ensure it did not move throughout the experiment. To ensure accuracy, it was confirmed that the camera was positioned appropriately to record the entire face of the participant by using the GoPro mobile application. The participant was then given a shopping list containing the products of interest and instructed to mark their purchasing decision beside each item on the list. Once the participant understood the process, they entered CUShop™ and recording of the Tobii Pro Glasses 2 and GoPro HERO4 Session camera began.

After completing the shopping process, the equipment was removed from the participant. The participant then completed a survey pertaining to their experience, emotions, and shopping behavior while in CUShop™. Finally, the participant was given a twenty-dollar incentive once they completed the study.

Statistical Analysis

Eye-tracking Metrics

The main key eye-tracking metrics are purchase decision (PD), total fixation duration (TFD), and time to first fixation (TTFF). PD is defined as the number of participants that chose to purchase the item. TFD is defined as the time in seconds that is spent on average by participants looking at an item. Package shelf performance is considered greater as the TFD increases. TTFF is defined as the time in seconds from when a package first enters the participant's field of view until the time they fixate on it. The lower the TTFF number, the better the package performed on the shelf.

Eye-tracking Analysis

Eye-tracking data was analyzed by using Tobii Pro Glasses Analyzer. Before analysis can occur, the user must upload a picture of the shelf that contains the products and packages of interest to the software. Next, the user isolates the different packages, otherwise known as creating an area of interest (AOI) (Figure 32). Areas of interest allow the software to quickly categorize and organize gaze data from eye tracking into the different AOI's. Once the data is categorized, the software analyzes different trends and produces the key metrics of PD, TFD, and TTFF, which provide insight into the appeal of the package design.

Data collected was exported out of Tobii Pro Glasses Analyzer and organized in Microsoft Excel. The eye tracking data was separated into the stimuli and control groups and compared by performing a t-test on each metric of data (PD, TFD, TTFF). The results were examined by using a 95% confidence interval to determine if there was any significance between the stimuli and the control for the metrics stated.

Figure 32: Areas of interests identified on the shelf

Facial Expression Analysis

Facial Expressions were analyzed using iMotions automatic facial coding engine. Automatic facial coding operates by first detecting the face of the subject in the video recording (Figure 33). This is achieved by applying the Viola Jones Cascaded Classifier Algorithm in order to frame the detected face (iMotions, 2016).

After the face is detected, the software categorizes facial features such as eyes, nose, mouth corner, brows, etc. (Figure 34). This acts as a simplified version of the participants face and adapts and follows instantaneously to face movements. The facial features are references to action units (AUs), a term given by Ekman and Friesen (1978) to all the major muscle movements possible in the human face. Different combinations of AUs are coded to interpret the emotion that caused them. So far, over 7,000 different combinations of AUs have been recorded (Tian, et al., 2001).

Once the simplified face model is applied, the position and orientation of facial features are processed through a classification algorithm that translates features into AUs, emotional states, and other affective metrics (iMotions, 2016). The facial features are translated into metrics statistically by comparing the configuration of the facial features numerically with normative databases. The database contains normative distributions and statistics of facial features from people across multiple geographic regions and demographic profiles.

An example is provided by iMotions (2016), "If the respondent's mouth corners are pulled upward, a human coder would code this as activity of AU12 ("lip corner puller") – stating that the respondent is smiling. The facial expression engine instead has to compute the vertical difference between mouth corners and mouth center, returning a value of 10 mm. This value is compared to all possible values in the database (values between 0 mm and 20 mm, for example)".

Figure 33: Example of face detection used in facial expression analysis

Figure 34: Example of feature detection and simplified face model

Figure 35: AU database function

Using this example, a recorded smile (or smile AU) is processed through the database and compared to other mouth configurations and AUs (Figure 35). It is possible that some smiles may be misclassified due to their subtle nature or a yawn that is processed as a smile. As a result, the result that is returned by the classifier is the likelihood that the expression is an authentic smile (iMotions, 2016). This classifier is done independently for each AU, emotion, facial features.

During this study, facial expression analysis data was analyzed from the moment the participant fixated on a single-serve coffee pod packaging product and ended once their purchase decision was made. Using this analysis method, the facial expression values of each shelf are compared against each other. This method assumes that if the packages of interest are different from one another (stimulus or control), then the values recorded in this time period will be different.

Another method could be used that was not used in this thesis, is to analyze the values from the moment the participant fixates on the package of interest until the purchase decision is made. If facial expression analysis is done to evaluate the expressions recorded after the package of interest is viewed, then it will capture facial expressions resulting from the package of interest. Using the previously mentioned analysis method captures the facial expressions resulting from the package of interest as well as the facial expressions recorded before the package of interest was viewed. Therefore, the results could be watered-down and expressions resulting from the package of interest will not be as prevalent.

Statistical Analysis of Facial Expressions

Videos were analyzed using the iMotions automatic facial coding software. The entire video was processed through the software, which produces values for basic emotions (joy, sadness, surprise, fear, contempt, disgust, anger) and valence (neutral, positive, negative). Once the data was collected, the researchers used the video to reference when the participant entered the area of analysis (AOA). Facial expression metrics were analyzed from the second the participant entered the AOA until the participant finished purchasing from the AOA.

The data from this sample period was collected and averaged in Microsoft Excel for each participant, which produced a summary of the emotions of their shopping experience while in the AOA. All data for each emotion and valences for the control and the stimuli were organized into a comprehensive Microsoft Excel spreadsheet.

T-tests were performed on each emotion and valence between the control and the stimuli. Even though the data is in a logarithmic scale, a t-test is the appropriate testing method since the assumptions are about the distributions. The results of the t-test were examined using a 95% confidence interval to determine if there was significance between the stimuli and the control. Findings were calculated and visualized using Microsoft Excel.

Integration of Eye-tracking and Facial Expression Analysis

Additional insights can be made from results gathered during the dynamic testing of eye-tracking and facial expression analysis methods by integrating the videos recorded from each device together. For example, researchers can use the Tobii Pro Glasses Analyzer software and find the exact moment participants fixated on a package. Then, using the iMotions facial expression analysis software, researchers can isolate facial expressions during this fixation time period to isolate results pertaining to the package. In this methodology experiment, both devices started recording simultaneously. However, due to human error, the videos will not always begin recording at the same time. If these types of inferences are desired, videos can be easily spliced together using basic video editing software.

CHAPTER FIVE

RESULTS & DISCUSSION

Introduction

The emphasis of this thesis is the creation of dynamic testing methodology for using facial expression analysis to evaluate packaging stimuli. This chapter is a presentation of the results discovered in the analysis of facial expressions from the evaluation of single-serve coffee pod packages. These results should serve as an example of the types of insights that can be obtained through dynamic testing methods using facial expression analysis.

In this study, data from 60 out of 74 participants were processed for facial expression analysis between the single-serve coffee pod stimulus and control packages. Seven participants from each experimental group were removed due to incomplete facial coding data or errors in video recordings that were unable to be processed. The data gathered from these participants were unable to be used and were removed from the study. After the removal of 14 participants, facial expression analysis and eye-tracking data were analyzed from the stimulus group and control group.

T-tests were performed for every emotion (joy, anger, sadness, surprise, contempt, fear, and disgust) and for valences (neutral, negative, positive) between the stimulus package and control package. Eye tracking t-tests were performed for the metrics of TFD and TTFF between the stimulus package and the control package. A 95% confidence interval was used to report differences between the two groups. The Analysis

ToolPak add-on for Microsoft Excel was used to calculate t-tests for facial expression analysis results and eye tracking results. Results were visualized using Microsoft Excel and Survey Monkey was used to collect and analyze survey data.

T-tests were conducted on the eye tracking metrics of TFD and TTFF at a 95% confidence interval. All findings were insignificant (p-value > 0.05). Eye tracking data will not be discussed in this thesis as the results of facial expression analysis are of interest. All eye tracking results can be found in Appendix E.

Facial Expression Analysis

Facial expression analysis was conducted using the iMotions automatic facial coding software. The software analyzes data by tracking how far action units (AUs) move from their original orientation of the participant in each frame. Results are given in a logarithmic scale (Table 1) that shows the probability of the facial expression occurring at that point in time. Results were analyzed at the point participants began shopping for single-serve coffee pod products until the point where they made their purchase decision and left the area of analysis. Alternative research methods are discussed in Chapter IV.

Table 1: Facial expression analysis explanation

Value	Channel	Description of Expression
2	Joy	The expression is 100 times more likely to be categorized by an expert human coder as joyful than not joyful.
1	Joy	The expression is 10 times more likely to be categorized by an expert human coder as joyful than not joyful.
0	Joy	There is equal chance that the expression is to be categorized by an expert human coder as joyful or not joyful.
-1	Joy	The expression is 10 times more likely to be categorized by an expert human coder as *not* joyful than joyful.
-2	Joy	The expression is 100 times more likely to be categorized by an expert human coder as *not* joyful than joyful.

Negative values represent the probability of the facial expression not occurring throughout the time of analysis for single-serve coffee pods. Likewise, positive values indicate the probability that the facial expression occurred during the same analysis time.

Facial Expressions of Emotion

The facial expressions of emotions for joy, anger, surprise, sadness, disgust, contempt, and fear were analyzed using the iMotions software. T-tests were conducted to compare the seven facial expressions of emotion listed between the stimulus package and the control package. Figure 36 shows an overall comparison of the averages for each facial expression of emotion between the two sample groups.

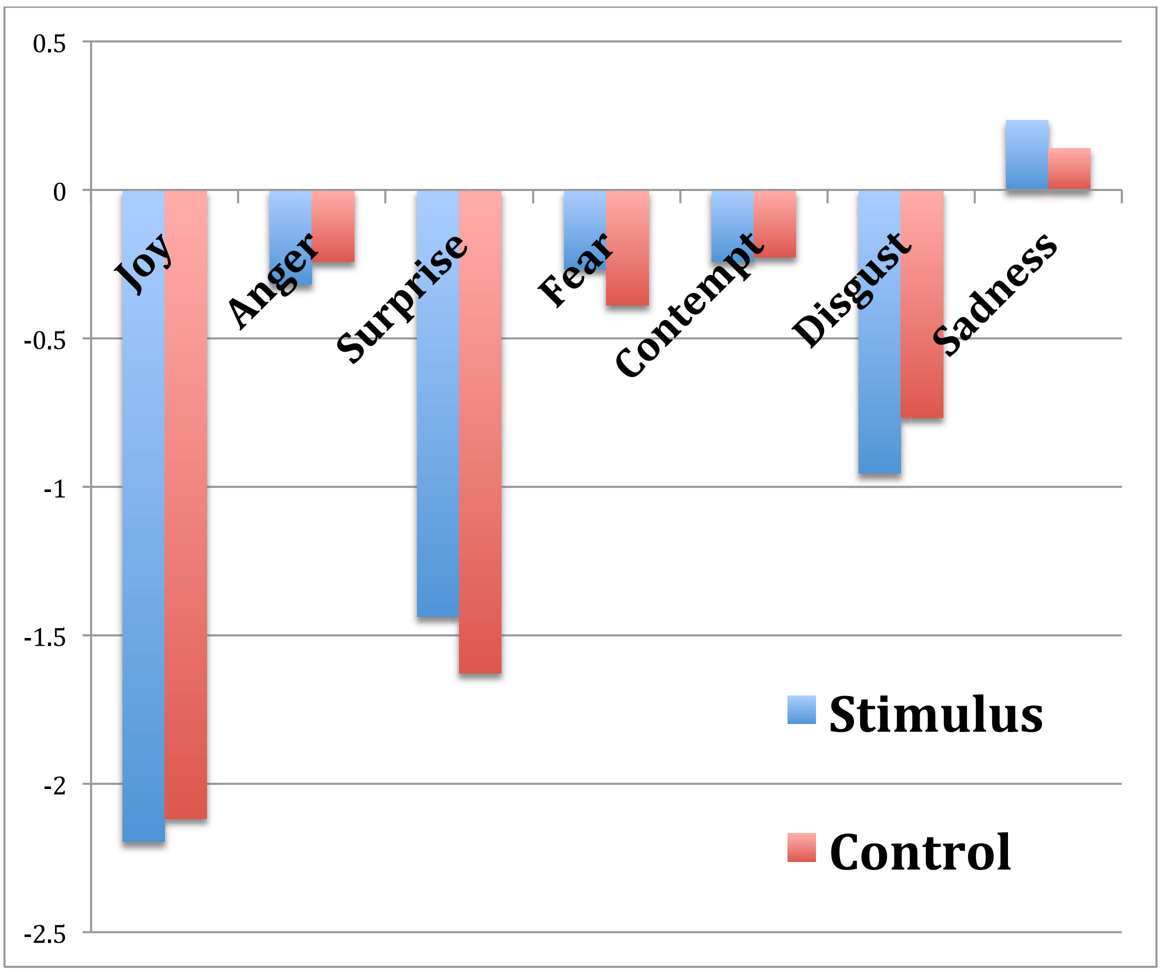


Figure 36: Comparison of averages of each facial expression of emotion

Joy

The average probability of the participant expressing the emotion of joy while shopping for the stimulus package was -2.196. This means that the expression is 157 times more likely to be categorized by an expert human coder as *not* joyful than joyful. The average probability of the participant expressing the emotion of joy while shopping for the control package was -2.118. The result is similar to that of the stimulus package and the facial expression is 131 times more likely to be categorized by an expert human coder as *not* joyful than joyful (Figure 37). No significance was found in the conducted t-test between the packaging of the stimuli and the control (p=0.7719).

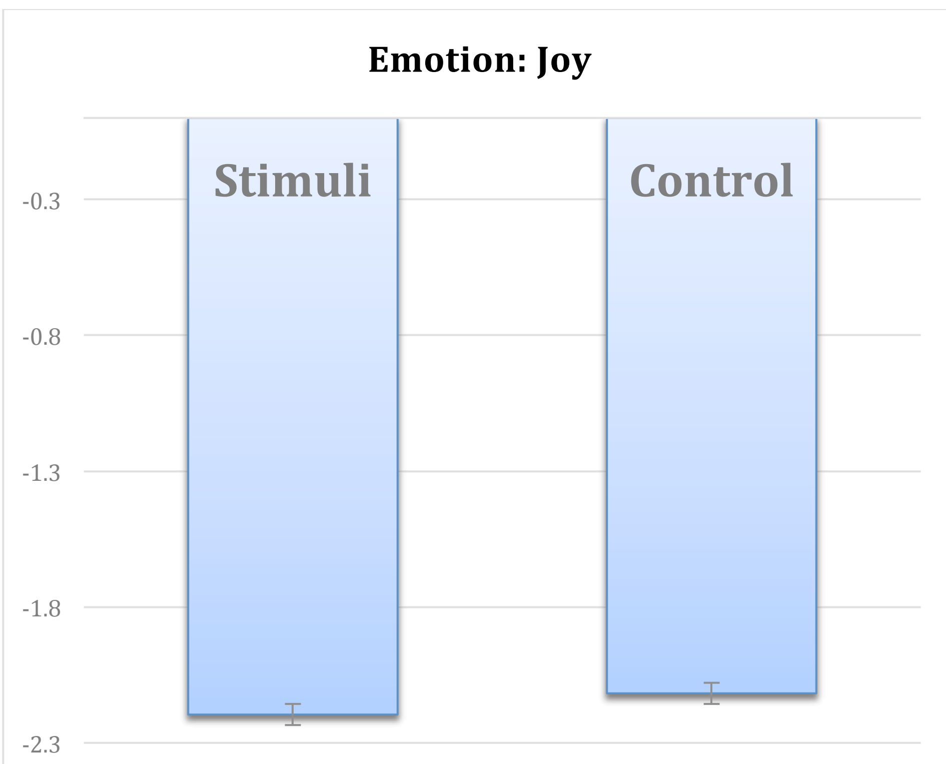


Figure 37: Average probability of expressing the emotion of joy, control vs. stimulus

Anger

The average probability of the participant expressing the emotion of anger while shopping for the stimulus package was -0.3184. This means that the expression is twice as likely to be categorized by an expert human coder as *not* anger than anger. The average probability of the participant expressing the emotion of anger while shopping for the control package was -0.242. The result is similar to that of the stimulus package and the expression is 1.75 times more likely to be categorized by an expert human coder as *not* anger than anger (Figure 38). No significance was found in the conducted t-test between the packaging of the stimuli and the control (p=0.5102).

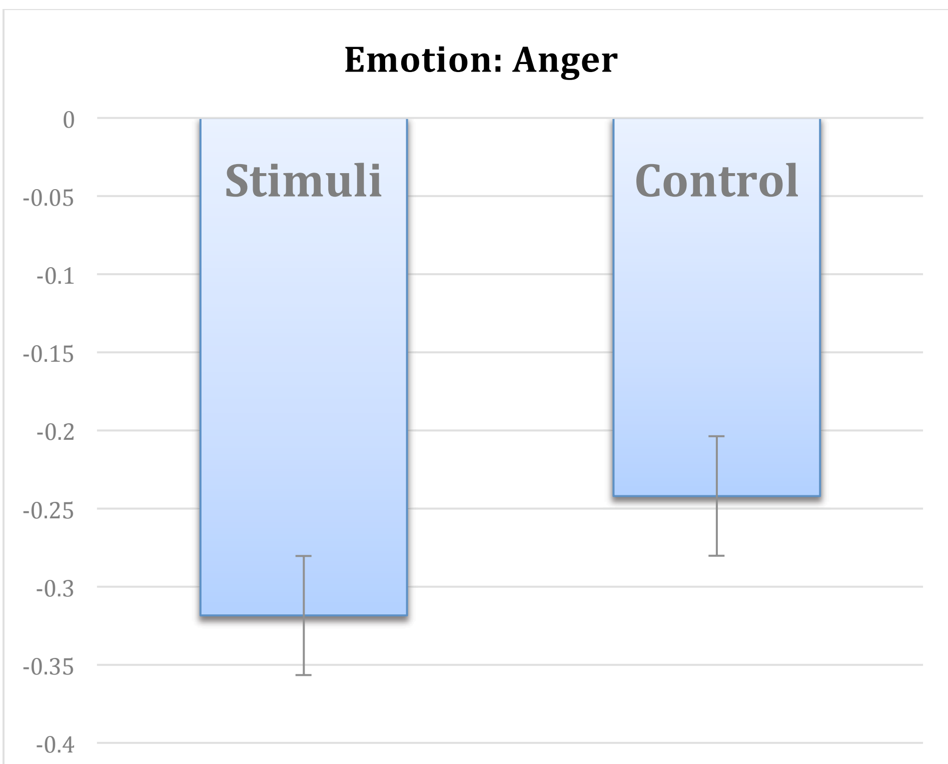


Figure 38: Average probability of expressing the emotion of anger, control vs. stimulus

Surprise

The average probability of the participant expressing the emotion of surprise while shopping for the stimulus package was -1.438. This means that the expression is 27 times as likely to be categorized by an expert human coder as *not* surprised than surprised. The average probability of the participant expressing the emotion of surprise while shopping for the control package was -1.627. The result is similar to that of the stimulus package and the expression is 42 times more likely to be categorized by an expert human coder as *not* surprised than surprised (Figure 39). No significance was found in the conducted t-test between the packaging of the stimuli and the control (p=0.3161).

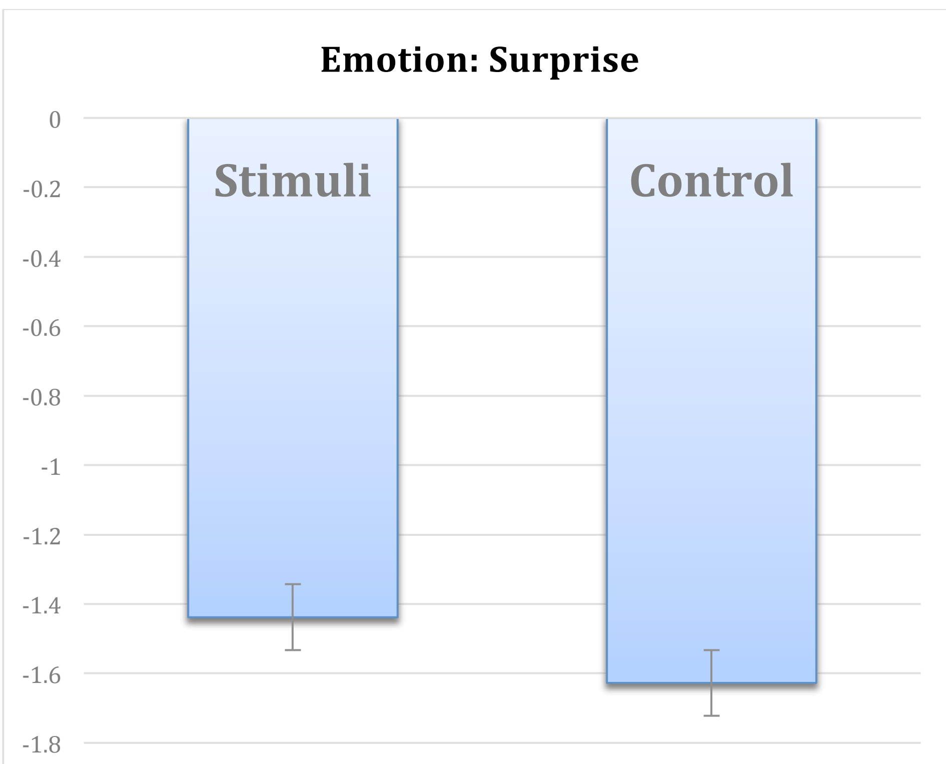


Figure 39: Average probability of expressing the emotion of surprise, stimulus vs. control

Fear

The average probability of the participant expressing the emotion of fear while shopping for the stimulus package was -0.266. This means that the expression is 1.85 times as likely to be categorized by an expert human coder as *not* fear than fear. The average probability of the participant expressing the emotion of fear while shopping for the control package was -0.387. The result is similar to that of the stimulus package and the expression is 2.4 times more likely to be categorized by an expert human coder as *not* fear than fear (Figure 40). No significance was found in the conducted t-test between the packaging of the stimuli and the control (p=0.3242).

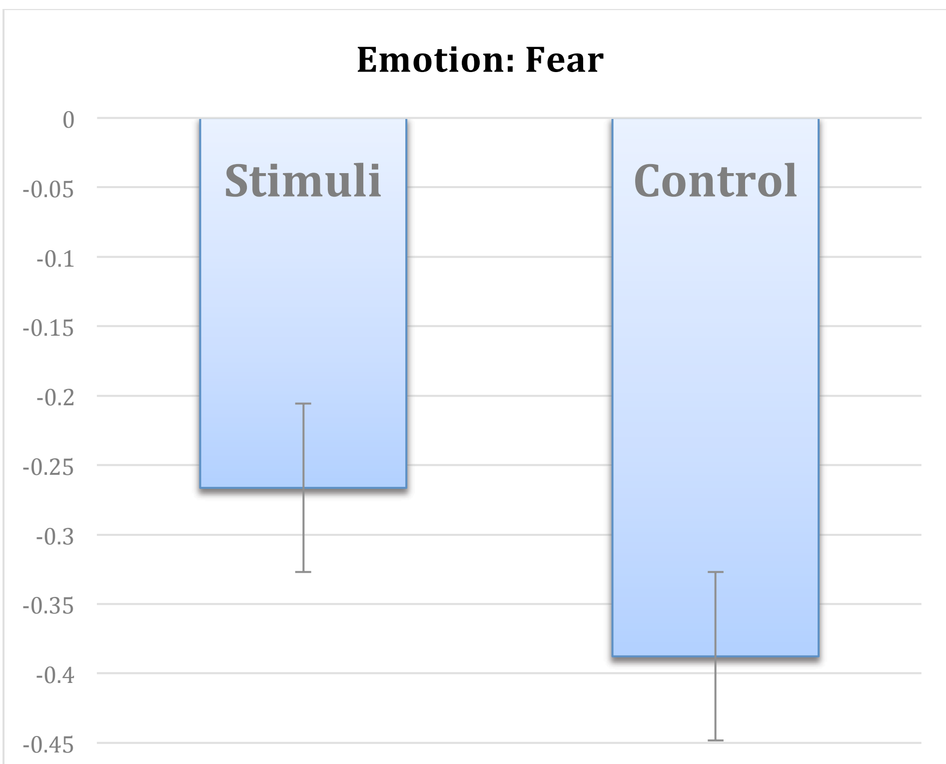


Figure 40: Average probability of expressing the emotion of fear, stimulus vs. control

Contempt

The average probability of the participant expressing the emotion of contempt while shopping for the stimulus package was -0.241. This means that the expression is 1.75 times as likely to be categorized by an expert human coder as *not* contempt than contempt. The average probability of the participant expressing the emotion of contempt while shopping for the control package was -0.226. The result is similar to that of the stimulus package and the expression is 1.68 times more likely to be categorized by an expert human coder as *not* contempt than contempt (Figure 41). No significance was found in the conducted t-test between the packaging of the stimuli and the control (p=0.8819).

