# Affective Color Palettes in Visualization

by

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# Abstract

The communication of affect, a feeling or emotion, has a central role in creating engaging visual experiences. Prior work on the psychology of color has focused on its effect on emotions, color preferences and reactions to color. Studies have attempted to solve problems related to improving aesthetics and emotions of images by improving color themes and templates. However, we have little understanding of how designers manipulate color properties for effective visual communication in information visualization. Designers manipulate color to communicate affect in visual representations, but the knowledge of how to effectively use color is largely rooted in the professional craft of the designer.

In this thesis, we report research into how different color properties lightness, chroma and hue contribute to different affective interpretations considered to be of interest in information visualization. We report results of several studies examining whether certain kinds of palettes (sets of colors) were more likely to be chosen to convey different affect. We found significant differences in lightness, chromaticity and hue patterns between desired affective impressions. Our results suggest guidelines for how color properties can be manipulated to achieve affective expressiveness in information visualization.

**Keywords**: Information Visualization; Affective Visualization; Color Perception; Visual Design

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# Chapter 1.

# Introduction

Powerful and expressive visuals evoke emotions and influence both how we use the information presented to us and how we are affected by its presence, driving a deeper level of engagement (Norman 2005). Norman stated "it is only through our emotions do we unravel problems, as the human emotional system intertwined with our cognitive abilities"; if the user finds a positive affection towards an object, our brains are encouraged to think creatively to solve any problem in which the object might present. Recent affective neuroscience and psychology studies have shown that human affect and emotional experience plays a significant role in human learning and decision making (Picard 1997); emotion can result from cognitive reasoning, and affect influences cognition.

We react affectively as well as cognitively to visual imagery (Norman 2005): this is important in visualization for supporting communicative intent (Cairo 2013), engagement, and problem-solving (Harrison et al. 2013). Thus affect is of importance in visualization for supporting communicative intent (Elliot and Maier 2014), engagement and problem-solving. While there is a long history of research and practice in how certain visual elements relates to affect, there are as yet no comprehensive framework grounding visualization principles for affective representations. The goal of our research is to examine the affective capacity of visual features such as color and as part of this emerging framework (Lockyer and Bartram 2012).

## 1.1. Motivation

Designers strive to find better and efficient visual design in information visualization, which is becoming an essential part of communicating the right context.

Such visualizations have the goal to evoke experiences and moderate the cognitive interpretation of the visualization. Getting the right visualization impression is a key to developing engaging experiences. For achieving this, choices like color, animation and shapes are carefully explored by designers to stimulate emotional response to communicating the desired context.

The use of color can help a story in the data be expressive. Also in situations where designers need to align a visualization design with the corporate identity and effectively communicate the affective context, corporate brand color can be manipulated to generate the right affective context. A designer can keep the hue scheme constant, but still improve the overall color palette expressivity by manipulating color properties like lightness and chromaticity. If the overall impression of visualization is to communicate information commonly associated with negativity, suggesting the designers statistically likely colors associated with negativity are useful.

There are currently very few guidelines on how to leverage color to improve expressivity that will help people absorb and understand data more effectively.

## 1.2. Color in Data Visualization

The study of color communication in data visualization is not new and is a fundamental character of perception, and its effects on cognition and behavior have been investigated extensively (Elliot and Maier 2014). Color palettes play a central role in data visualization and often used to label and to measure data for effective cognitive interpretation (Brewer 1994; Stone 2003) . If properly selected it conveys the underlying data accurately. In visualization it includes color gradients on maps and charts, color-coded fields in the flow visualization, or color icons displayed by real-time simulation systems. Principles for using color to represent data in information visualization are well established in the field and empirically validated, based on well-known properties of human perception (Ware 2008) . There are, however, few computationally tractable models that define how to use color in information visualization to amplify or reduce affect, either by altering individual properties such as hue, saturation or lightness or palette characteristics such as hue dispersion and color clustering. Designers and artists explore and manipulate color to communicate affect (the collection of user-generated palettes in the Adobe™ Kuler community provides numerous examples). The knowledge of how to effectively design affective palettes is primarily rooted in professional craft and qualitatively rather than empirically validated. We are interested in principled computational models of how color choice relates to the desired affect.