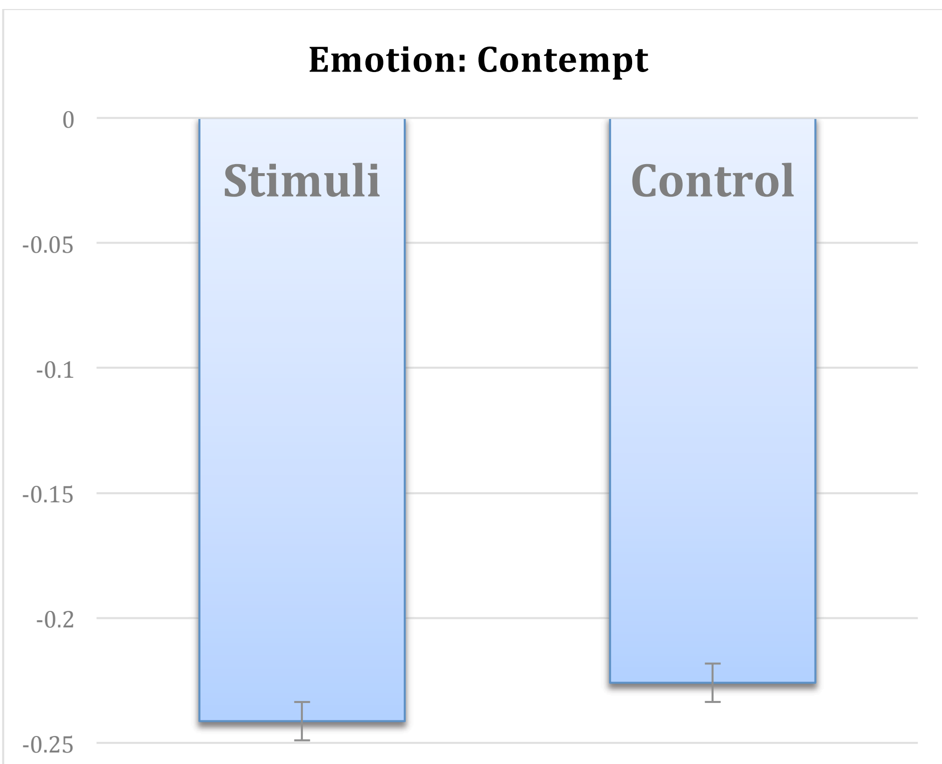


Figure 41: Average probability of expressing the emotion of contempt, stimulus vs. control

Disgust

The average probability of the participant expressing the emotion of disgust while shopping for the stimulus package was -0.954. This means that the expression is 9 times as likely to be categorized by an expert human coder as *not* disgust than disgust. The average probability of the participant expressing the emotion of contempt while shopping for the control package was -0.767. The result is similar to that of the stimulus package and the expression is 5.85 times more likely to be categorized by an expert human coder as *not* disgust than disgust (Figure 42). No significance was found in the conducted t-test between the packaging of the stimuli and the control (p=0.2227).

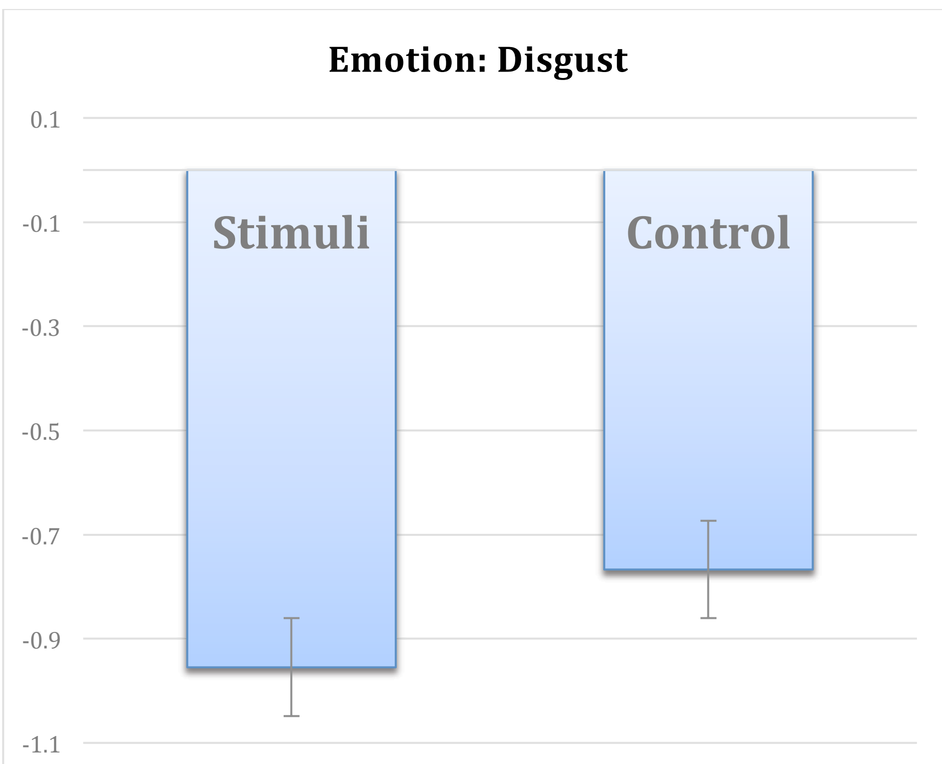


Figure 42: Average probability of expressing the emotion of disgust, stimulus vs. control

Sadness

The average probability of the participant expressing the emotion of sadness while shopping for the stimulus package was 0.235. This means that the expression is 1.7 times as likely to be categorized by an expert human coder as sadness than *not* as sadness. The average probability of the participant expressing the emotion of sadness while shopping for the control package was 0.140. The result is similar to that of the stimulus package and the expression is 1.38 times more likely to be categorized by an expert human coder as sadness than *not* as disgust (Figure 43). No significance was found in the conducted t-test between the packaging of the stimuli and the control (p=0.3773).

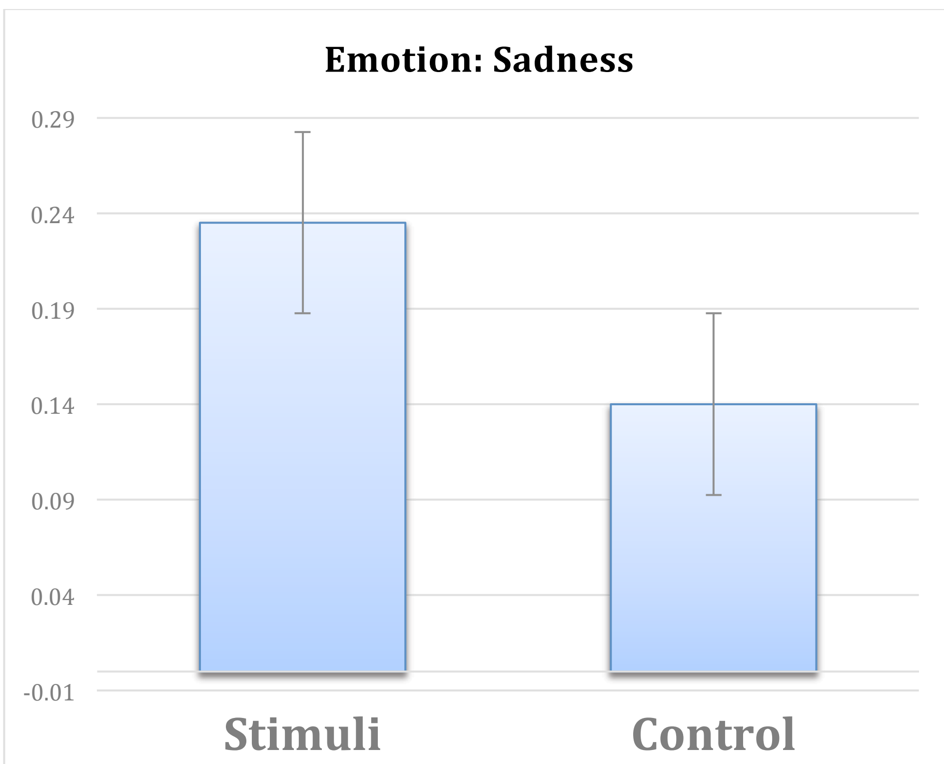


Figure 43: Average probability of expressing the emotion of sadness, stimulus vs. control

Discussion of Facial Expressions of Emotion

T-tests conducted for each emotion between the stimulus package and the control package showed that there was no significance at a 95% confidence interval (p-value > 0.05). Therefore, there is not enough evidence to conclude that the facial expressions of emotion between the stimulus package and the control package are different.

Examining Figure 36 shows that all of the facial expressions of emotion were most likely not expressed during the shopping of single-serve coffee pods except for the expression of sadness. It is unsure what is the cause of the expression of sadness, but it could be attributed to the Tobii 2 Pro Glasses eye tracking technology. The expression of sadness is expressed through the action units of '1' (neutral face), '4' (brow lowerer), and '15' (lip corner depressor). Action unit '4' (brow lowerer) consists of the procerus, depressor supercilii, and corrugator supercilii muscles. The procerus is the muscle that covers the top of the nose (Figure 22). The depressor supercilii (Figure 23) is an eye muscle and the corrugator supercilii (Figure 24) is located on the top of the eye.

Figure 22: Procerus muscle

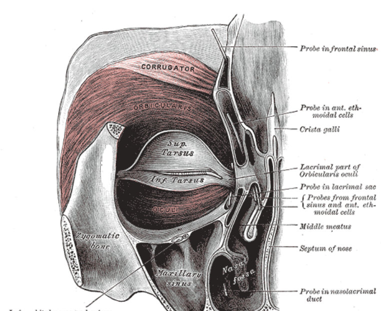


Figure 23: Depressor supercilii

Figure 24: Corrugator supercilii

Tobii 2 Pro Glasses cover a small portion of the muscles listed that make up action unit 4. However, iMotions software is compatible with this version of eye tracking glasses and differences in results between participants wearing eye-tracking glasses compared to participants not wearing eye-tracking glasses should be minimal. Further testing should be conducted to determine if Tobii 2 Pro Glasses significantly affect the results of the facial expression of sadness. Suggestions to address this issue are discussed in Chapter IV. It is also possible that the expression of sadness was being expressed during the shopping of single-serve coffee pods in CUShop™.

Results show, emotions that are associated with low arousal states such as sadness and contempt were more likely to be expressed than high arousal emotions such as disgust or joy. This can be expected due to the low arousing context of shopping in CUShop™. Arousal may be higher in real shopping situations due to the pricing variable and the risk associated with product purchasing. Since participants do not use money to purchase items in CUShop™, and the risk involved with each purchase decision is zero, the chance of experiencing highly arousing emotions decreases.

Using Valence as a Measurement for Emotional Value

One theory of emotion states that an emotion can be classified based on two dimensions, valence and arousal. Valence refers to the level of pleasantness (appetitive motivation) or unpleasantness (aversive motivation) of the emotion that is triggered by a stimulus. The other dimension, arousal, refers to the intensity of the emotional activation

(Lang et al., 1993). Using this theory, emotions can be classified by these two dimensions and plotted such as in Figure 44.

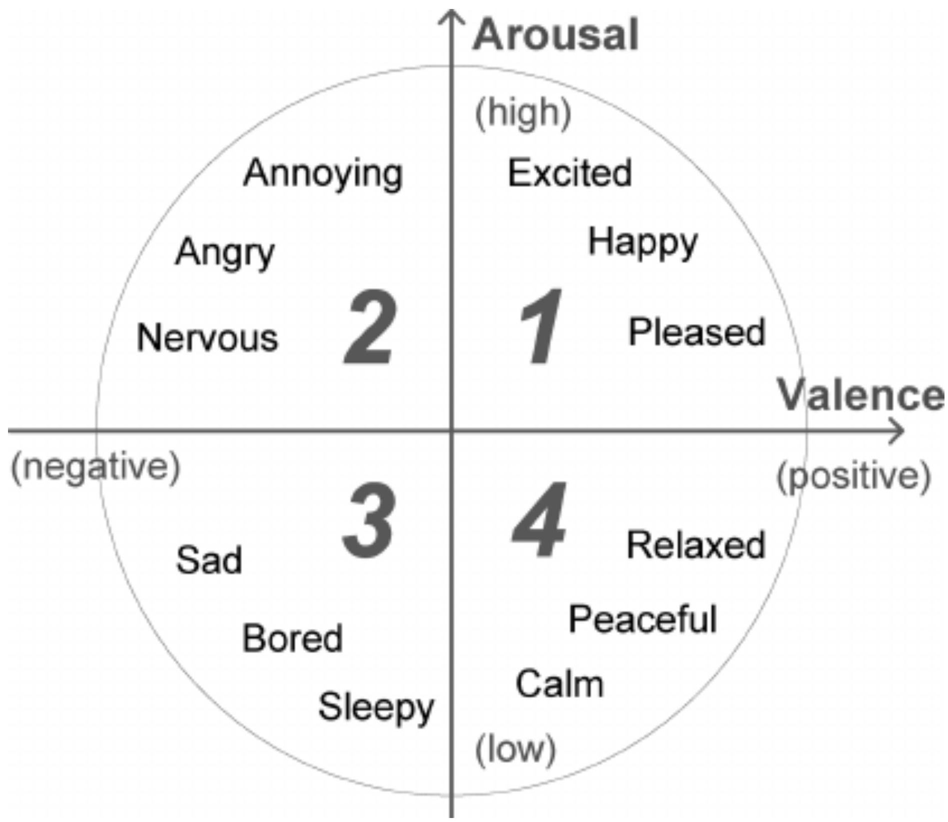


Figure 44: Valence and arousal emotional model

Using valence is a powerful method to get an overall understanding of the quality (positive or negative) of emotions being experienced. Valence can also assist in classifying emotions that can be either positive or negative such as surprise. Unfortunately, one of the limitations of facial expression analysis is its inability to assess the arousal of emotions being experienced. However, the dynamic testing of facial expression analysis can be paired with other biometric technologies such as galvanic skin response (GSR), electroencephalography (EEG), and eye tracking (measuring pupil dilation) in order to measure the arousal associated with the stimuli.

Figure 45 compares the averages of the probability of the valence occurring (negative, positive, neutral) while shopping for single-serve coffee pods containing the stimulus package or the control package.

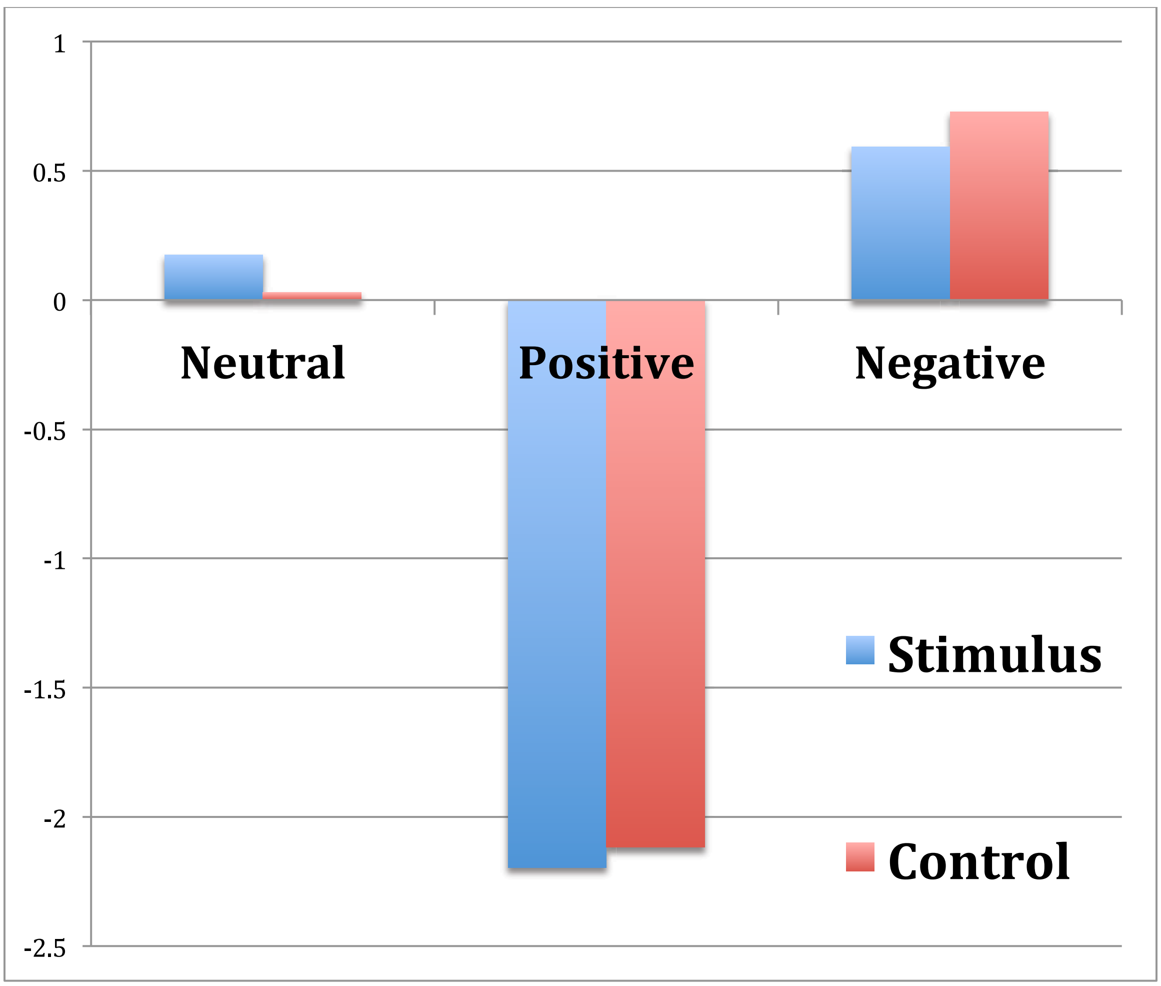


Figure 45: Average comparison of the probability of the valence being present, stimuli vs. control

Neutral Valence

The average probability of the participant expressing emotions of a neutral valence while shopping for the stimulus package was 0.175. This means that the overall sentiment of the participant is 1.5 times as likely to be categorized by an expert human coder as a neutral valence rather than a positive or negative valence. The average probability of the participant expressing the emotions of a neutral valence while shopping for the control package was 0.029. This means that the overall sentiment of the participant is 1.05 times as likely to be categorized by an expert human coder as a neutral valence rather than a positive or negative valence (Figure 46). No significance was found in the conducted t-test between the packaging of the stimuli and the control (p=0.2215).

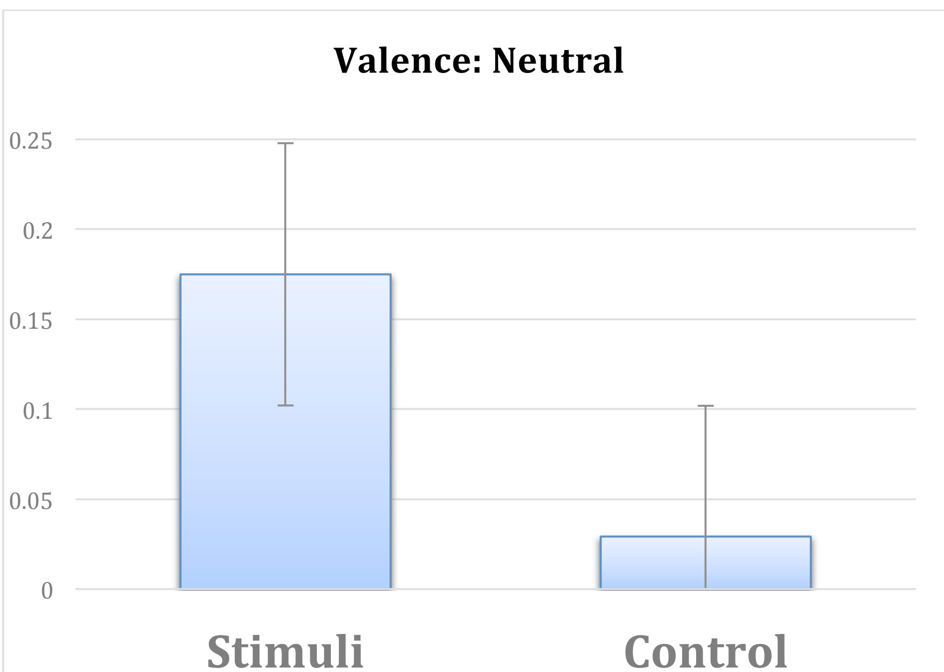


Figure 46: Average probability of a neutral valence being the overall sentiment, stimuli vs. control

Positive Valence

The average probability of the participant expressing emotions of a positive valence while shopping for the stimulus package was -2.196. This means that the overall sentiment of the participant is 157 times as likely to be categorized by an expert human coder as *not* a positive valence rather than a neutral or negative valence. The average probability of the participant expressing the emotions of a positive valence while shopping for the control package was -2.118. This means that the overall sentiment of the participant is 131 times as likely to be categorized by an expert human coder as *not* a positive valence rather than a neutral or negative valence (Figure 47). No significance was found in the conducted t-test between the packaging of the stimuli and the control (p=0.7719).

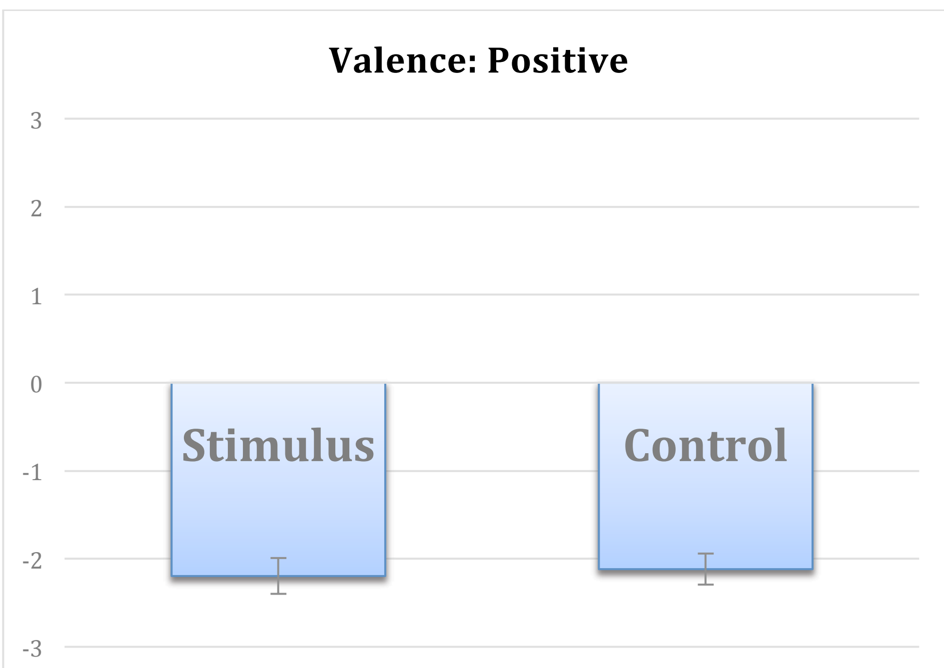


Figure 47: Average probability of a positive valence being the overall sentiment, stimuli vs. control

Negative Valence

The average probability of the participant expressing emotions of a negative valence while shopping for the stimulus package was 0.592. This means that the overall sentiment of the participant is 4 times as likely to be categorized by an expert human coder as a negative valence rather than a neutral or positive valence. The average probability of the participant expressing the emotions of a negative valence while shopping for the control package was 0.728. This means that the overall sentiment of the participant is 5.35 times as likely to be categorized by an expert human coder as a negative valence rather than a neutral or positive valence (Figure 48). The conducted t-test shows a significant difference between the negative valences experienced during the stimulus package versus the control package at a 95% confidence interval (p=0.0427)

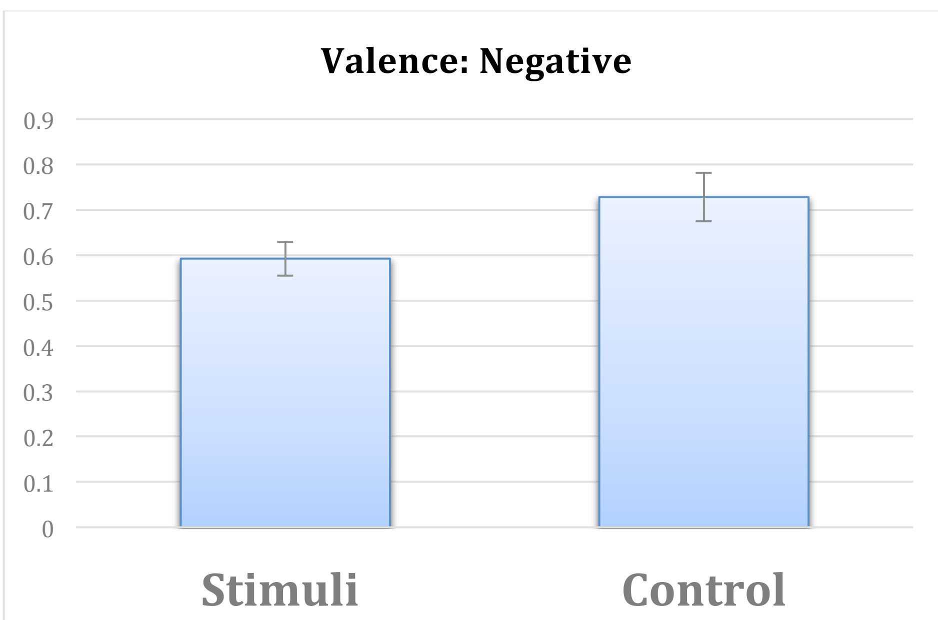


Figure 48: Average probability of a negative valence being the overall sentiment, stimuli vs. control

Discussion of Valence

T-tests conducted between the stimulus package and the control package measuring the probability of negative valence being experienced in participants as they shopped for single-serve coffee pods were determined to be significant. Therefore, there is enough evidence to conclude that there is a significant difference between the probabilities of negative valence being experienced while shopping for shelves containing the stimulus package compared to shelves containing the control package at a 95% confidence interval ($p=0.0427$).

The range between the value of the probabilities of a neutral valence occurring between the stimulus package (0.175) and the control package (0.029) was larger than the range between the stimulus package and the control package for negative valence. The large standard error between the participants was the reason the results were not significant in a 95% confidence interval (p-value = 0.221).

The values for negative, neutral, and positive valence are all consistent with the facial expressions of emotion data. Emotions associated with a negative valence such as contempt, anger, and disgust, were more likely to occur when shopping for the control package. This correlates with higher probability value for the negative valence of shopping for the control package.

Likewise, emotions associated with a neutral valence such as sadness, surprise, and fear, were all more likely to occur while shopping for the stimulus package. As seen in Figure 49, these emotions are classified as a neutral valence since they are all coded using the action code '1' which is classified by a neutral face. Therefore, the data correlates as expected since the probabilities of these expressions occurring are all higher for the stimulus group compared to the control group.

Emotion	Action Units
Happiness	6+12
Sadness	1+4+15
Surprise	1+2+5B+26
Fear	1+2+4+5+7+20+26
Anger	4+5+7+23
Disgust	9+15+16
Contempt	R12A+R14A

Figure 49: Basic emotion facial expression action codes

The probability of a positive valence occurring was very low for both the stimulus package and the control package. The two expressions that are analyzed through facial expression analysis that can be associated with a positive valence are joy and surprise. The expression of surprise is unique since it can be associated with both a negative and positive valence. However, Figure 37 and Figure 47 show that the data values for joy expressions and positive valence are identical. Therefore, a conclusion can be reached that any expressions of surprise that may have occurred were associated with a negative valence.

Survey Results

Participants completed a survey after the study that gathered qualitative data on the participant's emotional state as well as their personal packaging preferences. Results in Figure 50 show the qualities of the packaging design that participants used to describe the packaged products they purchased in CUShop™. The top five results were (1) brand that I trust, (2) easy to understand, (3) attractive, (4) premium, and (5) informative. The top result shows that many participants remained loyal to their brand while shopping in CUShop™. This statistic could explain the low amount of purchase decisions made in favor of the stimulus and control group despite the overwhelming response that preferred the stimulus package.

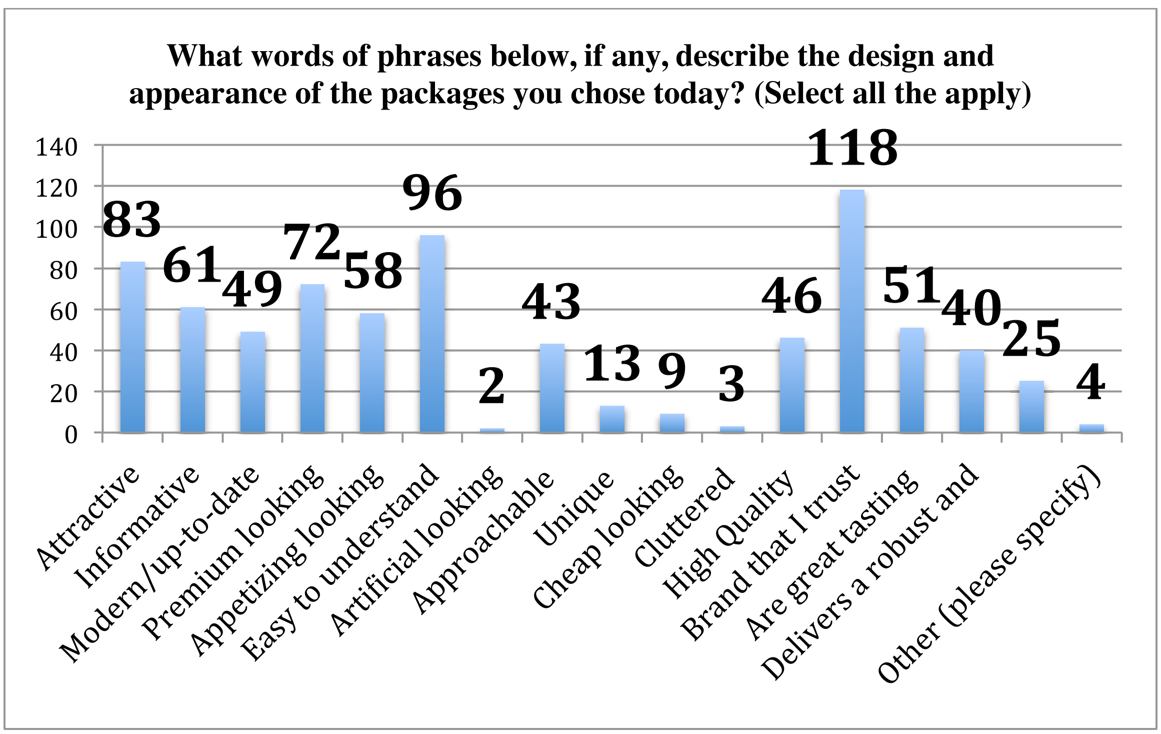
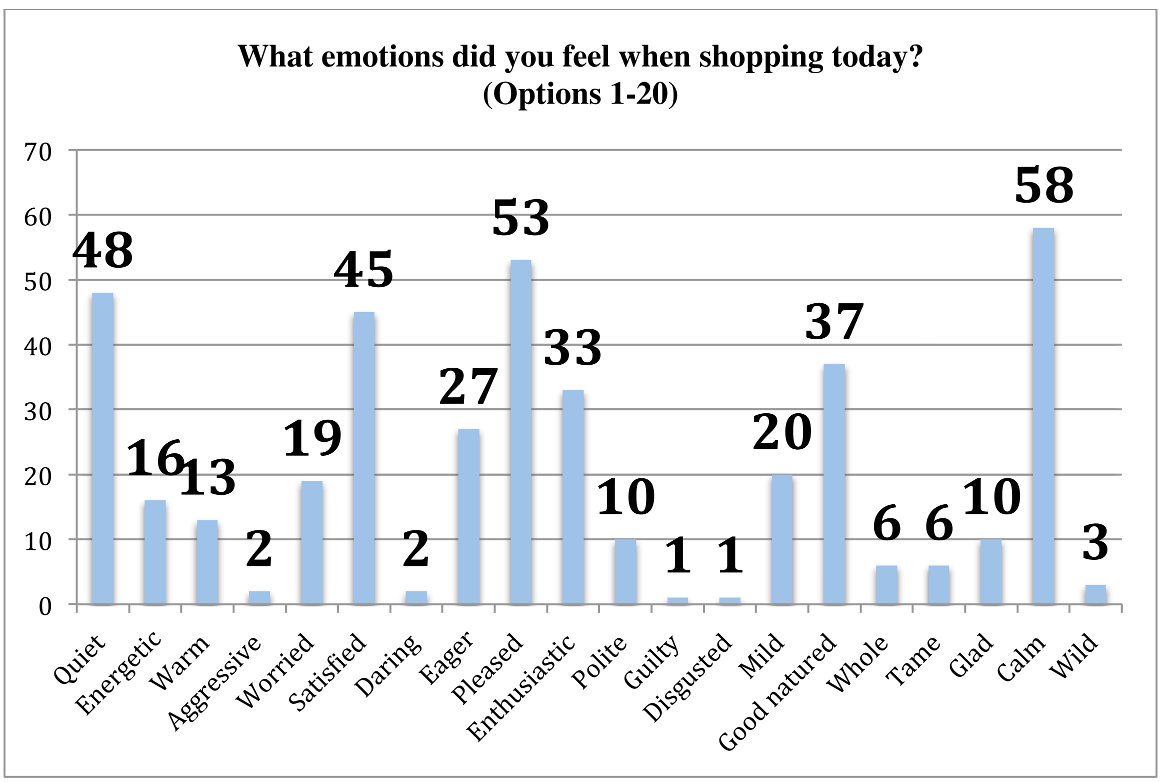


Figure 50: Qualities of package design of purchased products

Figure 51 describes the emotions of the participants that were present as they shopped in CUShop™. The main emotions experienced were: quiet, pleased, calm, interested, good. These emotions all have one quality in common; they are low arousal emotions. High arousal emotions such as joyful, disgusted, or loving were not experienced as near as many times. This shows that packaged product shopping in CUShop™ may not be an arousing task. Results from Figure 51 may be able to help explain why changes in overall valence were more prevalent than changes in individual emotions. More arousing stimuli would most likely elicit more behavioral responses from participants in the form of facial expressions.



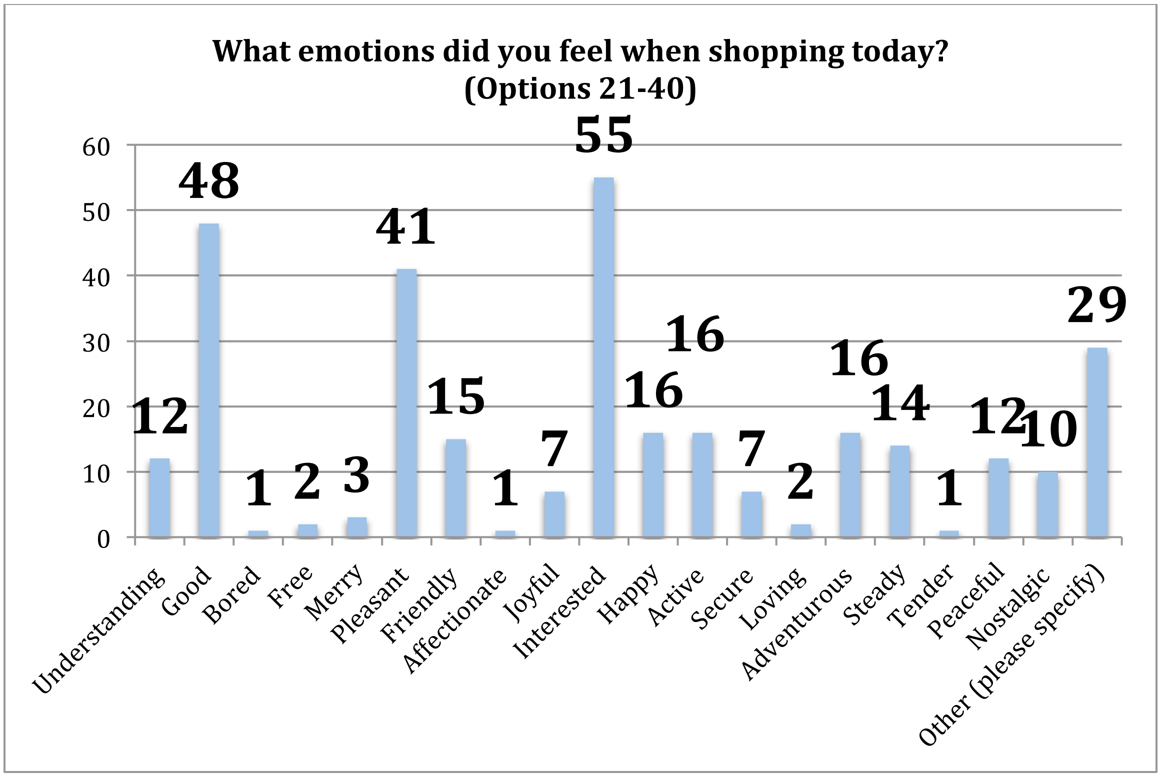


Figure 51: Emotions experienced while shopping in CUShop^{TM}

Figure 52 shows the how specialty-printing effects such as foil, reflective, or shiny materials of packaging affect the participant's purchase decision of food products. The majority reported that these qualities do are not important to have on food packaging. Figure 53 shows that only a slight majority of participants reported to perceive packages with these effects to be of higher quality. While this quality may not be extremely important, survey data comparing purchase decision between the stimulus package and the control package showed an overwhelming amount of preference for the stimulus package containing the foil stamp.

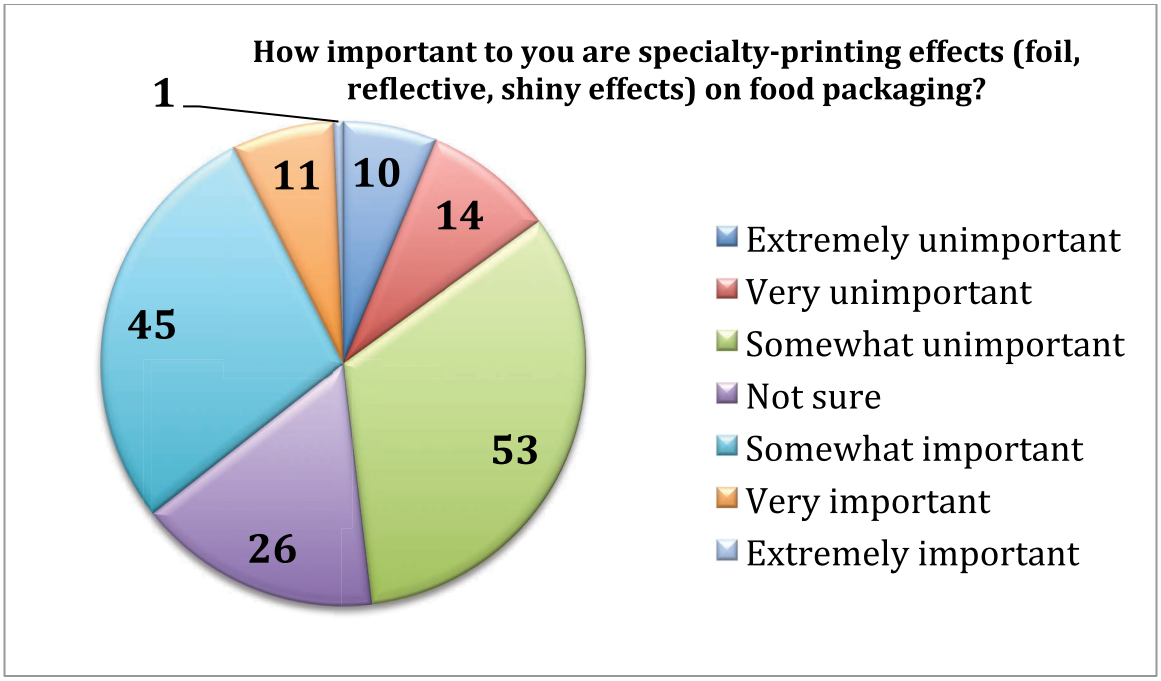


Figure 52: Importance of specialty-printing effect on food packaging

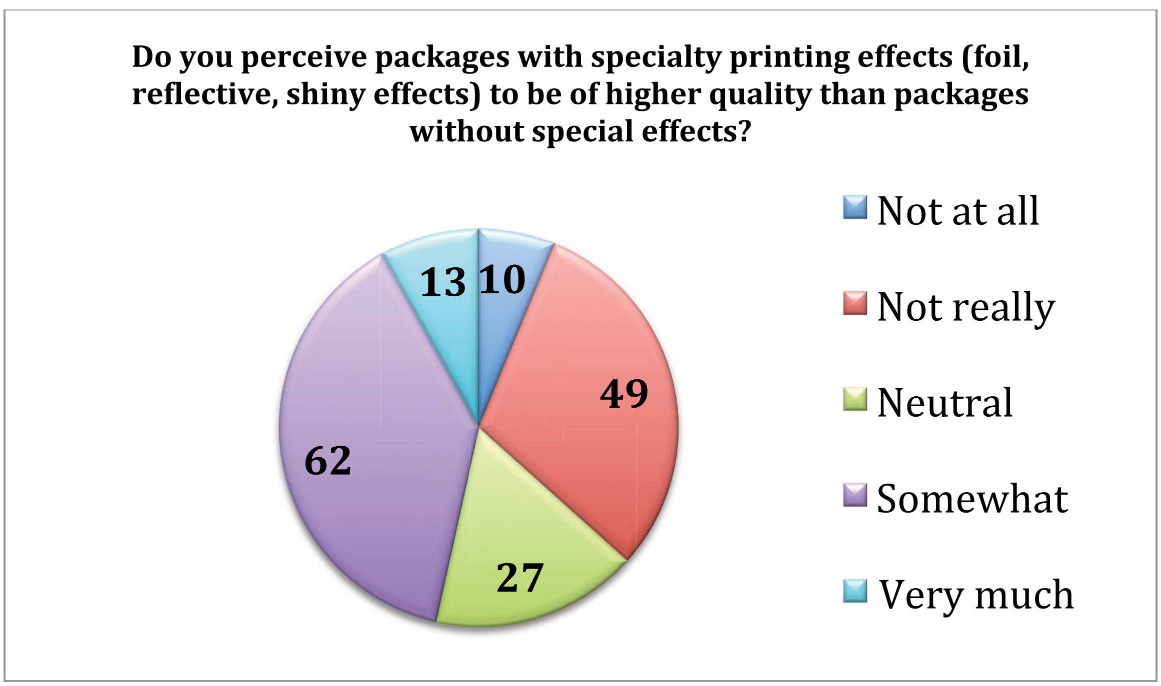


Figure 53: Perception of packages with printing effects

Facial Expression Analysis as a Dynamic Testing Method

In order to examine the validity of this methodology, a packaging performance experiment was designed to test the effectiveness of using facial expression analysis as a dynamic testing method in CUShop™. The objectives of the experiment, as stated in Chapter IV, were accomplished by the proposed methodology. Quantitative data that was gathered using facial expression analysis and the purchase decision data both show that participants favored the stimulus package compared to the control package. This was the expected result and dynamic testing methods using facial expression analysis were able to quantitatively support that result.

CHAPTER SIX

CONCLUSIONS

This thesis tests the validity of using facial expression analysis as a dynamic testing method to evaluate packaging design. Facial expression analysis is a valuable analytical tool that can provide insight into the mind of consumers as they make purchasing decisions. This analysis technique is unique because it can measure the probability that specific emotions are being experienced during the shopping process. However, facial expression analysis has been limited to static testing methods. The value in this thesis is transforming this static testing analysis method into a dynamic testing method that has proven to be valid in the evaluation of packaging design.

There was not a significant difference between the facial expressions of emotion values between the stimulus package and the control package (p-value > 0.05). However, there were problems experienced in this study that could have suppressed facial expressions from occurring. The combination of eye-tracking glasses and facial expression analysis equipment can feel obtrusive and could prevent the participant from behaving naturally as they would in a shopping context. Also, giving participants the task of shopping for unknown items could cause anxiety and disrupt natural shopping behavior.

It is also difficult to interpret values from individual facial expressions of emotion due to the lack of research on the topic of the effects of specific emotions on shopping behavior. It is assumed that positive emotions such as joy would increase the likelihood of the product being purchased. However, this information is unknown and concrete conclusions cannot be made correlating individual emotions to consumer behaviors such as purchasing decision. For that reason, it is difficult to infer many conclusions from the positive values of sadness expressions that were reported by the quantitative data.

The results also show a large difference between the values of highly arousing emotions such as joy, fear, anger, disgust, and surprise, compared to low arousal emotions of sadness and contempt. The activation level needed to elicit a behavioral response in the form of a facial expression of a highly arousing emotion may be too high to trigger from food packaging stimuli.

There was a significant difference found between the negative valence experienced between shopping for the stimulus package and shopping for the control package. Therefore, there is enough evidence to conclude at a 95% confidence interval that there is a difference between the negative valences experienced while shopping for the stimulus package compared to the control package (p-value $0.0221 < 0.05$).

Results from valence testing were more conclusive and informative compared to facial expressions of emotion. The range between the neutral valence values of the stimulus package and the control package were larger than both positive and negative valence and would have been significant at an 80% confidence interval. Levels of valence also correlated with the individual expressions of emotion that were associated with that valence. This suggests that using facial expression analysis predominantly as a test of valence may prove to be a more effective test method if being used in a low arousal context such as food product shopping.

Another significant takeaway from this study is the assurance that valence results from the dynamic testing of facial expression analysis can be of value when comparing items in a competitive shelf context. This was proven by drawing significant conclusions regarding the evaluation of the fictitious brand, Zapotec. By comparing the quantitative valence data and the purchase data, it can be concluded that a greater negative valence value decreases the packaging appeal and purchasing probability of the package in question.

Future studies should evaluate the correlation of expressive emotions and valence with various consumer behaviors such as purchasing decision. It would be beneficial to form a greater understanding on the individual effects of each expression of emotion on these consumer behaviors. Until then, it is difficult to form many firm conclusions and correlations between facial expressions and consumer behavior. However, this thesis shows that facial expression analysis can be used in dynamic testing methods and can provide valuable insight into the lightning fast decisions that are made by consumers at the point of purchase.

CHAPTER SEVEN

RECOMMENDATIONS

The amount of possibilities that can be done using similar context and facial expression analysis is enormous due to the lack of facial expression analysis being used with packaging stimuli. This is more evident now that facial expression analysis can be used in dynamic testing methods. In this chapter, details on how to make this thesis experiment more effective, future studies more effective, and possibilities that could be explored in the future, will be examined.