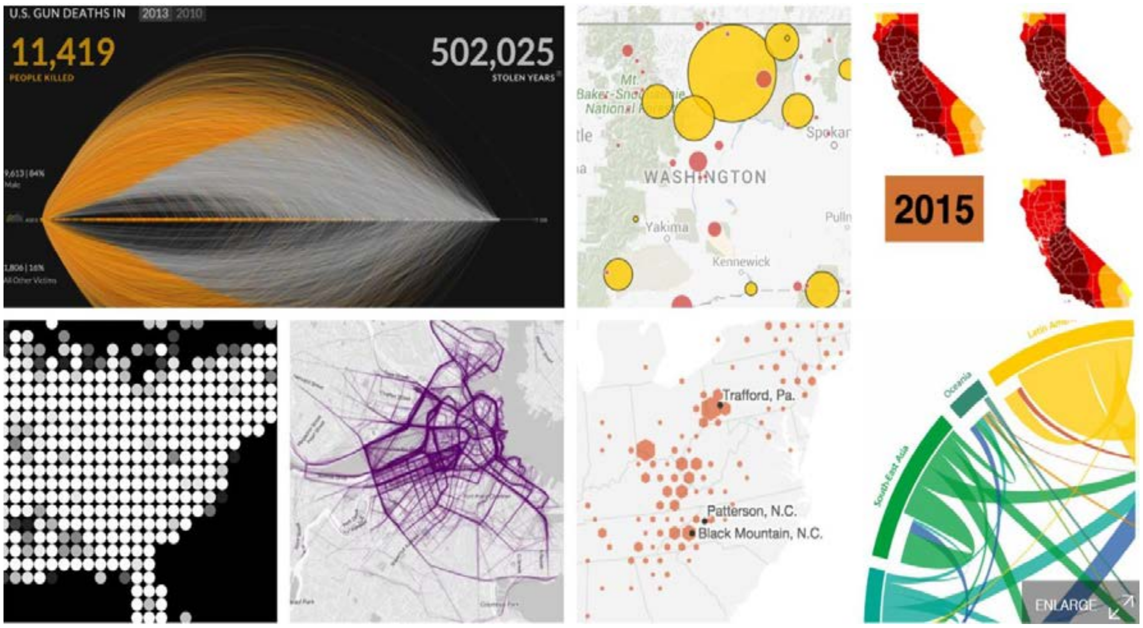


**Figure 1.1. These visualization are examples of expressive visualization because they communicate an impression that is affectively different. Clockwise from top left (United States Gun Death Data Visualization by Periscopic n.d.; This Week's Essential California - LA Times n.d.; Global International Migration Flows | Wittgenstein Centre n.d.; Scully 2014; Yau 2014; Chris Harrison - Data Mining: Text Mining, Visualization and Social Media n.d.)**

## 1.3. Affective Visualization

The role of affect in information visualization applications is an emerging field and important for understanding how can we communicate impressions of emotions using visual features. Visualization designers often use colors and other visual elements to create a visual metaphor of the data and the narrative context. The goal of this thesis is to identify design principles for influencing emotions which researchers have identified significant (Cairo 2013) in the narrative (Segel and Heer 2010), problem-solving (Norman 2005; Harrison et al. 2013) and contextual framing (Bartram 2015) . We term this affective visualization: the principled use of visual elements to change the affective nature of a presentation. The fundamental difference between data and affective visualization is in communicative intent. Information visualization seeks to represent data with visual features for effective cognitive interpretation.  In affective visualization, we transform the narrative context of the complex data into impressions aimed to evoke an affective state: an experience, emotion or feeling traditionally linked to emotional response. Emotions commonly described by factor-based classifications such as the well-known PAD (Posner, Russell, and Peterson 2005) model of affect that plots them in a dimensional space defined by pleasure (valence), arousal and dominance. The dimension of valence covers the hedonic range, from positive states (happiness, pleasure, love) to negative (pain, anger, sadness, fear). The dimension of arousal reflects the activation aspect of affective experience and ranges from unaroused (calm, relaxed, sleepy.) to high arousal (excited, stimulated, nervous, alert, etc.). The third dimension of dominance relates to social interaction. This dimension provides a nuanced way to refine emotions that are otherwise similarly located in the valence-arousal space: for example, while anger and fear are both negative and aroused, anger is dominant while fear is submissive. The basic emotions identified include anger, disgust, fear, sadness, pleasure, surprise, courage, joy, worry, pride, shame and guilt.  The emotional space includes a much broader definition space beyond standard emotions. In this thesis, we focus on affective states that cover the range and are of particular interest to visualization community. Rather than defining more detailed emotional interpretation such as “happy” or “sad” we consider affective impressions that visualization designers are interested in creating. These impressions are emotions which can be, a sense of interest, an atmospheric impression, or other such feelings related to but not exactly one of the basic emotional states. Such affective responses of potential interest in visualization applications may include those of importance to business and marketing (trust, seriousness, reassurance)  (Cyr, Head, and Larios 2010) or to narrative tone in storytelling (Cairo 2013; Segel and Heer 2010)  (playfulness, disturbing, threatening, amusing).