The biggest problem encountered in this thesis was the facial expression analysis equipment. Though the facial expression analysis equipment is accurate, it is unfortunately slightly obtrusive. However, alternative methods were evaluated and were not effective in recording facial expressions. The main problem is accounting for the up-and-down and side-to-side movement of the head. The solution has to contain a recording device that is able to follow the head movements of the participant. Ideas include using multiple cameras or 3D cameras. Software to conjoin these types of videos into a fluid and clean process does not exist at the academic level. Hopefully future technological advances will reveal less obtrusive methods to solve this problem.

The lack of arousal in CUShop™ was the reason for low values pertaining to facial expressions of emotion. Data collected would be more informative if arousal of the environment was similar to that of a grocery store. Many aspects of grocery stores contribute to the overall valence of customers that may not be realized immediately such as customer service, other consumers, shopping with others, and music. However, it would be difficult to implement any of these variables into CUShop™ effectively.

A possible solution to increase arousal is to introduce the variable of pricing. Traditionally, CUShop™ has been used to solely evaluate packaging design based strictly off of packaging appeal. But, introducing purchasing scenarios with money could raise the level of arousal by introducing the variable of risk. Participants currently do not face any risk while shopping in CUShop™. Their decisions do not have consequences. By actually purchasing the items, the weight of the decision is greatly increased since the participant now has to face the consequences that are associated with the item purchased. This will cause a greater amount of cognitive processing as well as emotional processing as making decisions are now more difficult.

Future researchers can greatly improve methods used in this research by attempting to account for emotions that are experienced before the study begins. For example, all participants have differing emotional states as they enter CUShop™ and make purchasing decisions. Ultimately, this affects the data that is collected. The issue is hard to account for since it is not possible to calibrate the participant to a neutral emotional state in order for the emotional state of every participant to be identical before beginning. It is also impossible to measure emotions beforehand in order to account for the participant's emotional state before entering CUShop™ during data analysis later.

The aim for future studies should focus on using facial expression analysis to define each individual emotions effect on consumer behavior. Understanding what emotions to attempt and elicit from consumers would be a great resource for packaging designers as well as marketers. Also, correlations between emotional magnitude and purchasing decision may be of interest. For example, if a participant data records a '4' for probability of experiencing anger, and keeping all other emotions at zero, would that increase the likelihood of purchase despite anger being a negative emotion? Do packaging designers want to focus on eliciting certain emotions or should they concentrate on intensely triggering any emotion? What are the effects of triggering multiple emotions at once?

Future studies should also include survey data that is sourced from psychological studies of emotion. The researchers developed the surveys used in this study without any reference to literature.

There are many questions that can be explored using dynamic testing methods with facial expression analysis. There are also metrics that were excluded from this thesis analysis such as action units that may be of interest. Hopefully future researchers can use this manuscript as a resource to construct their own studies, improve upon this methodology, and advance analysis techniques using facial expression analysis. The addition of other biometric devices such as electroencephalography (EEG) and galvanic skin response (GSR) could always be added to provide additional insight into the mind of the consumer. Many benefits await those who continue researching the synchronization of packaging, marketing, psychology, and neuroscience fields.

APPENDICES

Appendix A

Survey Questions

Pre-Survey

1. What is your participant number?

2. What is your gender?

- Male
- Female

3. How old are you?

- 25-34
- 35-54

4. Which of the following best describes your current relationship status?

- Married
- Widowed
- Divorced
- Separated
- In a domestic partnership or civil union
- Single, but cohabiting with a significant other
- Single, never married

5. What is your ethnicity? (check all that apply)

- African American
- Asian
- Hispanic
- Pacific Islander
- Caucasian

Figure A–1: Questions 1-5 of pre-survey.

6. Do you have any children under the age of 18 years?

- Yes
- No

7. What is the highest level of education you have completed?

- Less than high school degree
- High school degree or equivalent (GED)
- Some college but no degree
- Associate degree
- Bachelor degree
- Graduate degree or higher

8. Which of the following best describes your employment status? (Check all that apply)

- Employed, working full time
- Employed, working part time of les
- Not employed, looking for work
- Not employed, not looking for work
- Retired
- Disabled, not able to work
- Stay at home parent

9. What is your annual household income?

- $35,000 to $49,999
- $50,000 to $74,999
- $75,000 to $99,999
- $100,000 to $149,999
- $150,000 to $199,999
- $200,000 or more

Figure A–2: Questions 6-9 of pre-survey.

10. Are you the primary shopper for your household?

- ◯ Yes
- ◯ No
- ◯ Sometimes

11. How many adults are currently living in your household?

- ◯ 1
- ◯ 2
- ◯ 3
- ◯ 4
- ◯ 5 or greater

12. What region of the country are you from?

- ◯ Midwest (IA, IL, IN, KS, MI, MN, MO ND, NE, OH, SD, WI)
- ◯ Northeast (CT, DC, DE, MA, MD, ME, NH, NJ, NY, PA, RI, VT)
- ◯ Southeast (AL, AR, FL, GA, KY, LA, MS, NC, SC, TN, VA, WV)
- ◯ Southwest (AZ, NM, OK, TX)
- ◯ West (AK, CA, CO, HI, ID, MT, NV, OR, UT, WA, WY)

Figure A–3: Questions 10-12 of pre-survey.

Post-Survey

1. What is your participant number?

2. What words of phrases below, if any, describe the design and appearance of the packages you chose today? (Select all the apply)

- Attractive
- Informative
- Modern/up-to-date
- Premium looking
- Appetizing looking
- Easy to understand
- Artificial looking
- Approachable
- Unique
- Cheap looking
- Cluttered
- High Quality Brand that I trust
- Is a staple in my pantry
- Encourages me to cook
- Are great tasting
- Can be used on a wide variety of foods
- Adds great flavor
- Delivers a robust and bold flavor
- Made with pure and natural spices
- Other (please specify)

Figure A–4: Questions 1 and 2 of post-survey.

3. What emotions did you feel when shopping for spices today? (Select all that apply)

- Quiet
- Energetic
- Warm
- Aggressive
- Worried
- Satisfied
- Daring
- Eager
- Pleased
- Enthusiastic
- Polite
- Guilty
- Disgusted
- Mild
- Good-natured
- Whole
- Tame
- Glad
- Calm
- Wild
- Good
- Bored
- Free
- Merry
- Pleasant
- Friendly
- Affectionate
- Joyful
- Interested
- Happy
- Active
- Secure
- Loving
- Adventurous

☐ Steady
☐ Tender
☐ Peaceful
☐ Nostalgic
☐ Other (please specify)

4. Which of these packages shown below do your prefer?

☐ A
☐ B
☐ Both are equally appealing

5. Discuss why you selected your preference (or lack of preference) for the packages shown above.

Figure A–5: Questions 3-5 of post-survey.

6. How important to you are specialty-printing effects (foil, reflective, shiny effects) on food packaging?

Extremely unimportant	Very unimportant	Somewhat unimportant	Not sure	Somewhat important	Very important	Extremely important
○	○	○	○	○	○	○

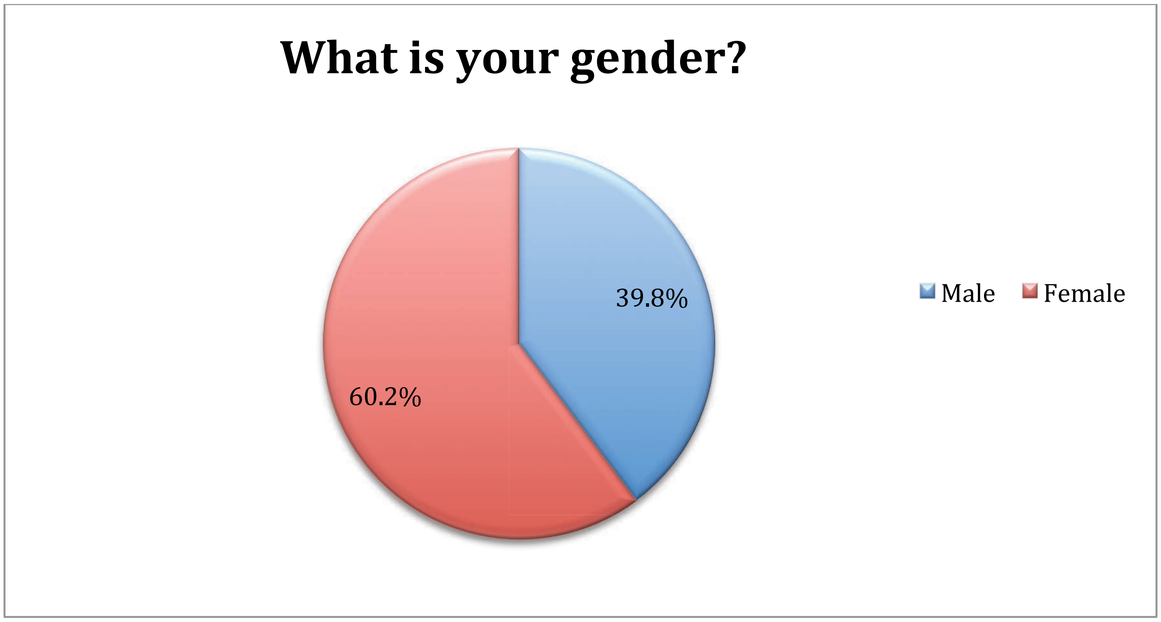
7. Do you perceive packages with specialty printing effects (foil, reflective, shiny effects) to be of higher quality than packages without special effects?

Not at all	Not really	Neutral	Somewhat	Very much
○	○	○	○	○

Figure A–6: Questions 6 and 7 of post-survey.

Appendix B

Demographic Results



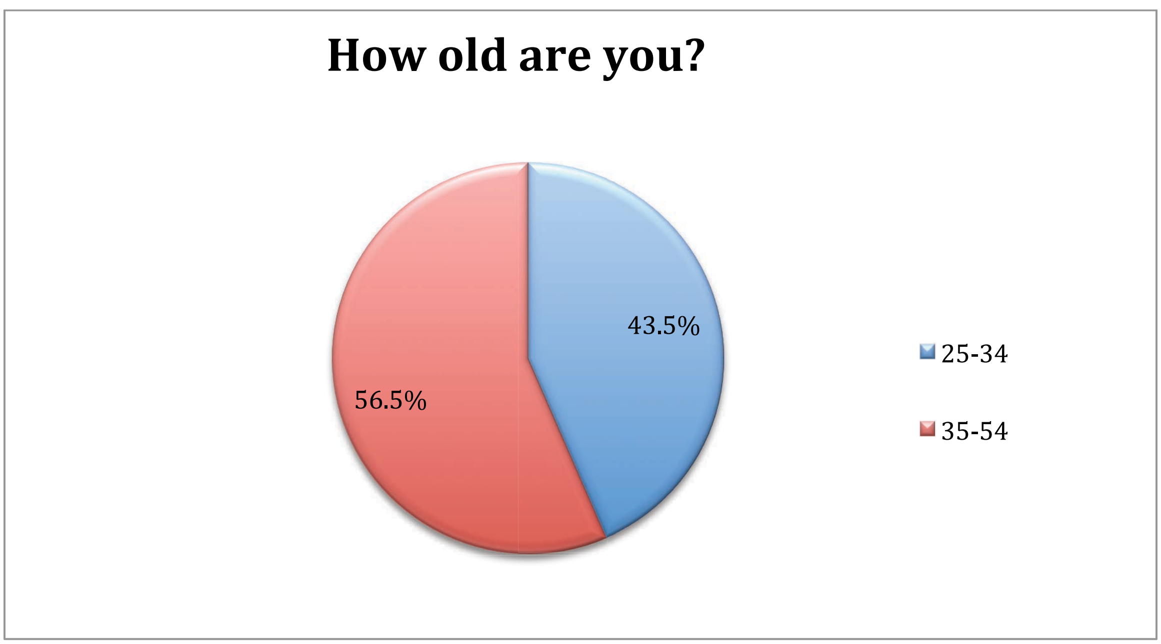
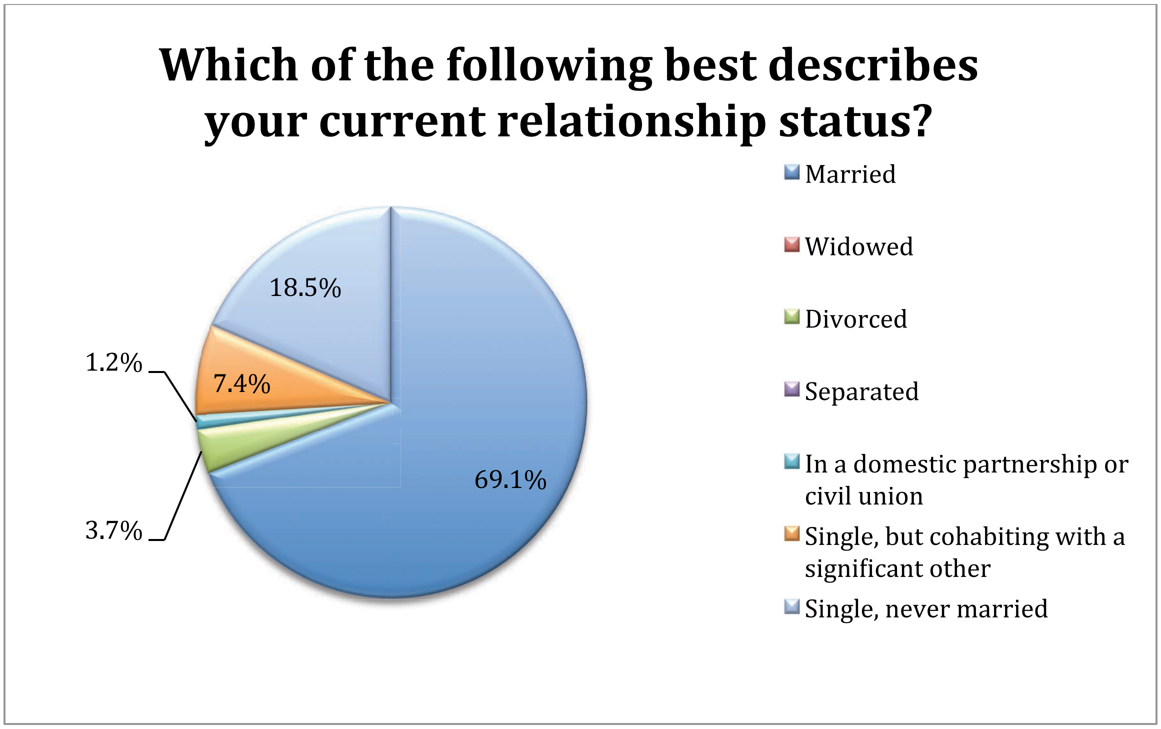


Figure B–1: Results of questions 1 and 2 of pre-survey.



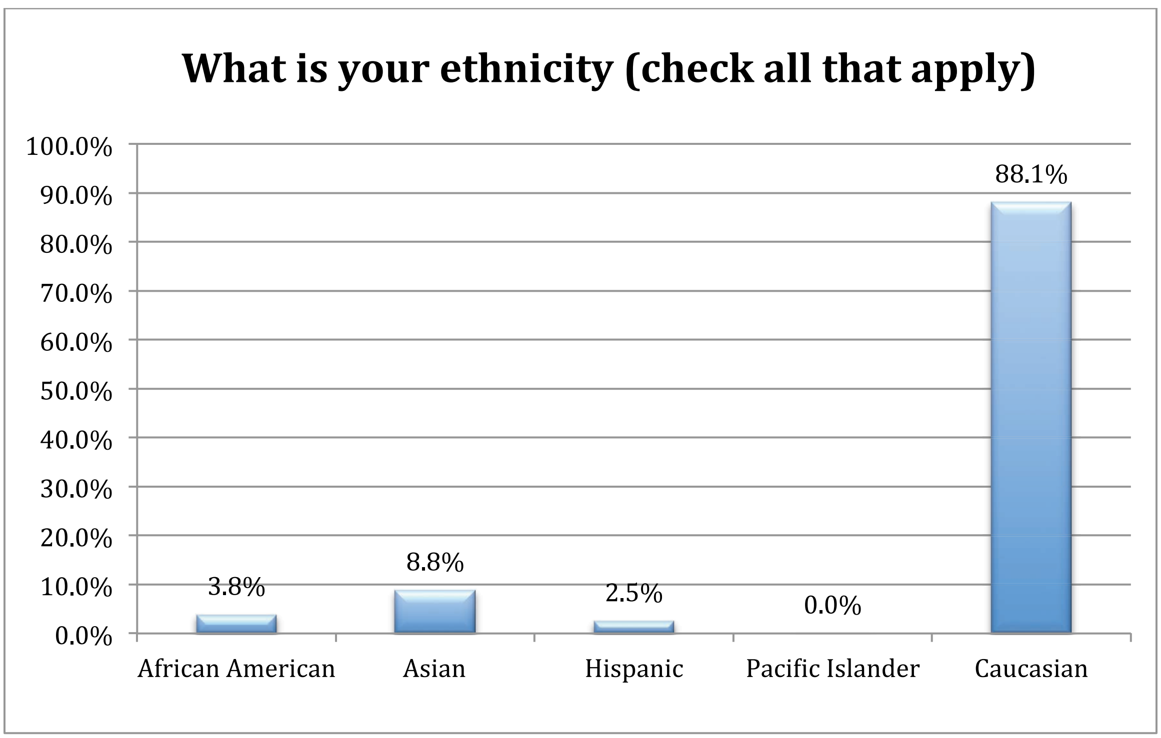
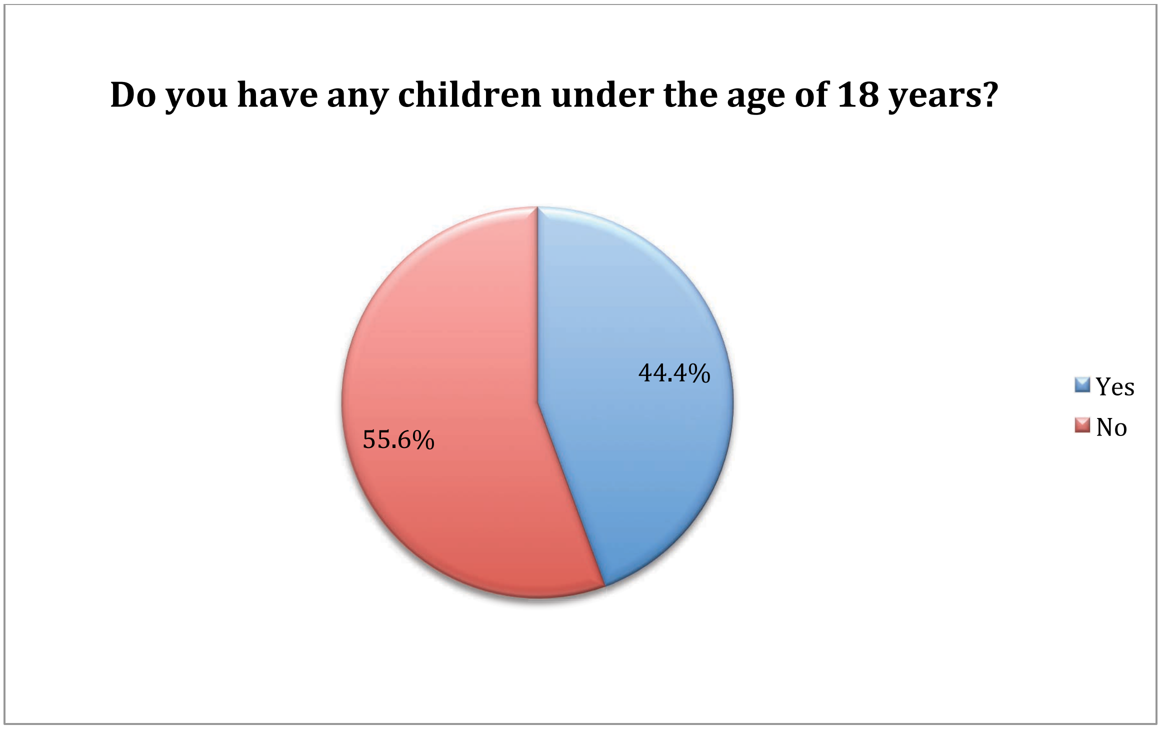


Figure B–2: Results of questions 3 and 4 of pre-survey.



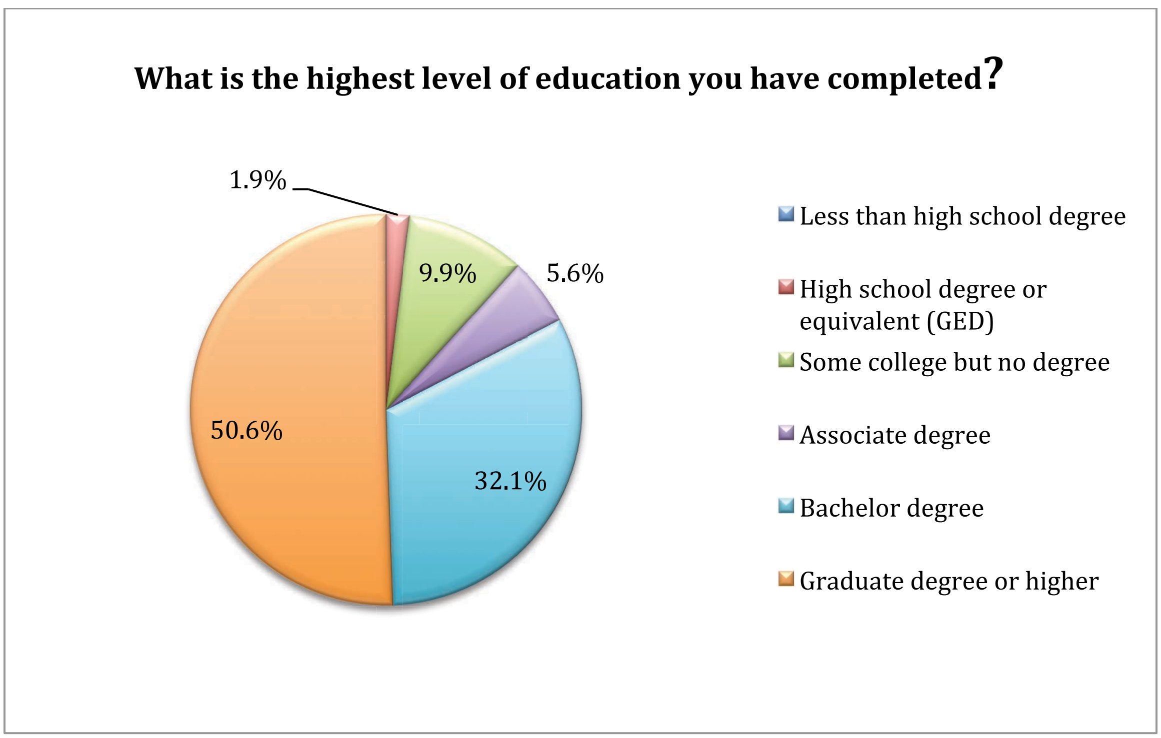
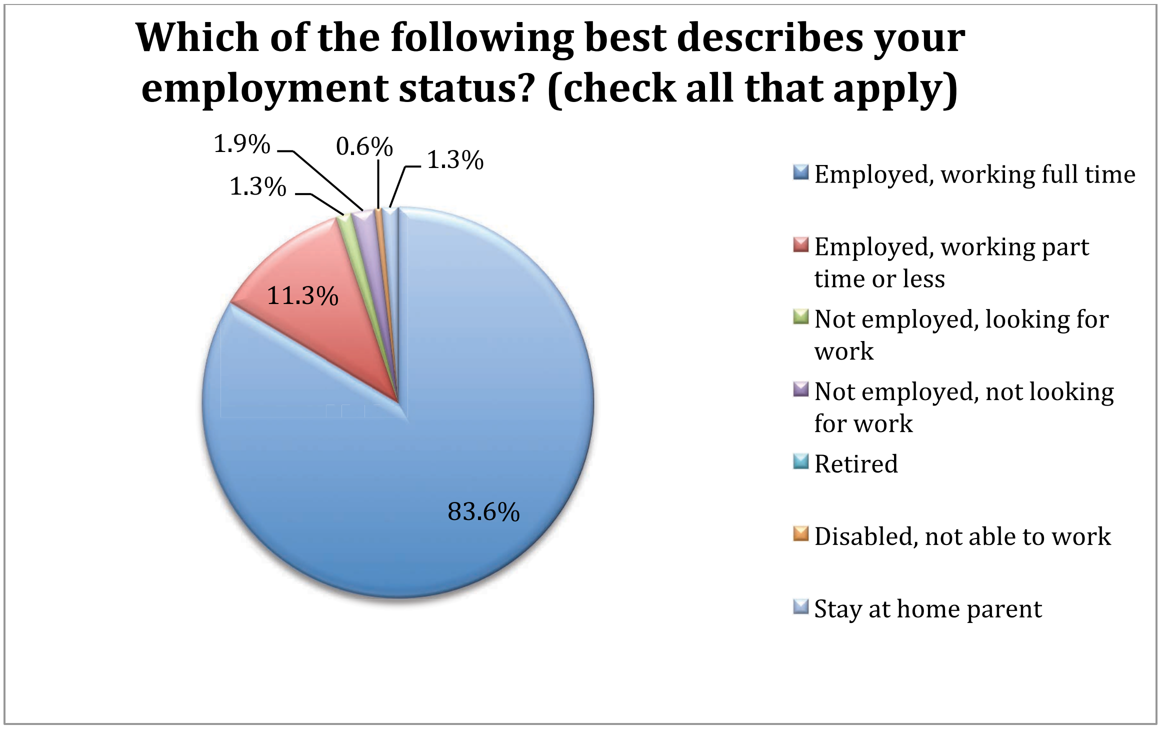


Figure B–3: Results of questions 5 and 6 of pre-survey.



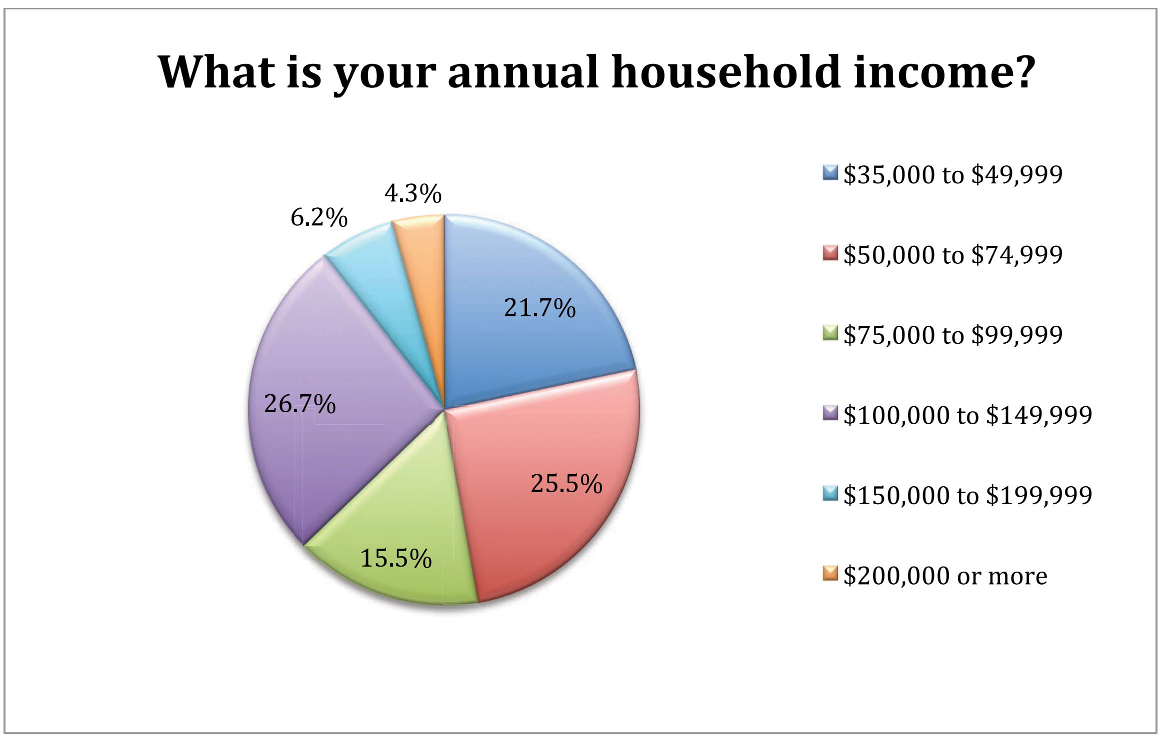
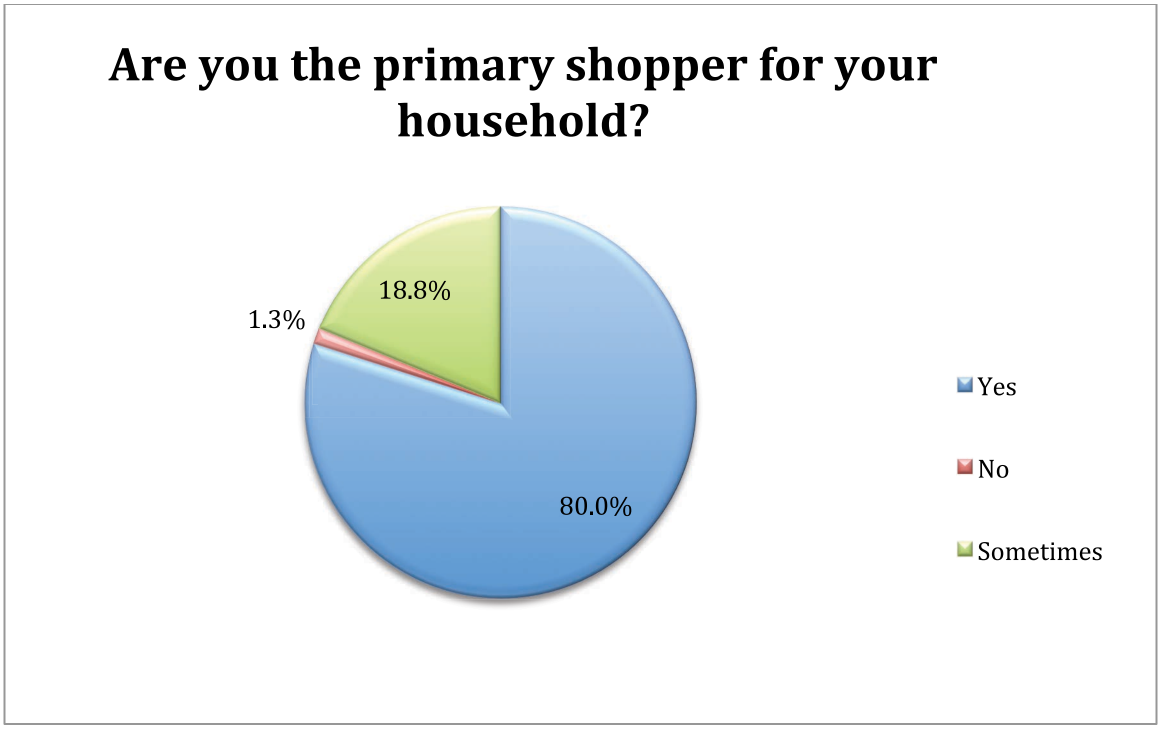


Figure B–4: Results of questions 7 and 8 of pre-survey.



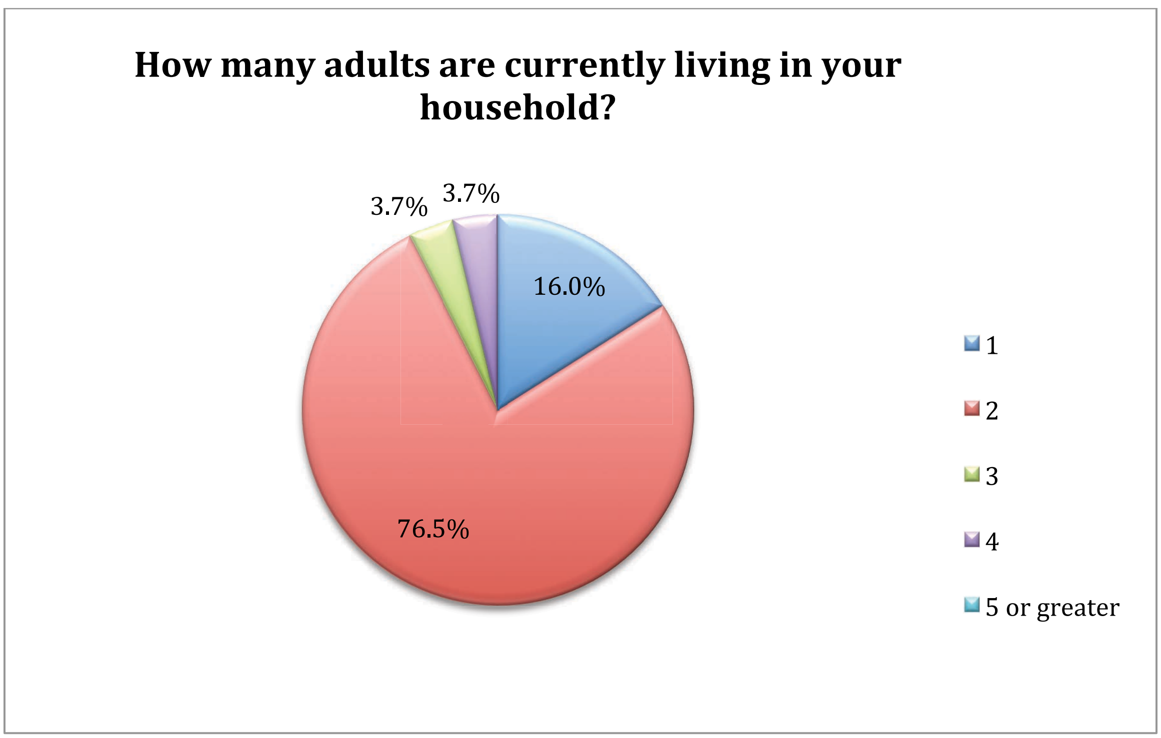


Figure B–5: Results of questions 9 and 10 of pre-survey.

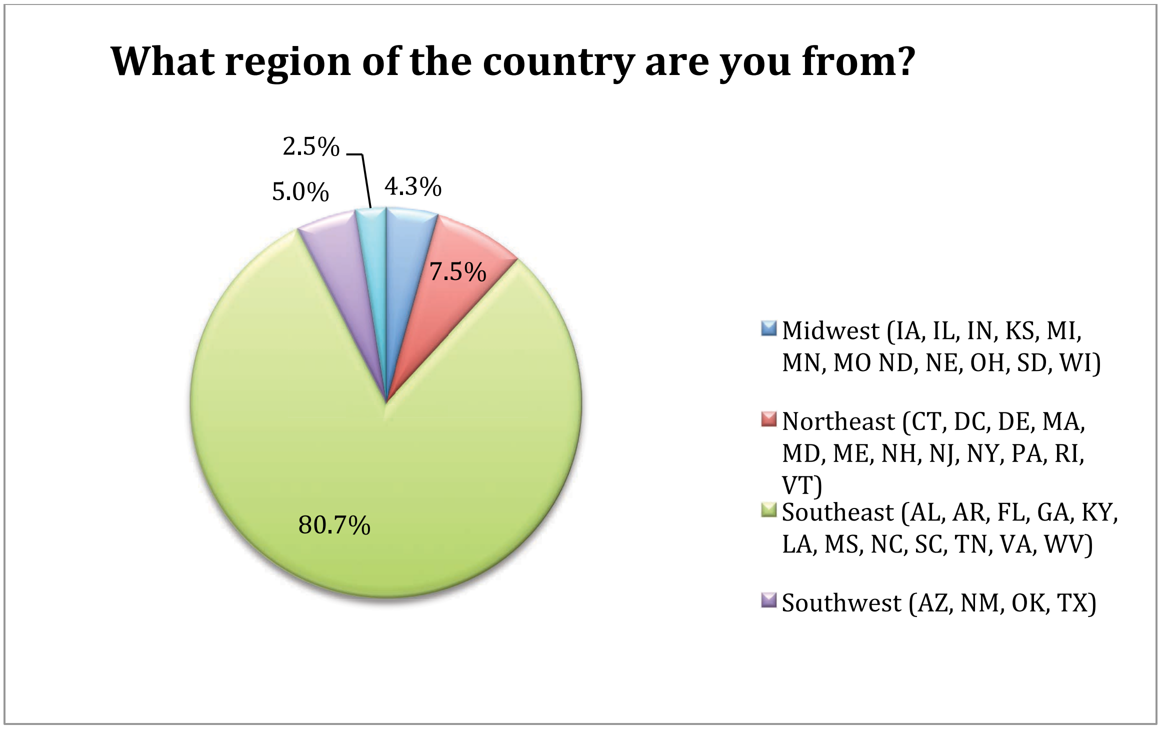


Figure B–6: Questions 11 of pre-survey.

Appendix C

Post-Survey Results

What words of phrases below, if any, describe the design and appearance of the packages you chose today? (Select all the apply)

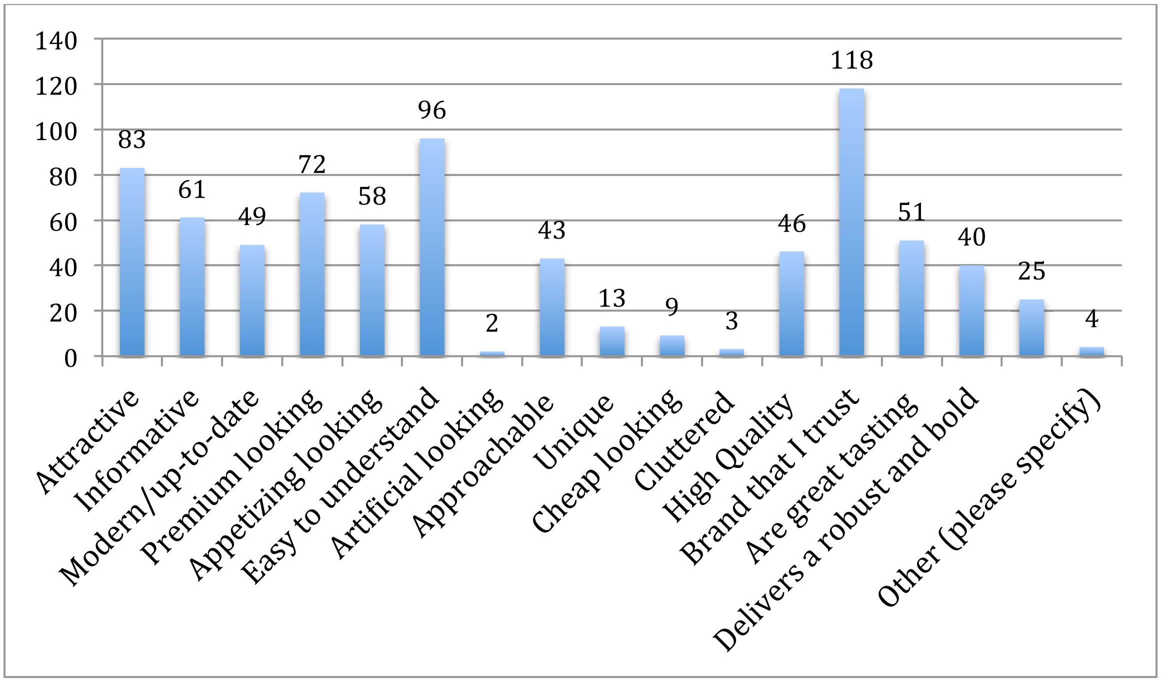
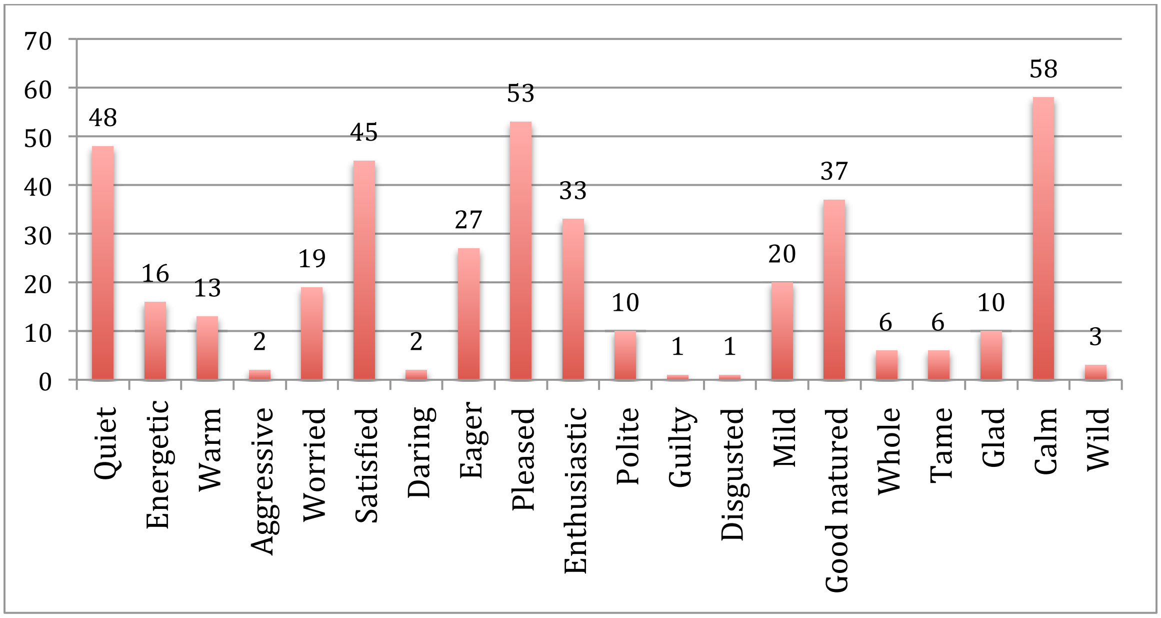


Figure C–1: Question 2 post-survey results.

What emotions did you feel when shopping today? (Select all that apply)



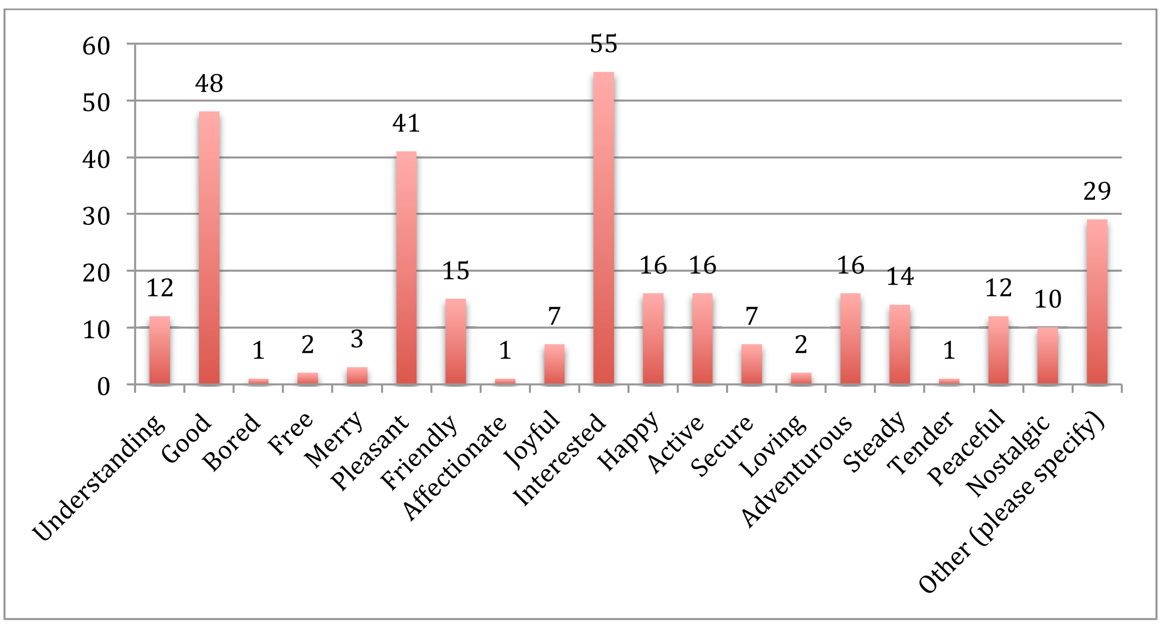


Figure C–2: Question 3 post-survey results.

Which of these packages do you prefer?

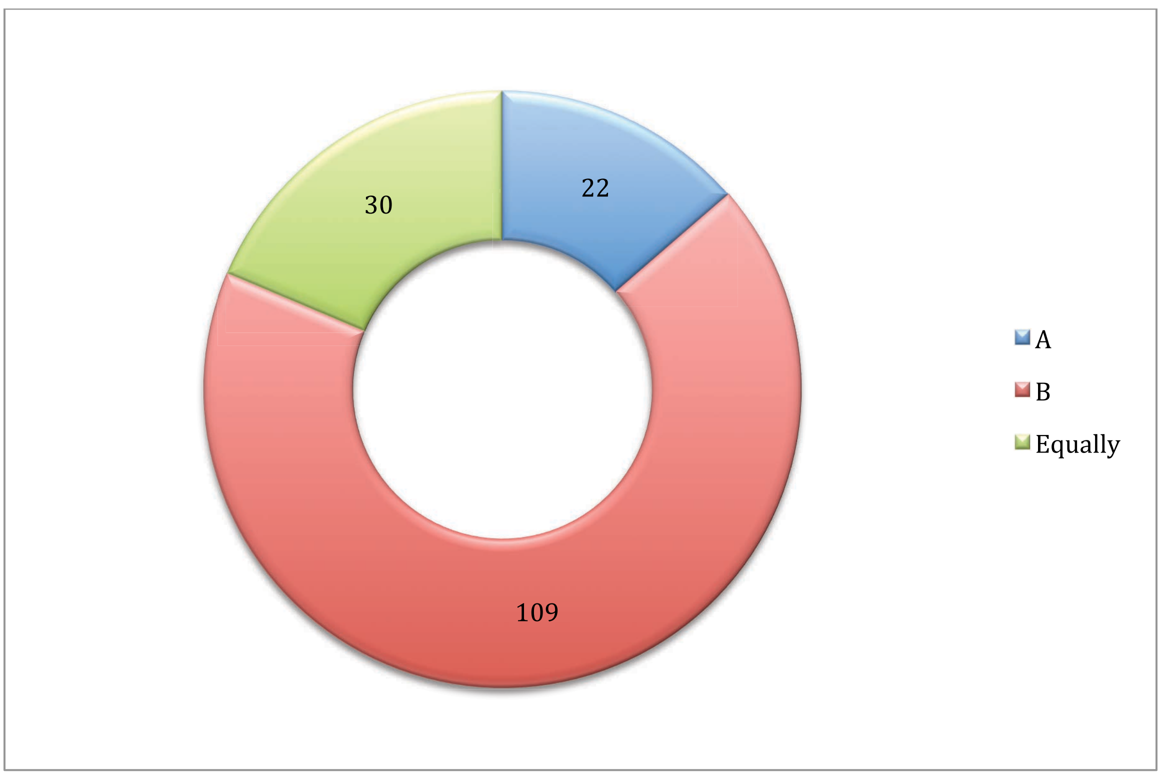


Figure C–3: Question 4 post-survey results.

How important to you are specialty-printing effects (foil, reflective, shiny effects) on food packaging?