## 1.4. The research question

There is an extensive history of psychological research into individual color-affect, influence, but to date there are no studies on how combinations of colors (palettes) may convey different affect in information visualization. In this thesis, we report three studies that examined how different perceptual properties of color palettes were associated with different affective impressions.

We ask two basic research questions.

1. Can we capture affect as properties of a color palette in abstract images such as simple visualizations?
2. What might this mean operationally for the design of affective color palettes that are useful in designing categorical information visualization? Can we derive guidelines for how color can be manipulated to enhance a desired affective impact or minimize an unintended one?

Our results show a correlation between perceptual color properties (hue, chroma and lightness), palette composition (hue clusters, color dispersion) and certain types of affect. While preliminary, in that we only examined a limited range of meaning, our studies affirm the rich potential of color for conveying meaning and identify initial palettes that enhance these affective impressions. These results build on traditional color psychology to contribute to the development of operational principles for evoking affect using color combinations, and we propose that such studies from the beginning stages of research into expanding the expressive capacity of effective visualization.

## 1.5. Scope of this thesis

The palettes studied in this thesis are limited to five colors categorical colors. We consider only eight affects on two visualization types: a bar and US map chart. We just focus on the color choices provided by users in the study design tasks which do not include the effect of chart size or the visual weight of the color. Our work focuses on answering what palettes should one choose for a given affect; it does not answer a much harder question: given a palette, what does it convey? We are not expecting to be able to quantify all possible palettes with respect to affect, but rather to understand what might make a desired affective impression comparatively stronger or weaker.

## 1.6. Thesis Overview

This thesis is organized into seven chapters. Chapter one discusses the motivation and research question. Chapter two discusses relevant research in perception and social psychology and information visualization. The chapter provides a review of the use of affective motion as communication. In chapter three we describe our research goals, motivation, and approach. We describe methods of capturing how designers use color to create affective impressions in design. Following which we conduct three sets of experimental studies for this research. The first study, described in Chapter four is an analysis of creative imagery tagged with relevant affective terms. In this study, we analyzed images from two large image databases, Flickr™ and deviantArt.com, to explore whether there were noticeable differences in the color palettes of images associated with our affective terms of interest. Next, we conducted two user experiments in which participants selected color palettes for information visualizations to communicate the desired affect. Chapter five describes the methodology and reports the results of another experiment that shows how particular attributes of color contribute to certain emotional interpretation. Later in chapter six, we used the previous results to build affective palettes and asked participants to rank how well the palettes matched to the affective impressions on simple visualization charts. Finally, Chapter seven discusses results by providing a summary of it and its implications for information visualization and user interface design. Chapter seven also includes discussion about the limitations and future work.

# Chapter 2.

# Background

## 2.1. Color Psychology

There is a large body of research into the psychology of color that covers a wide range of varieties and interests. The field of color psychology examines the interplay between color, cognition, affect and behavior. Depending on the context color is interpreted in different ways, as found in previous studies, e.g. (Madden, Hewett, and Roth 2000; L. Bartram, Cheung, and Stone 2011; Elliot and Maier 2014). Elliot et.al (Elliot and Maier 2014) conducted experiments to demonstrate that relationship between color red and psychological functioning in achievement context. Most of the experiments used an IQ test for tracking performance in tasks that had an achievement context i.e. contexts where the competence is evaluated. Their results suggested that perception of red before a task completion impairs performance relative to the perception of green. This illustrates that color could act as an important environmental cue that influences behavior. Madden (Madden, Hewett, and Roth 2000) explored consumer preferences for different colors and color combinations. They studied participants from 8 countries and evaluated 10 colors. Participants rated the colors and then to get meaning and color combination preferences arising from colors, participants colored logos. They found that the colors blue, green and white shared similar meanings across countries and overall it suggested consumers exhibit similar color preferences and color meaning associations. Particularly around consumer preferences people in different cultures are exposed to different color associations. Hence considering factors of culture is important to tap into the aesthetic impressions stemming from a selection and combinations of colors (Cyr, Head, and Larios 2010; Madden, Hewett, and Roth 2000).