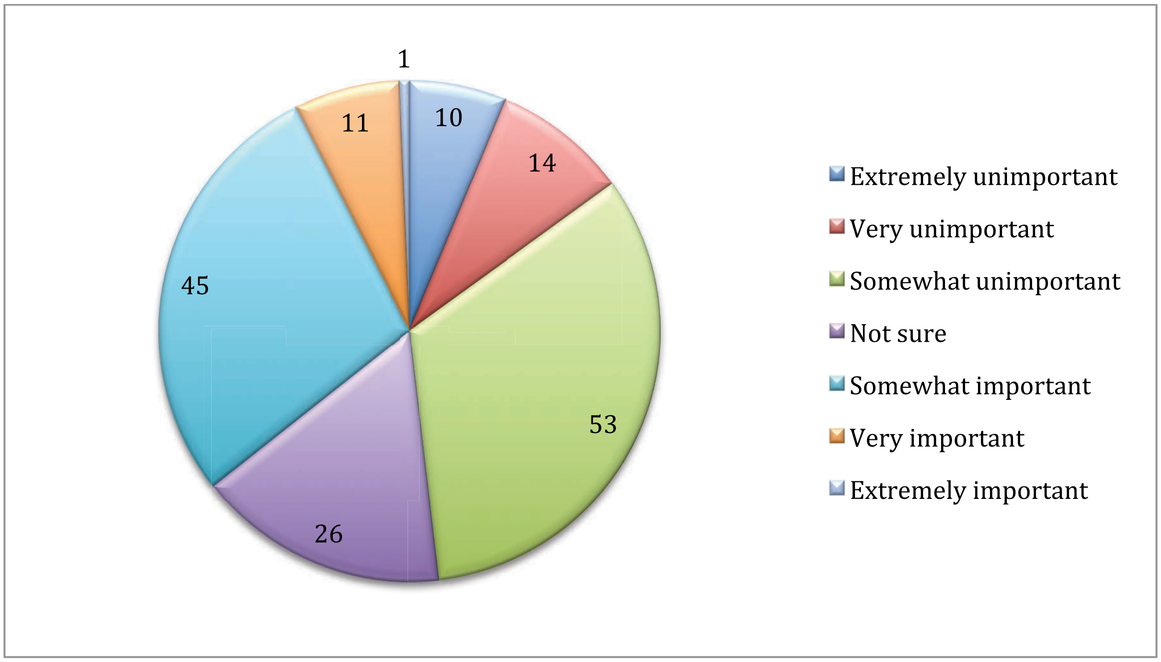


Figure C–4: Question 6 post-survey results.

Do you perceive packages with specialty printing effects (foil, reflective, shiny effects) to be of higher quality than packages without special effects?

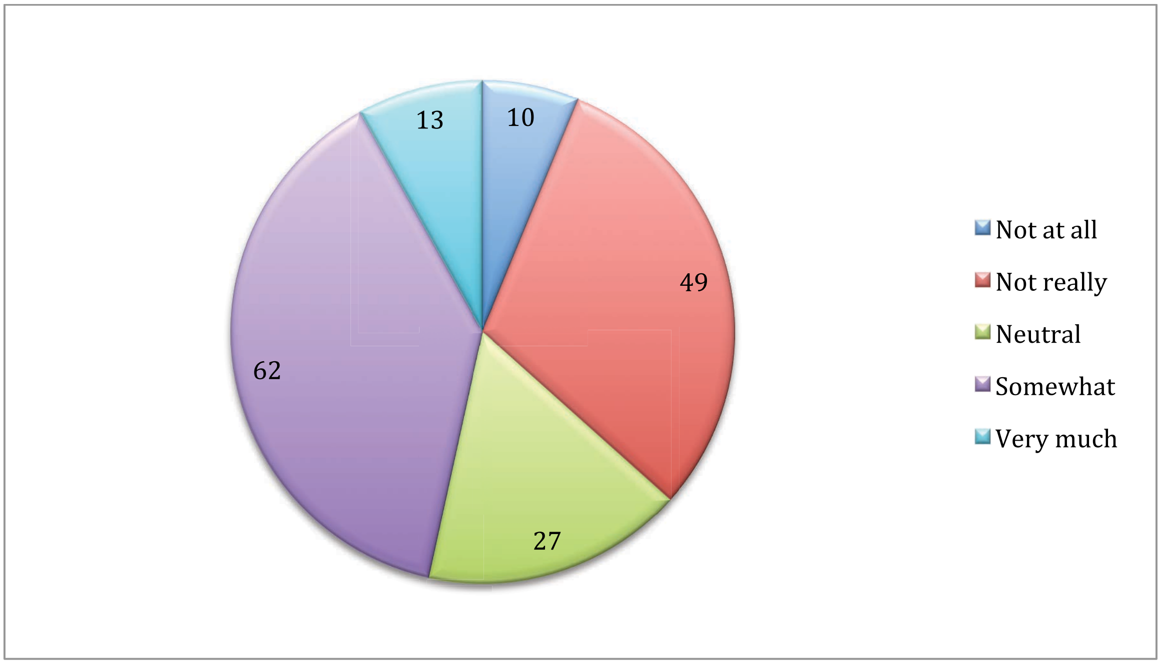
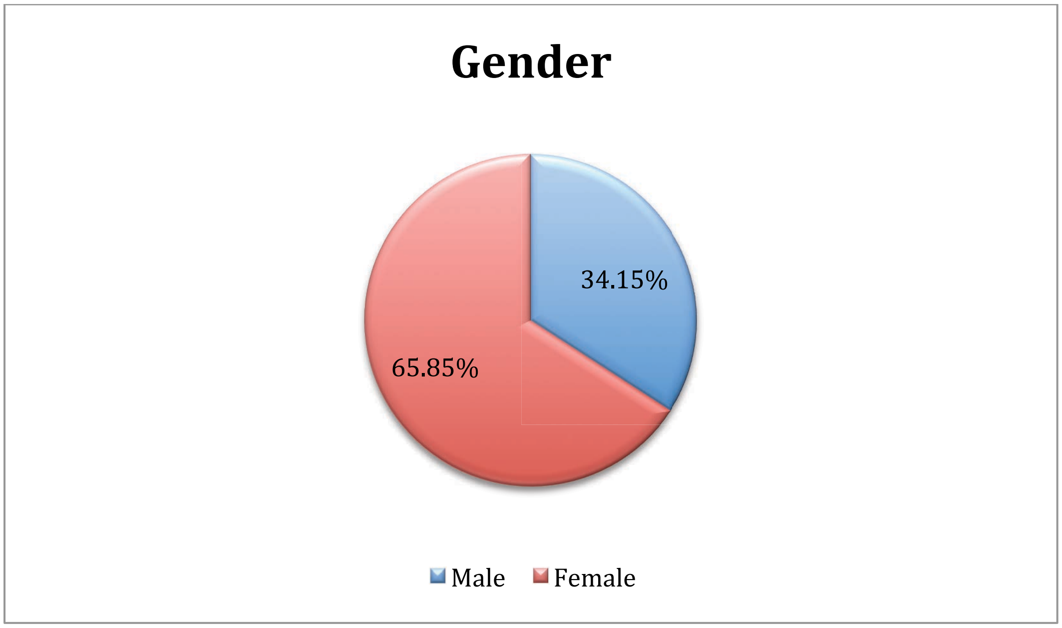


Figure C–5: Question 7 post-survey results.

Appendix D

Pilot Study Survey



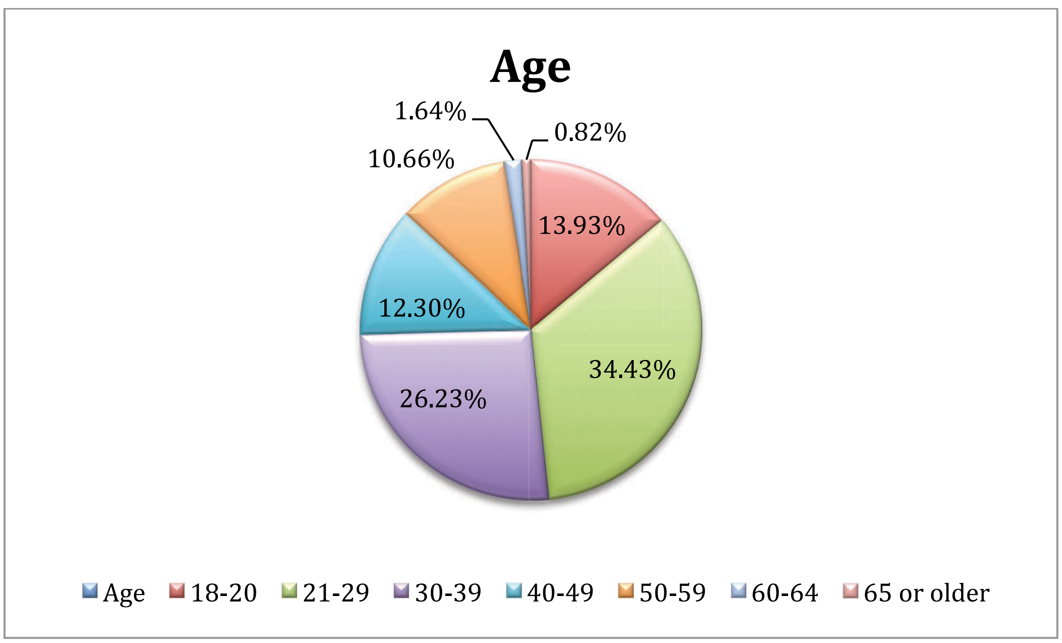
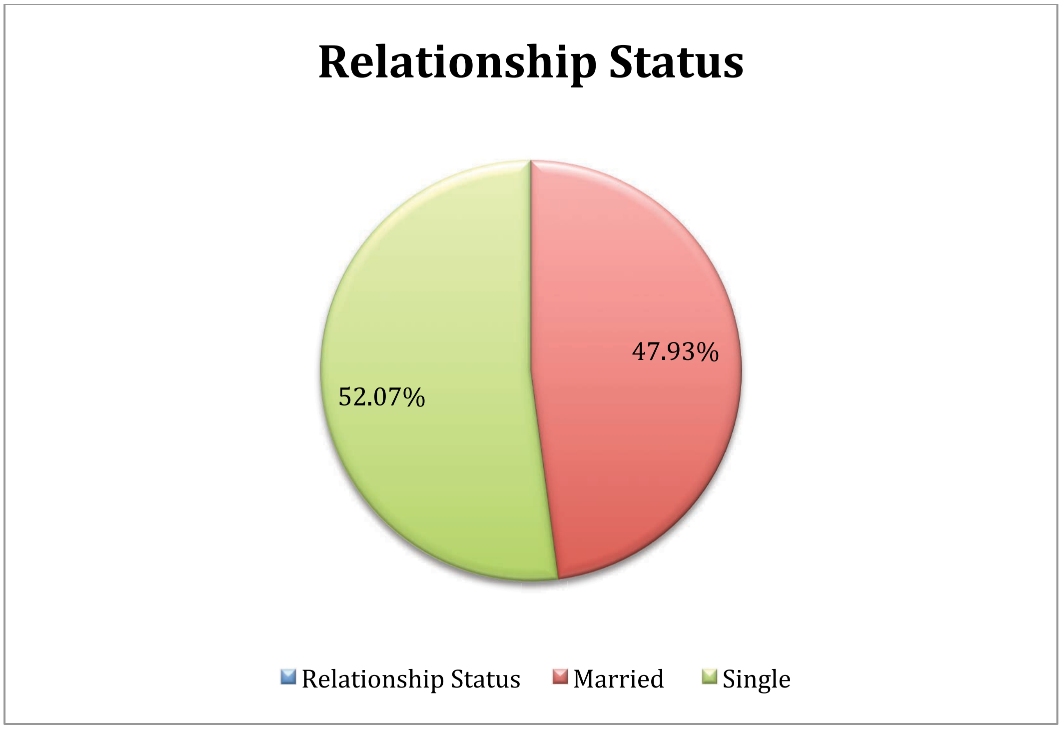


Figure D–1: Questions 1 and 2 of pilot study survey.



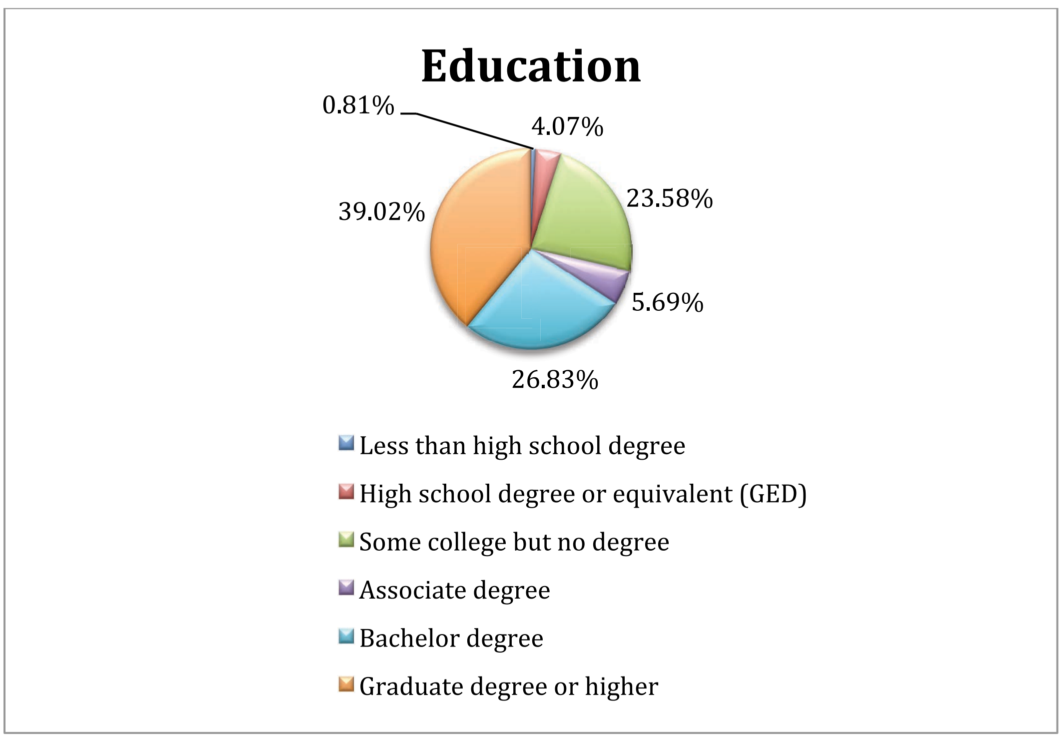
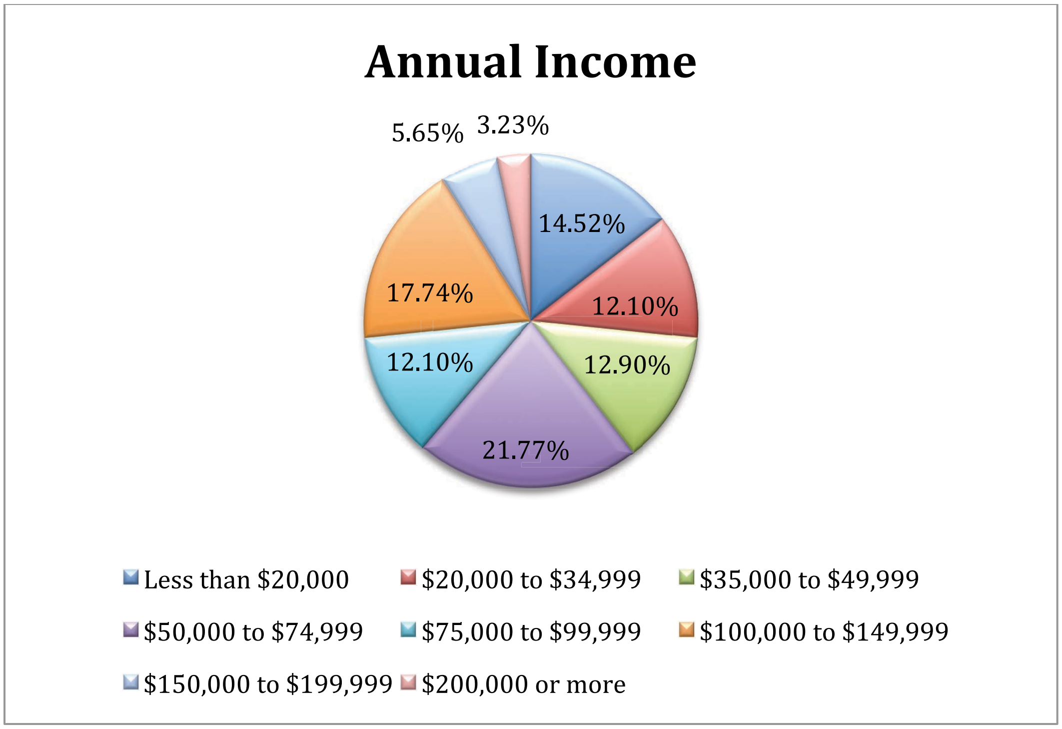


Figure D–2: Questions 3 and 4 of pilot study survey.



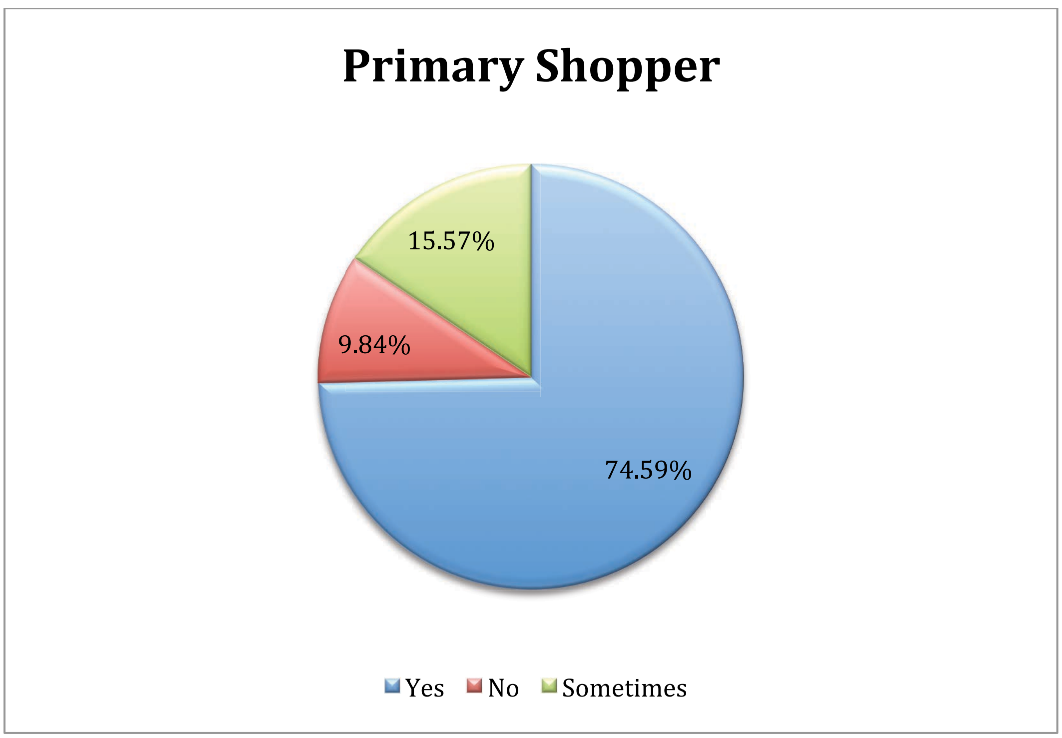
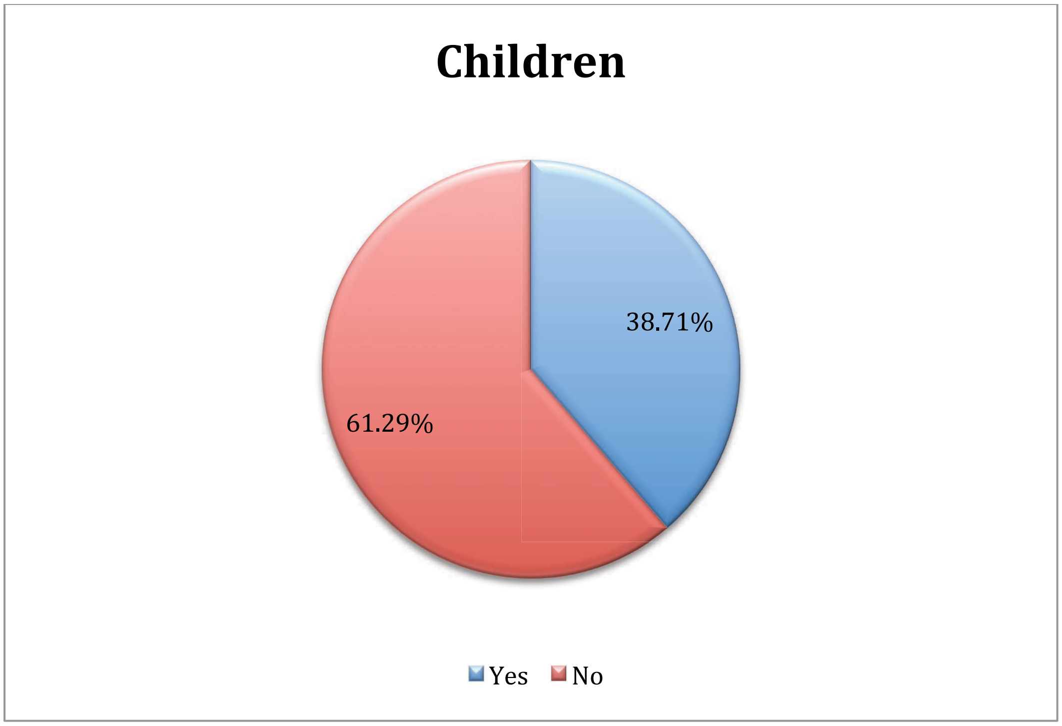


Figure D–3: Questions 5 and 6 of pilot study survey.



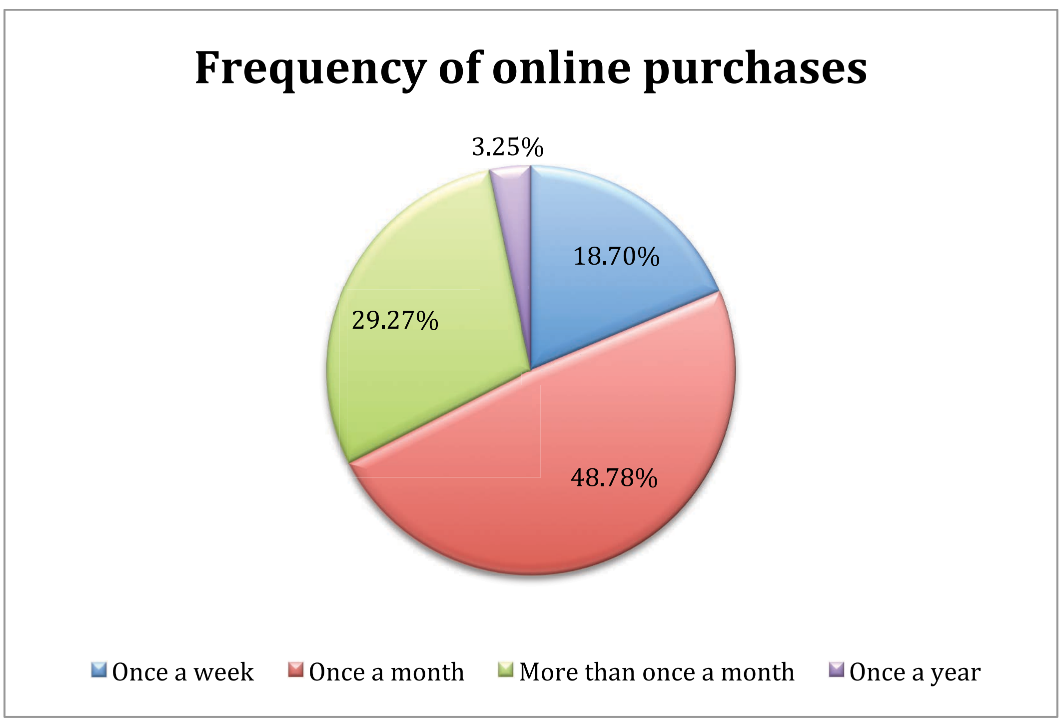
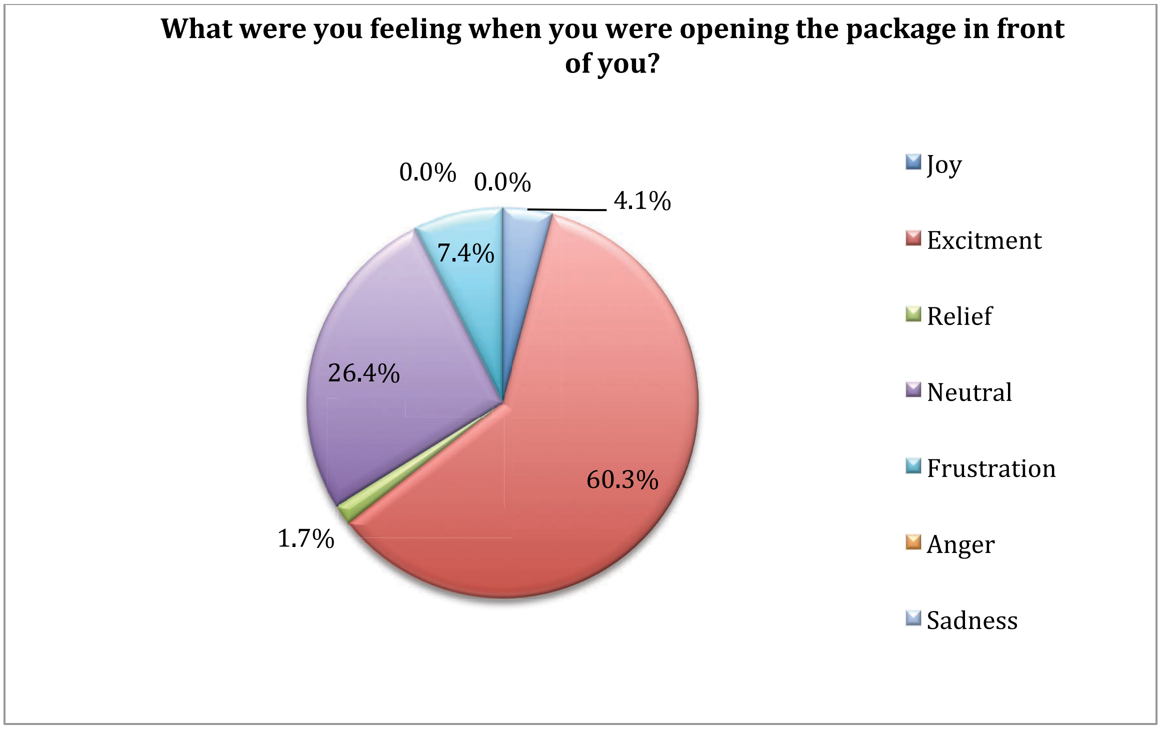


Figure D–4: Questions 7 and 8 of pilot study survey.



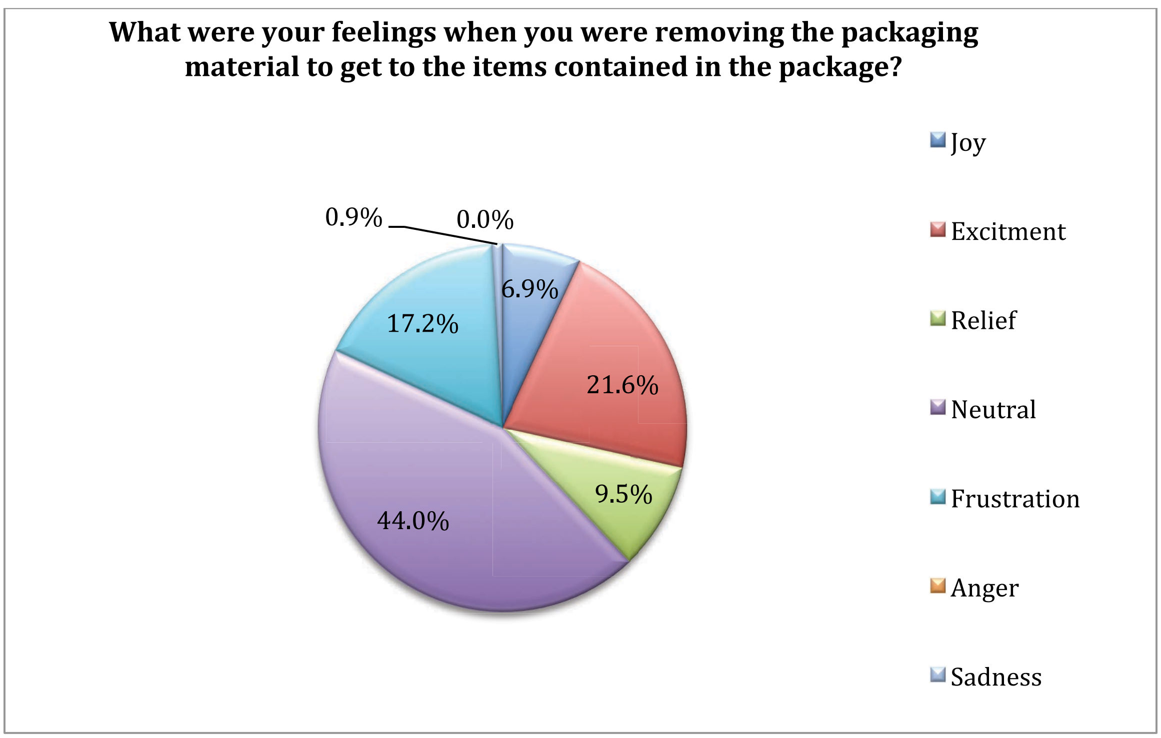
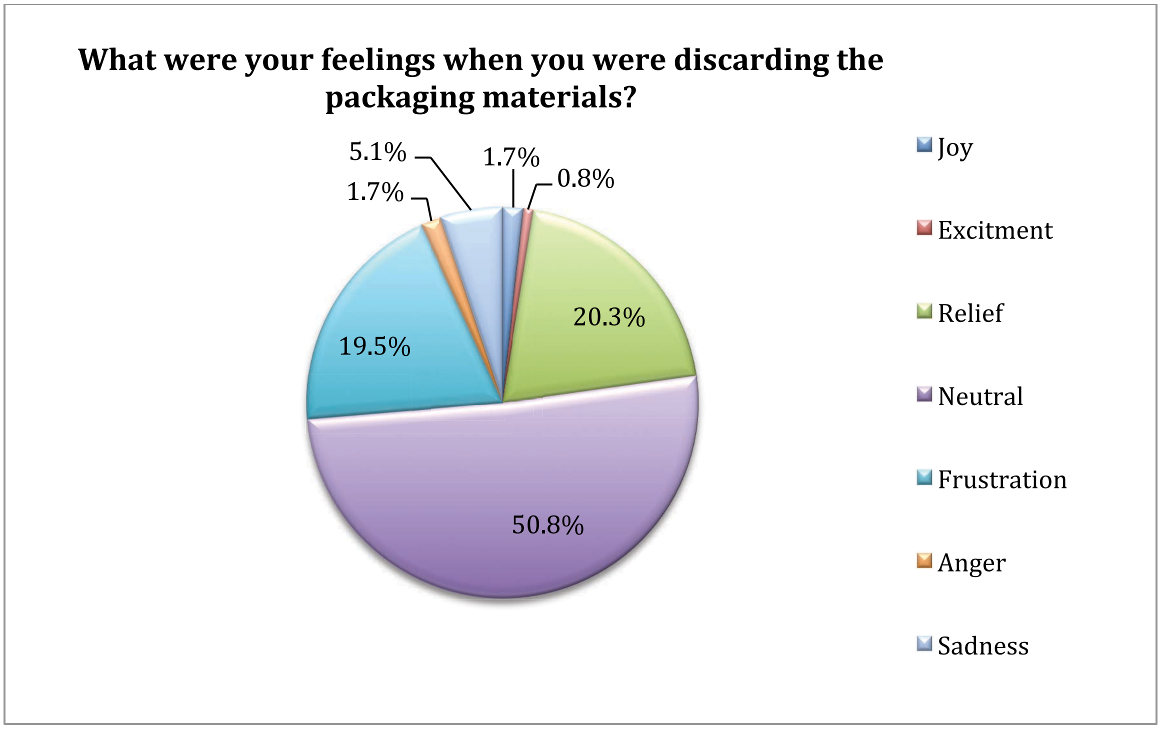


Figure D–5: Questions 9 and 10 of pilot study survey.



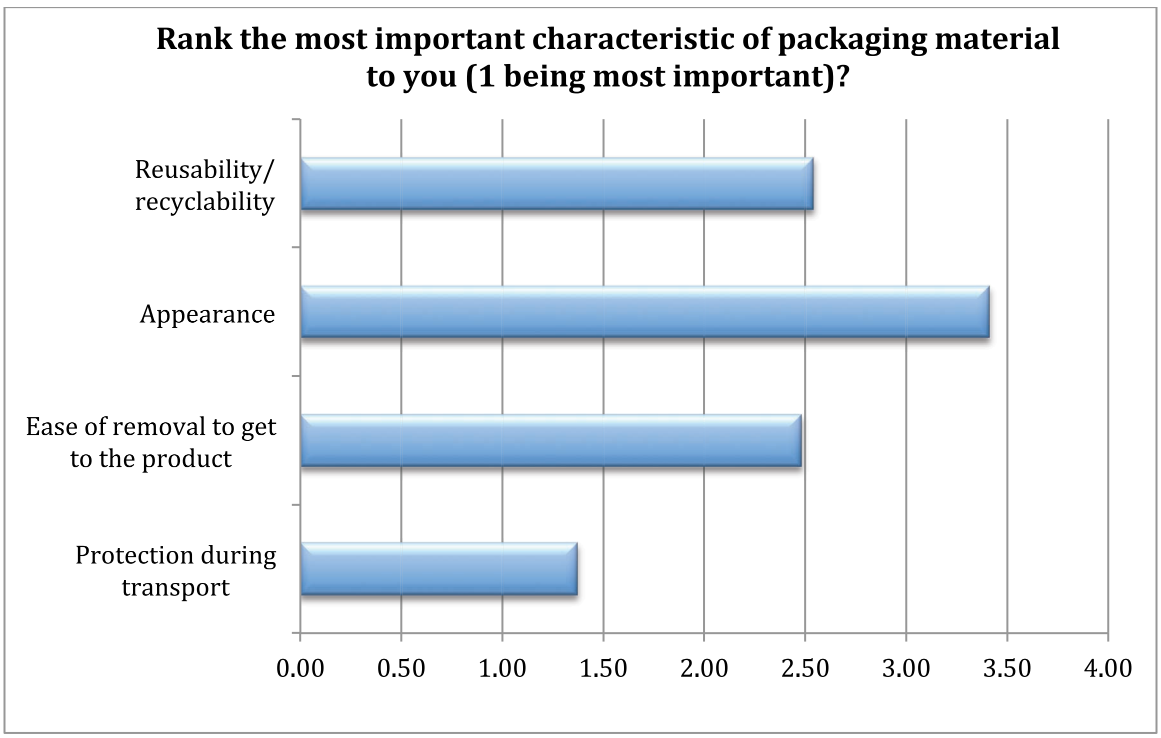
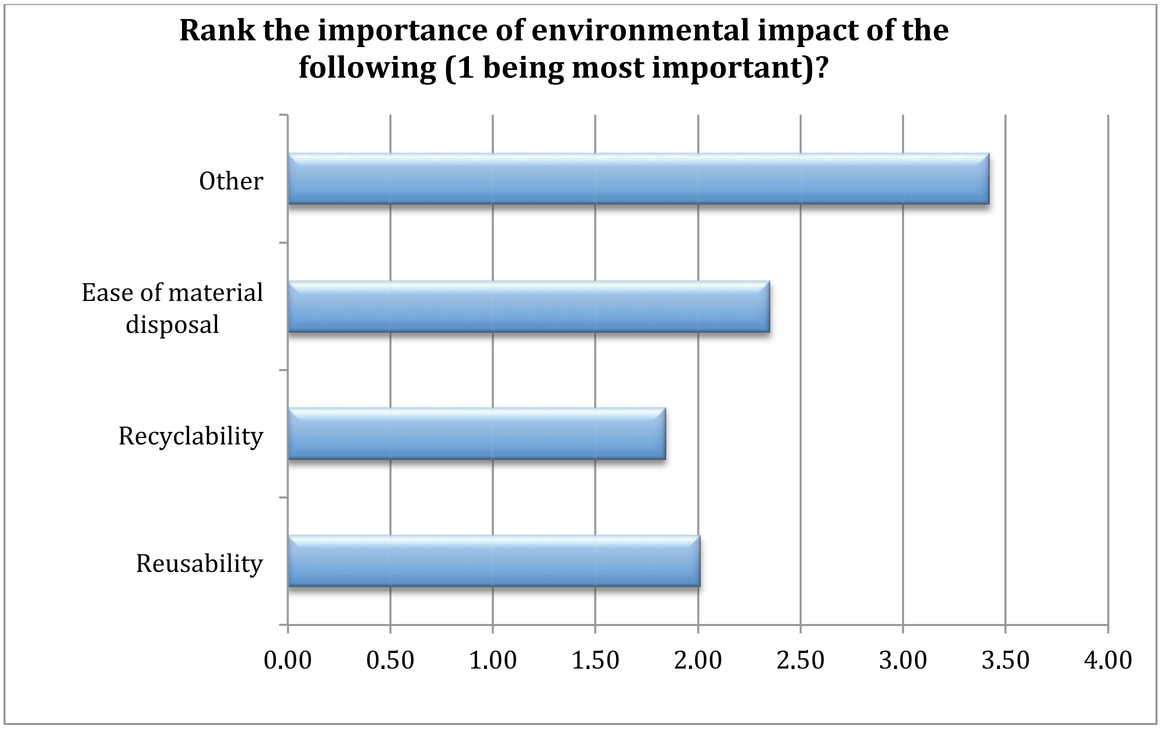


Figure D–6: Questions 11 and 12 of pilot study survey.



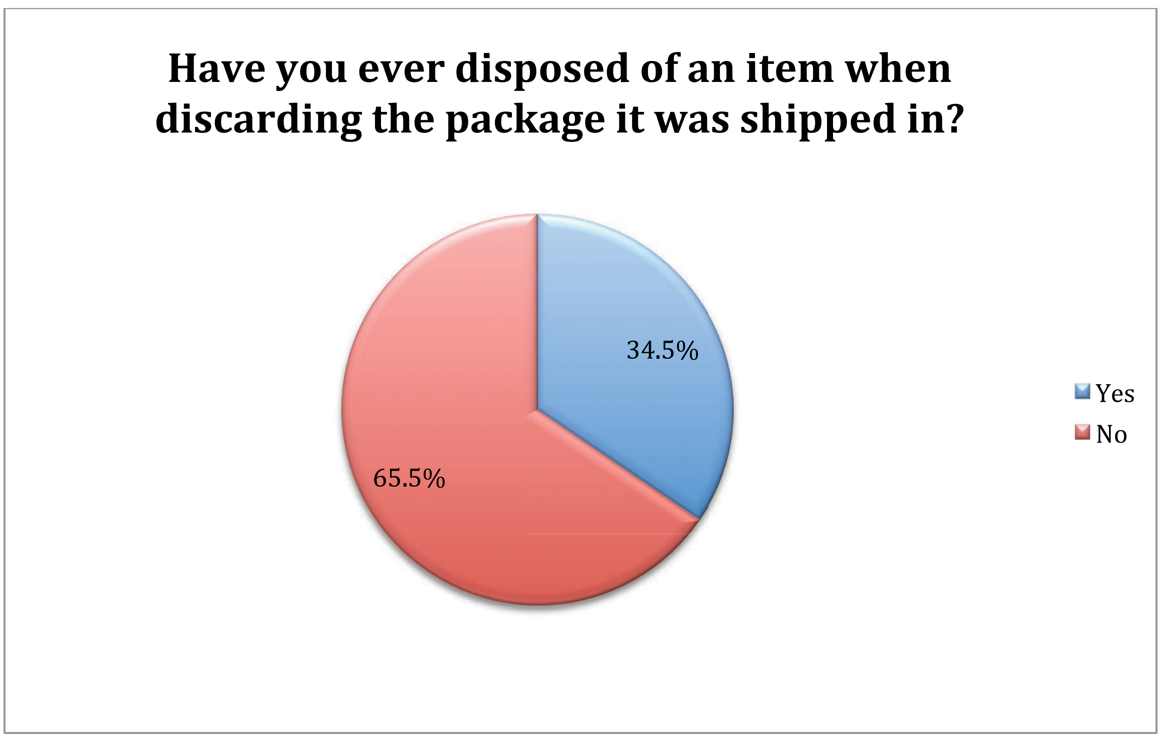
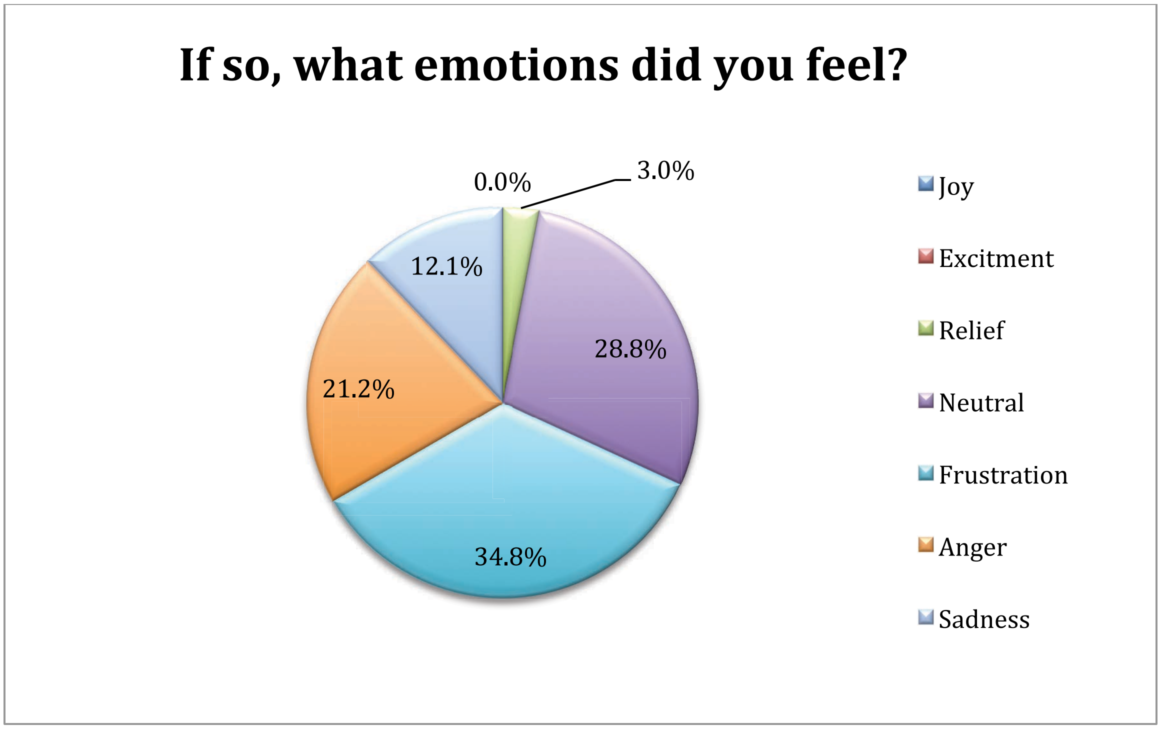


Figure D–7: Questions 13 and 14 of pilot study survey.



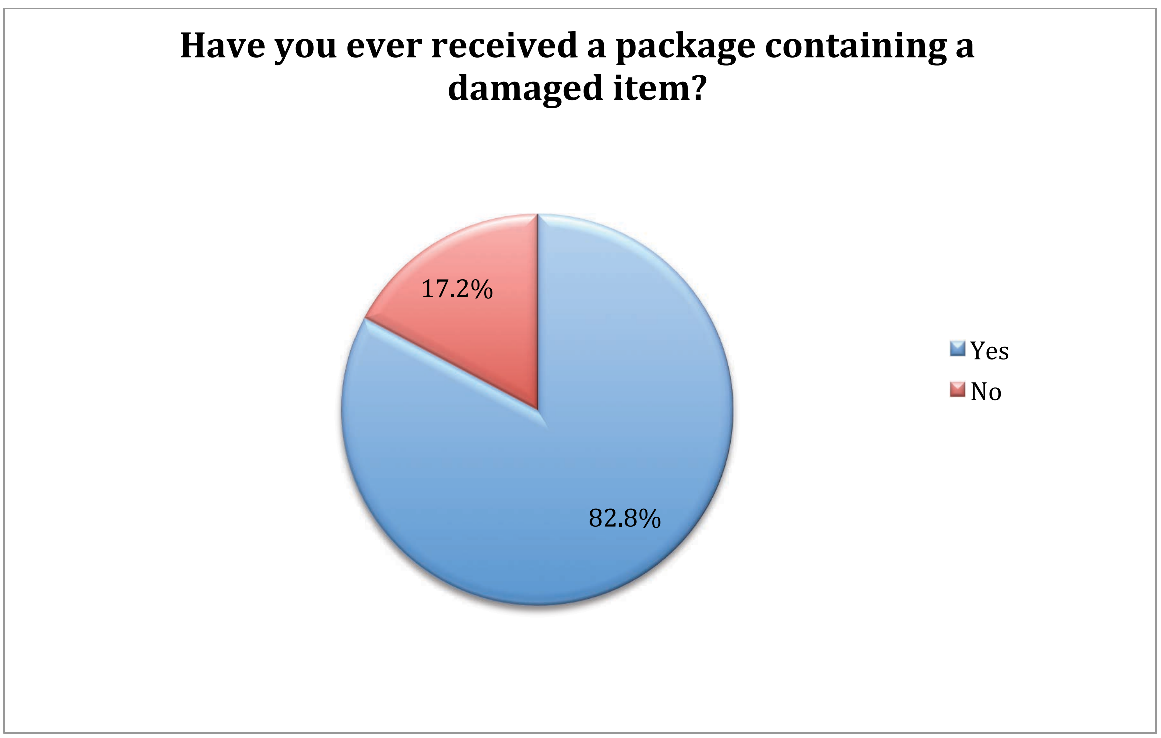
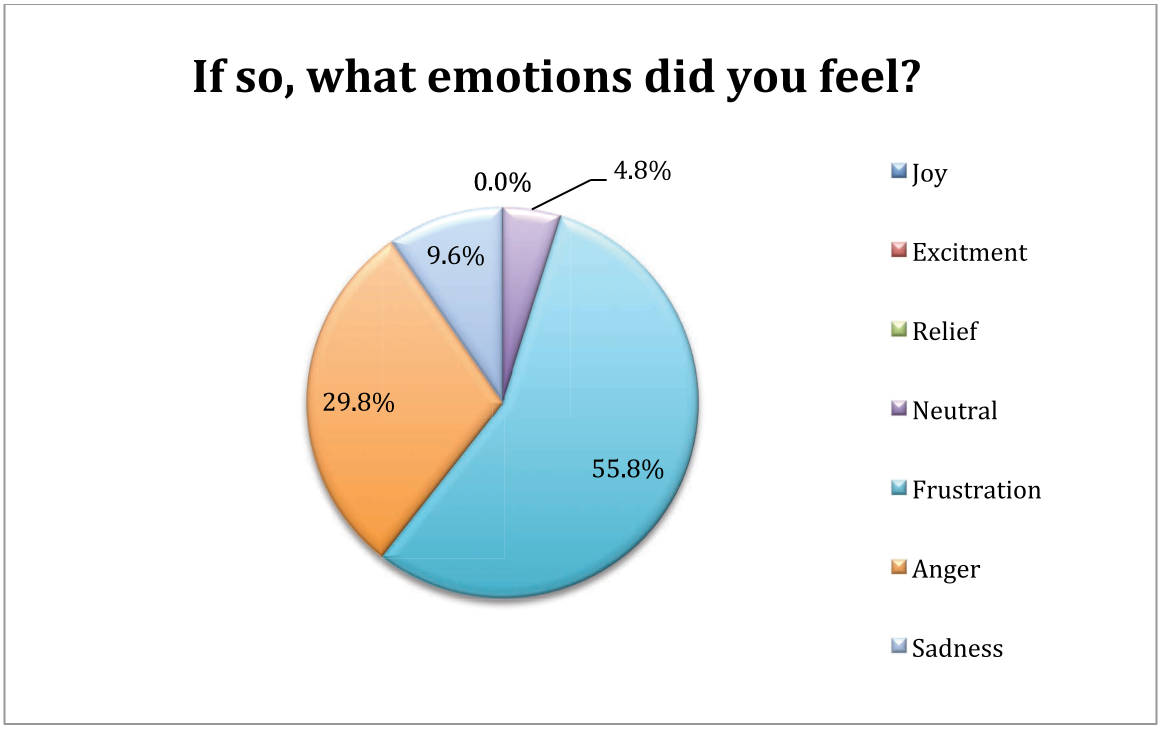


Figure D–8: Questions 15 and 16 of pilot study survey.