The meaning of color is dependent on the context and therefore color has different implications for emotions and thoughts in different contexts. Colors vary in perceived typicality, chromaticity, and lightness, as well as hue and their proportions are important parameters to elicit emotions (Kwallek, Lewis, and Robbins 1988; Valdez and Mehrabian 1994). Valdez et.al conducted experiments to investigate emotional responses to color hue, saturation and brightness based on the Pleasure-Arousal-Dominance emotion model. Using linear regression analysis, they found that brighter and more saturated colors were pleasurable. It indicated that less bright and more saturated colors were more arousing and darker colors elicited feelings of strength. Hue preferences for pleasant were cool hues: Blue, blue-green, green, purple-blue, red-purple, and purple.  Yellow, green-yellow, and red-yellow were the least pleasant. The most arousing hue was green-yellow, followed by blue-green and green, whereas the least arousing hues were purple-blue, yellow-red, and red-purple. Finally, dominance reactions were greatest to green—yellow and yellow and differed from reactions to red-purple, which elicited submissive feelings.

Research also suggests that colors play a major role in shaping feelings which play a major role in the formation of perception, attitude and judgments. Further research has studied how colors can be an influential mediator in explaining the relationship between cognitive and behavioural reactions to stimuli (particularly around consumer response) (L. Bartram, Cheung, and Stone 2011; Labrecque and Milne 2012; Bellizzi and Hite 1992). Christine et.al studied (Lichtlé 2007) the effect of lightness, saturation and hue on the emotions it evokes on human attitude towards it. They examined and compared the effects of different tones and of varying lightness and saturation on the emotions aroused by advertisements. Their research integrated color stimuli into the explanation of attitude towards an advertisement. They found that preference toward the ad is more favorable when the ad is a red hue and when it is strongly saturated. Similar research was done by (Labrecque and Milne 2012) to investigate the role of color in marketing based on evidence from research in aesthetics, color psychology and associative learning. They found that red, orange and yellow hues are related to the perceived excitement of a brand and black, purple, and pink hues improved the perceived elegance of a brand. High Saturation increased arousal and excitement while high lightness decreased arousal.

Various studies show that “warm” colors (red, yellow and orange) are more physiologically stimulating (arousing) than “cool” hues of blue and green (Bellizzi and Hite 1992; Mehta and Zhu 2009). Color is a strong visual component of a physical setting that draws attention and stimulates emotional responses. People are drawn to warm colors, but they find them to be unpleasant (Bellizzi and Hite 1992). Color elements such as hue, brightness, and saturation are likely to affect our perceptions, physiological, emotional or behavioral reactions (Valdez and Mehrabian 1994). In the commercial realm, color influences our attitude and expectations toward brands. Red is considered hot, vibrant and intense across cultures (Madden, Hewett, and Roth 2000; Elliott and Objects 2008; Labrecque and Milne 2012) and most likely to induce arousal and anxiety (Kwallek, Lewis, and Robbins 1988).

Color as a concept of expressing semantic meaning and feelings have been identified in previous studies. Yellow, orange and brown have less consistency of affective response, although yellow is also considered exciting. In a study of web site color for e-commerce across cultures, Cyr et .al found that respondents disliked the yellow scheme, terming it “too showy” and not “appropriately professional” (Cyr, Head, and Larios 2010). Studies have also associated brown with “sad” and “stale” ratings (Madden, Hewett, and Roth 2000) in Western culture. More recent research has considered the cooler hues. Blue, and to a lesser extent green, has positive links to the natural world and are associated with positive content (Elliot and Maier 2014; Madden, Hewett, and Roth 2000; Mehta and Zhu 2009). In particular, blue is strongly associated with peacefulness and calm across cultures (Cyr, Head, and Larios 2010). In the advertising domain, blue is associated with trust (Cyr, Head, and Larios 2010), competence (Labrecque and Milne 2012) and produces stronger buying impulses than red (Bellizzi and Hite 1992). On the other hand, Kwallek found that in room colors, blue was more likely to be associated with depression, and red with anxiety (Kwallek, Lewis, and Robbins 1988). Clearly, context is a critical moderating factor in these studies.

Previous research studies found that longer wavelength colors like red and orange are more arousing while shorter wavelength colors like green and blues perceived as calming. Most color research has focused on hue rather than saturation and lightness, although researchers now recognize the importance of the latter properties (Elliot and Maier 2014; Labrecque and Milne 2012). Lichtle's studies show the influence of lightness and saturation on affective response (Labrecque and Milne 2012). Highly saturated colors are exciting and intense; desaturated colors are calmer and less dominant. Cyr found greys considered as "serious" and "professional" (Cyr, Head, and Larios 2010). Lightness is associated strongly with calm (Valdez and Mehrabian 1994). Valdez found that lighter colors are considered more pleasant, less arousing and less dominant than darker colors. Black is negative and dominant (Madden, Hewett, and Roth 2000; Valdez and Mehrabian 1994); dark browns are sad. In one study, subjects were less upset when they read about murder on light pink paper than on white (light purple is lowest dominance) (Valdez and Mehrabian 1994). These findings may be useful when hue choice is limited by branding or other assignment, because lightness and saturation can be altered without contravening categorical meaning or desired "personality" (Labrecque and Milne 2012).

As Lyn et.al has suggested (Lyn, Abhisekh, and Maureen 2017) relatively little research has examined color palettes and effect. Madden identified two strategies of color association in logo design (which colors are used together): consistency (colors have a similar meaning) and complementarity (each color, is associated with a different meaning) (Madden, Hewett, and Roth 2000). He found a consistent pattern of color clusters that emerged for each country. The most striking patterns are the clustering of blue, green, white and of black and brown. The blue, green, and white clusters indicate that they share similar meaning associations. In all countries, blue, green, and white are tightly linked with peaceful and calming. Across many cultures black and brown strongly associated with sad and stale. The color red is perceived as unique in terms of its meaning and consistently associated with hot and vibrant. Madden' results (Madden, Hewett, and Roth 2000) showed that when blue was used as the designated logo color, it was most often paired with white, green and yellow (largely a consistency strategy). In contrast, when red was the designated main color, respondents preferred a complementary strategy, with the secondary colors different across cultures. When green was the focal color, the strategies varied. Their results indicate that in many parts of the world, consumers exhibit similarities in color liking and color meaning associations. How colors are blended for logos, shows that cultural similarities and differences exist in the ways consumers select color combinations. These results show that there exists a pattern of both similarity and dissimilarity in cross culture color preferences and mining associations. Such cross-cultural differences have tangible effects on consumer behavior and due to the presence of such patterns; the possibility of managing color for better communication strategies for brands communication and the study of impact of colors on consumers and web design has been extended.

## 2.2. What is Affect and its impact in Visualization?

Affect is a feeling or a response generated due to its surroundings or a visual impression. This definition of affect can vary between different people and can span a range of basic to complex emotions. Recent research has identified emotions that are comparatively consistent and as identified by emotion theorist they are termed as “Basic Emotions”. These emotions include anger, disgust, fear, sadness, sensory pleasure, surprise, joy, worry, courage, pride, shame and guilt (Ekman 1992). These basic emotions are distinguishable and avoid overlapping. Affect is also defined as “neurophysiological state consciously accessible as a simple primitive non-reflective feeling most evident in mood and emotion but always available to consciousness" by Russel (Posner, Russell, and Peterson 2005). Further, researchers have developed numerous dimensional models to classify emotions; the most widely accepted is the circumplex model proposed by Russel. According to this model, the affective space is composed of two orthogonal and bipolar dimensions – valence and arousal. Affective states lie along the perimeter of the circle defined by the two axes and various affective states combinations of these 2 basic constituents.