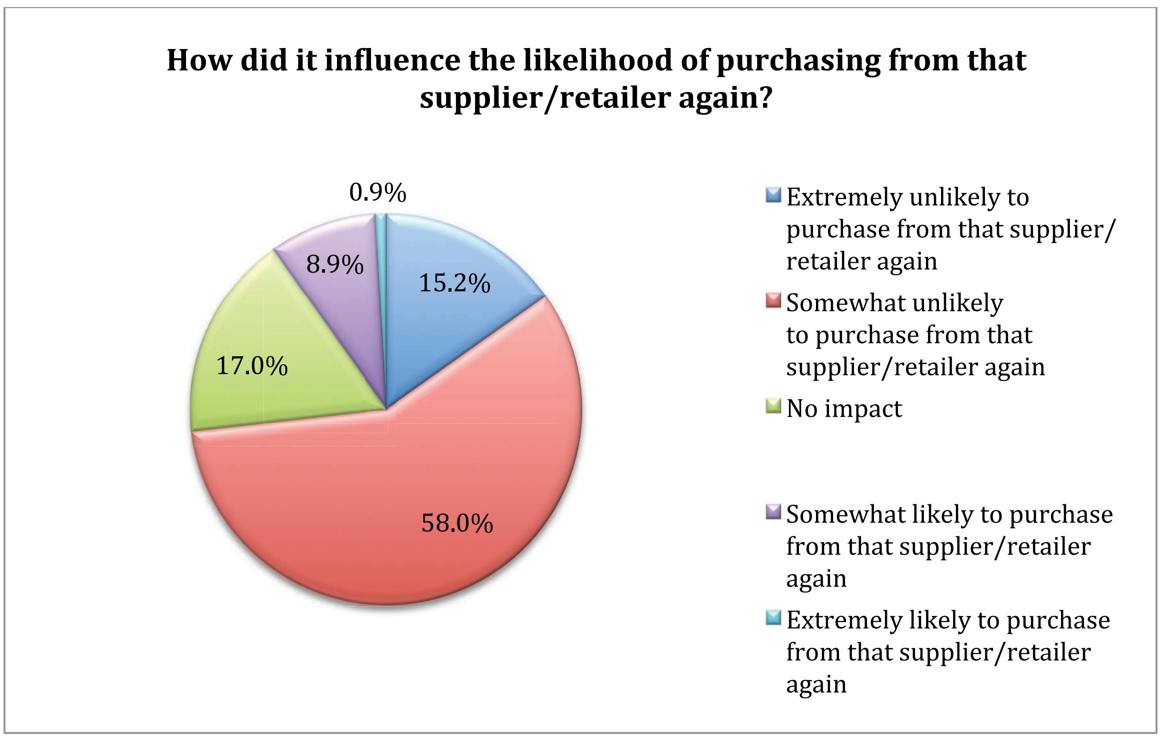
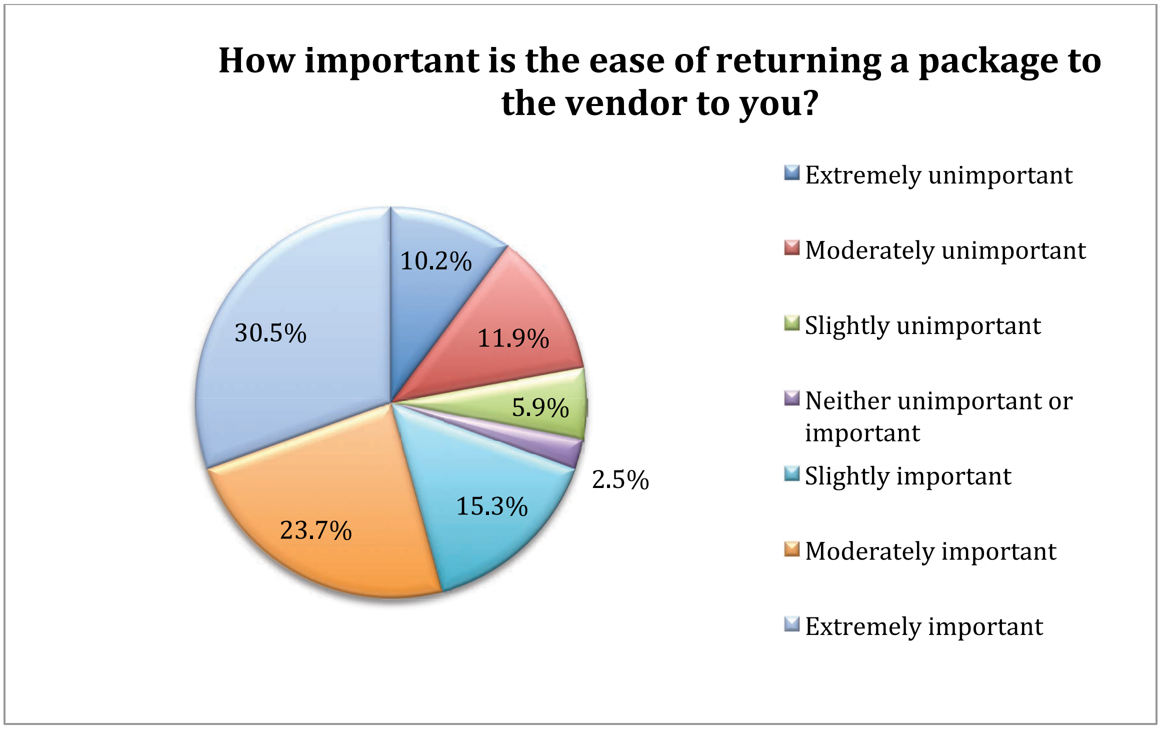


Figure D–9: Questions 17 and 18 of pilot study survey.



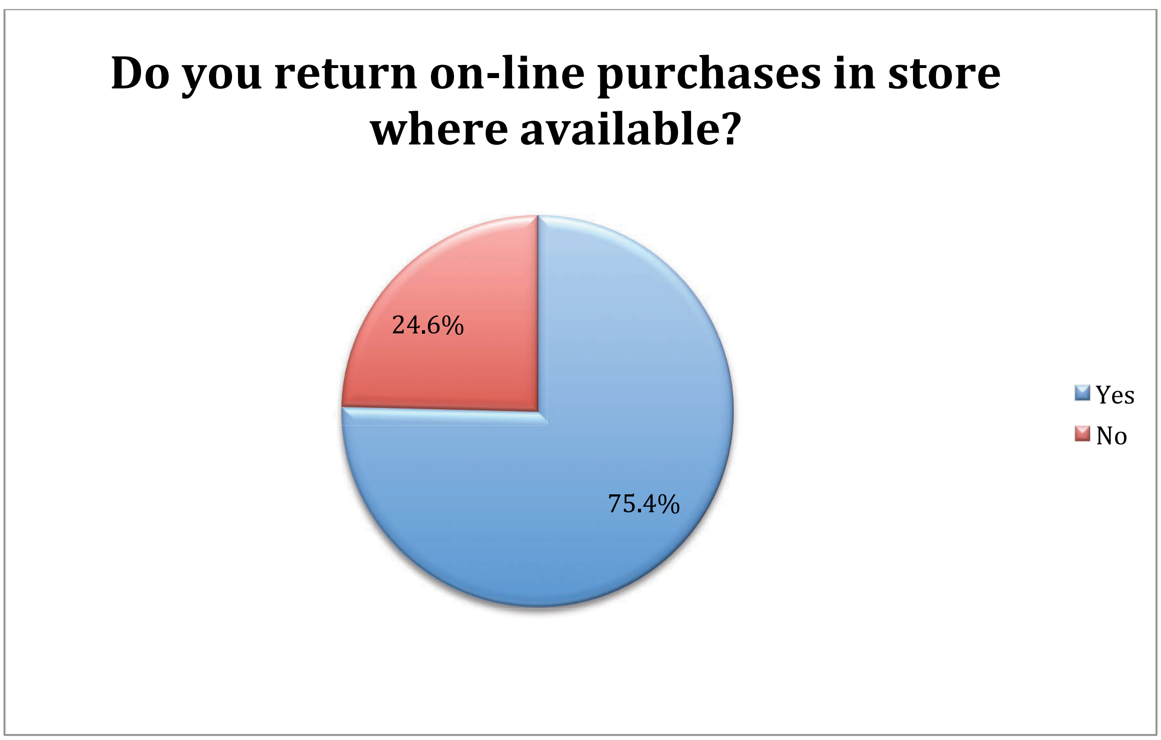
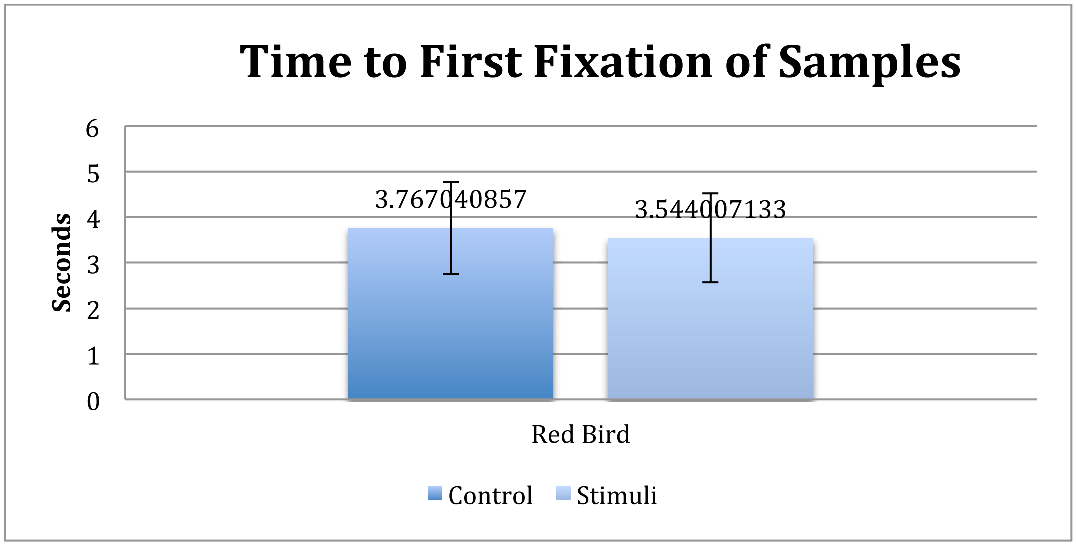


Figure D–10: Questions 19 and 20 of pilot study survey.

Appendix E

Eye tracking Results



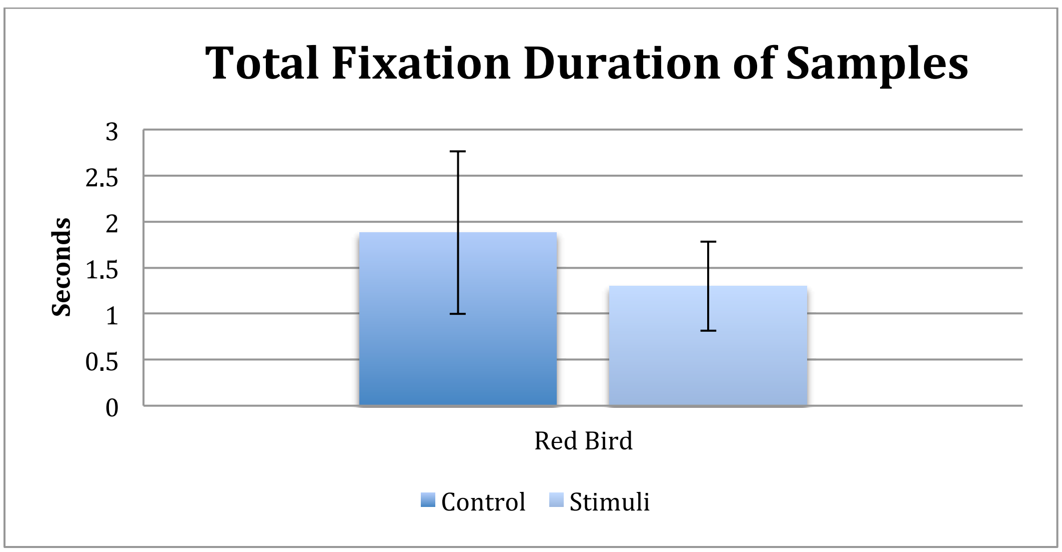


Figure E–1: Time to first fixation and total fixation duration eye tracking results.

Appendix F

Facial Expression Analysis Tables

Table F–1: Facial expression analysis average data for joy, anger, surprise, fear, and contempt of stimulus group.

Participant	Joy	Anger	Surprise	Fear	Contempt
2	-1.4395	0.1083	-0.8041	-0.1096	-0.2751
3	-3.3834	0.1759	-1.0200	-0.4348	-0.5372
4	-3.0354	-0.7303	-0.9067	0.3549	-0.9158
6	-1.4239	-0.7521	-0.9638	-0.1968	0.0864
7	-2.2409	-0.4244	-0.9129	-0.0864	-0.0991
10	-2.0791	-0.5547	-1.5355	0.0182	-0.3242
11	-2.8271	-0.5571	-1.1196	-0.9098	-0.3540
12	-4.1832	0.1685	-2.0413	-0.3408	-0.9439
13	-1.7483	-0.7292	-1.8929	-0.5312	0.3535
14	-2.6086	-0.0451	-2.6067	-0.7478	-0.6987
16	-2.3134	-0.8744	-1.5641	-0.0101	0.2327
17	-2.9159	-0.4520	-1.3599	-1.0524	-0.2911
20	-1.3722	0.2790	-1.8414	-0.6998	0.1026
21	-3.7271	-0.3139	-1.1955	-0.9531	-0.1771
22	-1.1474	0.2408	-2.4474	-0.1553	0.0814
23	-1.6479	-0.3196	-1.2424	0.5908	-0.0175
24	-2.5601	-0.3107	-1.8448	0.2045	0.3202
25	-1.6125	-0.2534	-1.8807	-0.9973	-0.1323
26	-2.5734	0.0463	-0.4630	-0.8599	-0.3477
27	-2.8399	-0.3433	-3.2716	0.1331	-0.1962
28	0.2820	-0.9972	-1.1022	-0.1789	-0.4042
29	-3.4850	-0.3333	-1.5009	0.7262	-0.9971
30	-3.8970	-0.3945	-0.5616	-0.4354	-0.6081
31	-1.8635	-0.5516	-0.9062	-0.0343	-0.2500
33	-2.7576	-0.5564	-2.1857	0.2071	-0.6527
34	-0.3854	-0.5942	0.0891	-0.2557	0.2620
35	0.4150	-0.1266	-0.6013	0.0535	0.2755
37	-1.8448	0.0401	-1.7733	-0.9647	-0.2642
39	-2.7808	-0.0869	-1.8812	-0.8137	-0.2586
40	-1.8778	-0.3101	-1.8089	0.4882	-0.2086
Average	-2.1958	-0.3184	-1.4382	-0.2664	-0.2413

Table F–2: Facial expression analysis average data for disgust, sadness, neutral, positive, and negative valence of stimulus group.

Participant	Disgust	Sadness	Neutral	Positive	Negative
2	-0.5885	0.5873	0.3135	-1.4395	0.6064
3	-0.5290	0.2235	0.5586	-3.3834	0.6074
4	-1.8787	0.4694	-0.7469	-3.0354	0.7174
6	-0.6012	0.0095	-0.0670	-1.4239	0.6245
7	-0.2210	-0.0256	0.5220	-2.2409	0.6110
10	-0.6296	0.6521	0.2560	-2.0791	0.8045
11	-1.4417	0.4239	0.8194	-2.8271	0.4260
12	-1.0588	0.6155	0.4575	-4.1832	0.7168
13	-0.2843	-0.1406	0.0448	-1.7483	0.5720
14	-0.2826	0.2563	-0.1894	-2.6086	0.4389
16	-1.0702	-0.2127	0.6577	-2.3134	0.6536
17	-1.4360	0.0143	1.0905	-2.9159	0.1489
20	-1.0631	-0.1621	0.0522	-1.3722	0.5536
21	-2.5921	0.5430	0.3591	-3.7271	0.7091
22	-1.5930	-0.5185	-0.4554	-1.1474	0.8249
23	-1.6990	0.0238	0.4274	-1.6479	0.7007
24	-1.1889	-0.1966	0.2330	-2.5601	0.6499
25	-0.6332	0.3301	0.2541	-1.6125	0.4739
26	-1.0761	0.2388	-0.0406	-2.5734	0.5583
27	-1.7386	0.4401	-0.1187	-2.8399	0.6537
28	-0.1992	-0.8256	-0.7632	0.2820	0.1802
29	-1.3223	0.6981	-0.8623	-3.4850	1.0730
30	-1.8221	0.2140	0.5347	-3.8970	0.3866
31	-0.7314	0.0896	0.8623	-1.8635	0.2130
33	-0.1497	0.6004	0.5553	-2.7576	0.7130
34	-0.1404	0.4837	0.2629	-0.3854	0.5087
35	0.0166	0.3605	-0.3612	0.4150	0.4794
37	-0.7198	0.5744	0.2021	-1.8448	0.6431
39	-1.1480	0.4552	0.3651	-2.7808	0.5232
40	-0.8249	0.8309	0.0225	-1.8778	0.9988
Average	-0.9549	0.2351	0.1749	-2.1958	0.5923

Table F–3: Facial expression analysis average data for joy, anger, surprise, fear, and contempt of control group.

Participant	Joy	Anger	Surprise	Fear	Contempt
1	-3.0305	-0.4445	-1.1122	-0.7276	-0.8880
2	-1.4381	0.4125	-1.8570	-0.8573	-0.0136
3	-0.9972	-1.0008	-0.7669	0.1074	0.9159
4	-1.9472	-0.6328	-3.4415	-0.2649	-0.1098
5	-2.4567	0.1182	-1.9548	-0.3783	-0.6832
6	-2.0822	-0.1318	-1.8677	0.1270	-0.1196
7	-3.5356	0.1037	-1.1032	-0.5615	-0.7163
8	-2.2255	-0.8408	-0.6521	0.2392	-0.6870
9	-2.4632	0.2536	-2.1181	-0.7727	-0.4624
10	-2.3266	-0.4472	-1.6157	0.1534	-0.2315
12	-0.9729	-0.9545	-0.8477	-0.3892	-0.2420
14	-1.5953	-0.0332	-2.4597	0.6805	-0.1616
15	-3.8900	0.9178	-2.4689	-1.0234	-0.3327
16	-1.6000	-0.3769	-1.7311	-0.5776	-0.2061
17	-1.9566	-0.4755	-0.8637	-0.4143	-0.2034
18	-2.7013	-0.1068	-1.5219	-0.9445	-0.2302
19	-1.3574	0.0531	-1.3623	-0.7379	0.0050
20	-1.3098	-0.0911	-2.2181	-0.9919	-0.1079
21	-4.5059	0.4290	-1.9671	-0.8345	-1.0611
23	-1.4506	-0.5406	-0.6539	-0.1798	-0.3330
24	-1.7958	-0.6542	-1.2514	-0.0952	-0.1655
25	-2.7792	-0.0691	-1.0554	-0.4828	-0.3447
27	-2.0645	-1.0483	-0.5803	-0.1190	0.1599
28	-2.3286	-0.4113	-1.9754	-0.4719	0.6294
29	-2.0418	-0.0121	-2.4137	-0.1809	-0.3001
30	-2.1872	1.1151	-3.1725	-0.8463	-0.0897
31	-0.7653	-0.6384	-1.5234	-0.2925	0.0954
32	-0.7208	-0.4894	-1.3203	-0.4541	0.2430
37	-4.0091	-0.4069	-2.1594	-0.7513	-1.0193
38	-0.9955	-0.8578	-0.7860	0.4110	-0.1184
ALL	-2.1177	-0.2420	-1.6274	-0.3877	-0.2259

Table F–4: Facial expression analysis average data for disgust, sadness, neutral, positive, and negative valence of control group.

Participant	Disgust	Sadness	Neutral	Positive	Negative
1	-0.0038	0.2310	0.6893	-3.0305	0.3911
2	-0.4637	-0.5550	-0.2462	-1.4381	0.7044
3	-1.0565	-0.7282	-0.6855	-0.9972	1.2877
4	-3.1409	0.4287	-0.8515	-1.9472	1.5584
5	-0.3274	0.3268	-0.0683	-2.4567	0.6607
6	-0.6196	-0.3405	0.0018	-2.0822	0.7419
7	-1.2025	0.5358	0.1708	-3.5356	0.6137
8	-0.5423	0.2936	0.1318	-2.2255	0.6288
9	-0.6164	0.1478	-0.3870	-2.4632	0.8227
10	-0.4501	0.3670	0.4789	-2.3266	0.7041
12	-0.6821	-0.5819	-0.8252	-0.9729	0.5195
14	-0.7071	0.2523	-0.1796	-1.5953	0.9332
15	-0.9034	-0.3701	0.0033	-3.8900	0.9971
16	-0.7450	0.7900	0.2750	-1.6000	0.8672
17	-0.5838	-0.1683	0.4864	-1.9566	0.2724
18	-1.1864	0.5895	0.7723	-2.7013	0.6216
19	-0.5373	0.2135	0.3245	-1.3574	0.4994
20	-0.6780	0.2914	0.2471	-1.3098	0.4665
21	-0.8181	0.0812	0.4952	-4.5059	0.5193
23	0.2069	-0.1892	-0.1599	-1.4506	0.6464
24	-0.8242	-0.1681	0.4369	-1.7958	0.3665
25	-1.0684	0.6358	0.4892	-2.7792	0.6552
27	-1.0273	-0.5231	-0.3522	-2.0645	0.7657
28	-0.9599	0.2655	-0.1510	-2.3286	0.9860
29	-0.8090	-0.1580	-0.0590	-2.0418	0.4290
30	-0.5549	-0.0385	-0.6596	-2.1872	1.1862
31	-0.5407	0.4731	0.0783	-0.7653	0.5972
32	-0.8601	0.8908	-0.1048	-0.7208	0.9259
37	-0.6726	0.2889	0.4860	-4.0091	0.4141
38	-0.6385	0.9185	0.0381	-0.9955	1.0618
ALL	-0.7671	0.1400	0.0292	-2.1177	0.7281

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