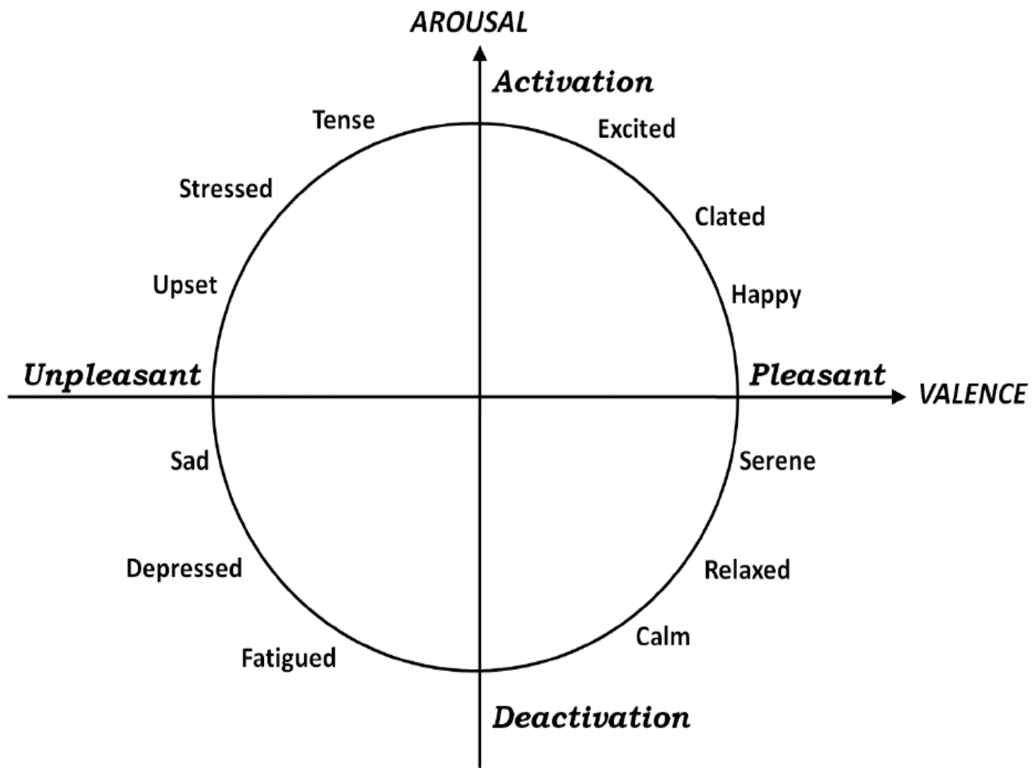


**Figure 2.1. Circumplex model of affect is composed of two orthogonal and bipolar dimensions. One is the valence (a pleasure –displasure continuum) and second Arousal or alertness.**

The valence dimension is also known as pleasantness dimension while the arousal dimension concerns the intensity of the emotion. In the PAD model an additional dimension of affect has been identified known as Dominance (Mehrabian 1996). Dominance was attributed for parts of the affective states that were related to social orientation and control. Dominance is related to aggression and provides a way to distinguish between affects that are similar in the arousal and valence dimension, like fear and anger. The study by Russell (Posner, Russell, and Peterson 2005) showed that two dimension (shown in figure 2.1) in the circumplex model Pleasure and Arousal account for the major portion of the affective states and is more consistent based on recent findings from affect studies.

The PAD scale used in consumer research studies looked at the effect of color on consumer behavior. Other studies, like Vaez et al (Valdez and Mehrabian 1994) conducted, found positive correlation of brightness and saturation with pleasure and arousal while dominance has a negative correlation to brightness. The circumplex model has been further used in the development of picture stimuli, the Internationally Affective Picture System. It is a large set of color photographs which are capable of stimulating and evoke emotional feelings. Humans rated these images for pleasure arousal and dominance. It currently includes more than 1000 images of human experience- joyful, sad, fearful, angry, threatening, attractive, ugly, dressed and undressed people; house, art and many other categories characterizing emotion stimulating images.

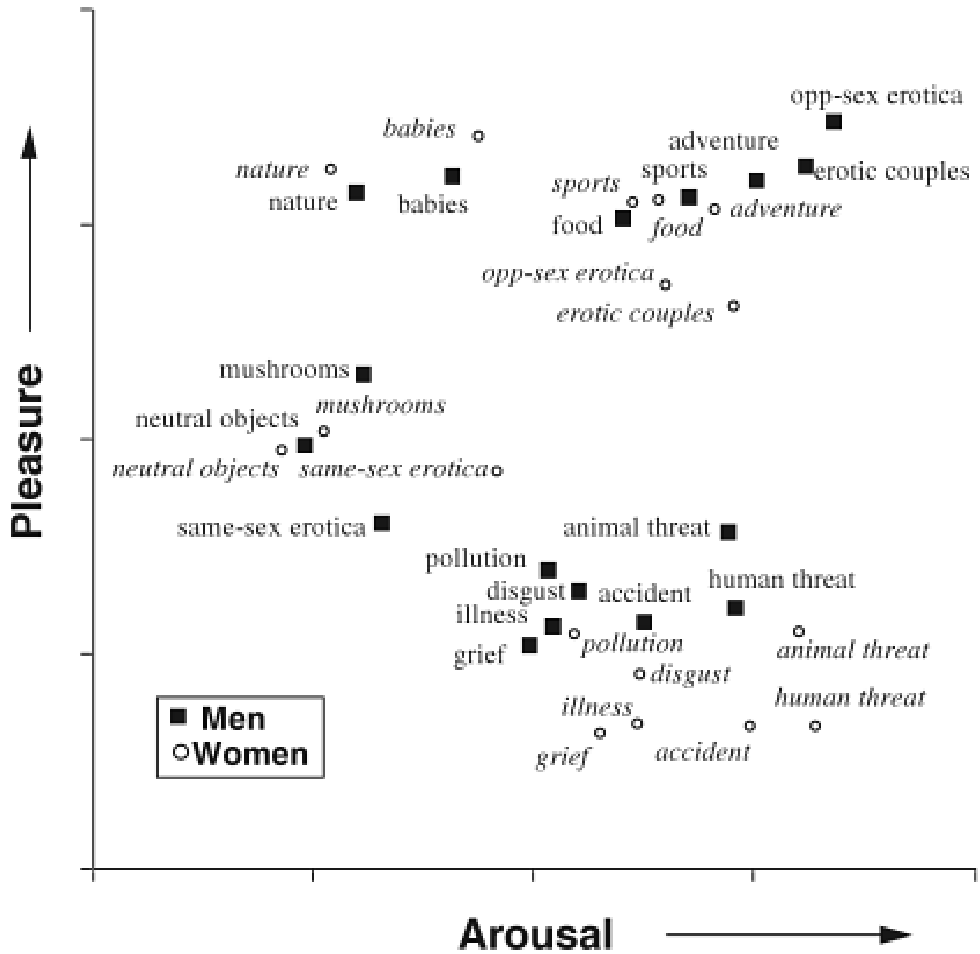


**Figure 2.2. IAPS Images-Affect Responses.**

These pictures help to control the emotional impact when investigating the effects of hedonic valence. To measure pleasure and arousal, they used the Self-Assessment manikin tool. Machajdik et.al (Machajdik and Hanbury 2010) used the IAPS images as a training set in her study for identifying visual features to classify affective images. They recognized that color features become a much more important factor when identifying emotion patterns in art and abstract sets. We used similar approaches of using abstract and natural artistic images to detect color patterns and design color palettes for further studies.

## 2.3. Affect in Design and Information Visualization

Designers have used visual features like color; type and animation into data visualization design to elicit empathy (Cairo 2013). As described by (Boy et al. 2017) empathy is “an affective response appropriate to someone else’s situation rather than ones own”. Affective expression is a critical aspect of visual presentation as it relates to experiencing an emotional state making visualizations more expressive. Researchers have explored and studied the importance of art in information visualization (Lau and Moere 2007) drawing inspiration for analyzing how abstract shapes and motion create affective responses in information design (Lockyer and Bartram 2012; Lockyer et al. 2015). Motion has pre-attentive characteristics that help emphasize represented attribute. Lyn et al (Bartram and Nakatani 2010; Lockyer and Bartram 2012; Feng, Bartram, and Gromala 2016) explored motion factors (speed, direction and path curvature) and texture as a method to enhance visualization for conveying information with affective contextualization. Users provided affective ratings for factors like speed, direction and path curvature of 2D motion textures and 3D motionscapes. These affective contexts evaluated were valence (positive—negative), intensity (calming—exciting), threat/dominance (reassuring— threatening), urgency (urgent—relaxed) and interest (attracting— rejecting). They found that speed, shape (linear, radial, spherical, and circular patterns formed by motion), and in certain shapes, direction and path curvature all contributed to influence, affect leading to the development of computational models of expressive capacity of motion (Lockyer et al. 2015).

The importance of eliciting emotion in visualization has recently gained traction in visual design. Kosara (Kosara and Mackinlay 2013) points out that in storytelling, news media where is an important scenario where it is important that the presentation created can get a point across for the viewers to understand and also trust the real facts and data. One key point that Kosara point out in such presentations is the need to create interest and raise awareness about the contextual background of the story. Other scenarios include live presentations given to the audience where interaction techniques allow the presenter to carry forward the story. In such scenarios proper annotation, highlighting and animation techniques can be useful to evoke an affective state among the audiences. Kosara additionally identified that artistic visualization along with being expressive in nature also has the goal to invoke personal reflections. Others include Cairo, Lambert Rees and Schwabish and ZerAviv who have also spoken about the role of making data affective in narratives especially related to politics and humanity. Though the importance of affect has been identified in storytelling very few studies (Lockyer and Bartram 2012; Feng, Bartram, and Gromala 2016) till present, have studied and measured the effectiveness of triggering affective states using visual feature considered important in visualization.

## 2.4. Color, Affect and Aesthetics

Designers incorporate aesthetic principles in color palettes allowing them to move beyond functionality and be more expressive. Typically these principles are expressed as color harmony, an attempt to model, which colors work together visually. Color harmony is commonly expressed as geometries on hue wheel, as well as careful control of lightness variation (Itten 1974; Cohen-Or et al. 2006; Wang and Mueller 2008). (Itten 1974) The concept of color harmony is well known and goes back to Itten. Matsuda (Cohen-Or et al. 2006) devised the set of 80 color schemes based on Itten's color theory. It combined different types of hue and tone distributions. Cohen et al used the eight harmonic hue templates that are shown in Figure 2.3.

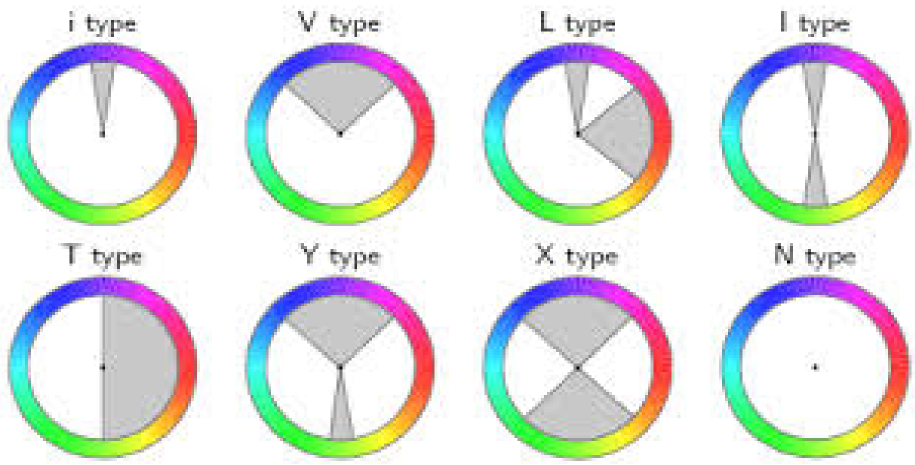


**Figure 2.3. One of the most popular theories in color is the notion of Harmonic Hue Templates. Hue templates are expressed as geometries on hue wheel and are defined independently on the underlying hue wheel.**

Harmonic hues occupy the gray sectors in any of these eight templates. The N-type is only composed of gray hues. These templates are fixed and can be rotated across the hue wheel. Itten (Itten 1974) was a color theorist who focused on harmony of color compositions. Itten formalized the concepts of warm and cool colors, and postulated that tints (light colors) represent the brighter and greater aspects of life, while shades (dark colors) represent the darker, sadder, and negative forces. Itten defines the seven kinds of color contrast: the contrast of hue, light-dark contrast, cold-warm contrast, complementary contrast, simultaneous contrast, the contrast of saturation, and contrast of extension. Itten contrasts have been used in image analysis of affective colors (Machajdik and Hanbury 2010) and aesthetic color selections (Lu et al. 2014). However, his principles of emotional color are only qualitatively and subjectively grounded. In exception, Kobayashi (Kobayashi 1981) provided a system that has 130 basic colors, giving 1170 three-color combinations palettes. Every combination is identified with one of 180 high-level semantic concepts, like ”elegant”, ”romantic”, ”provocative”, etc. Moreover, words are located in a two dimensional semantic space, and arranged into groups based on perceived similarity. Kobayashi was a color theorist who’s Color Image Scale of color association with linguistic concepts is well-received in art and design practices. Kobayashi defines a meaning scale to relate “worlds of people and objects with worlds of colors” and terms it Color Image Scale (Figure 2.4). This scale comprises of two bipolar dimensions, warm-cool and soft-hard. Kobayashi’s scale has significant contributions to visual design: it is based on 3-color combinations (3-color palettes) and single colors; it also relates these 3-color combinations with two levels of abstractions, one with 180 semantics, and the other with 15 higher semantics.

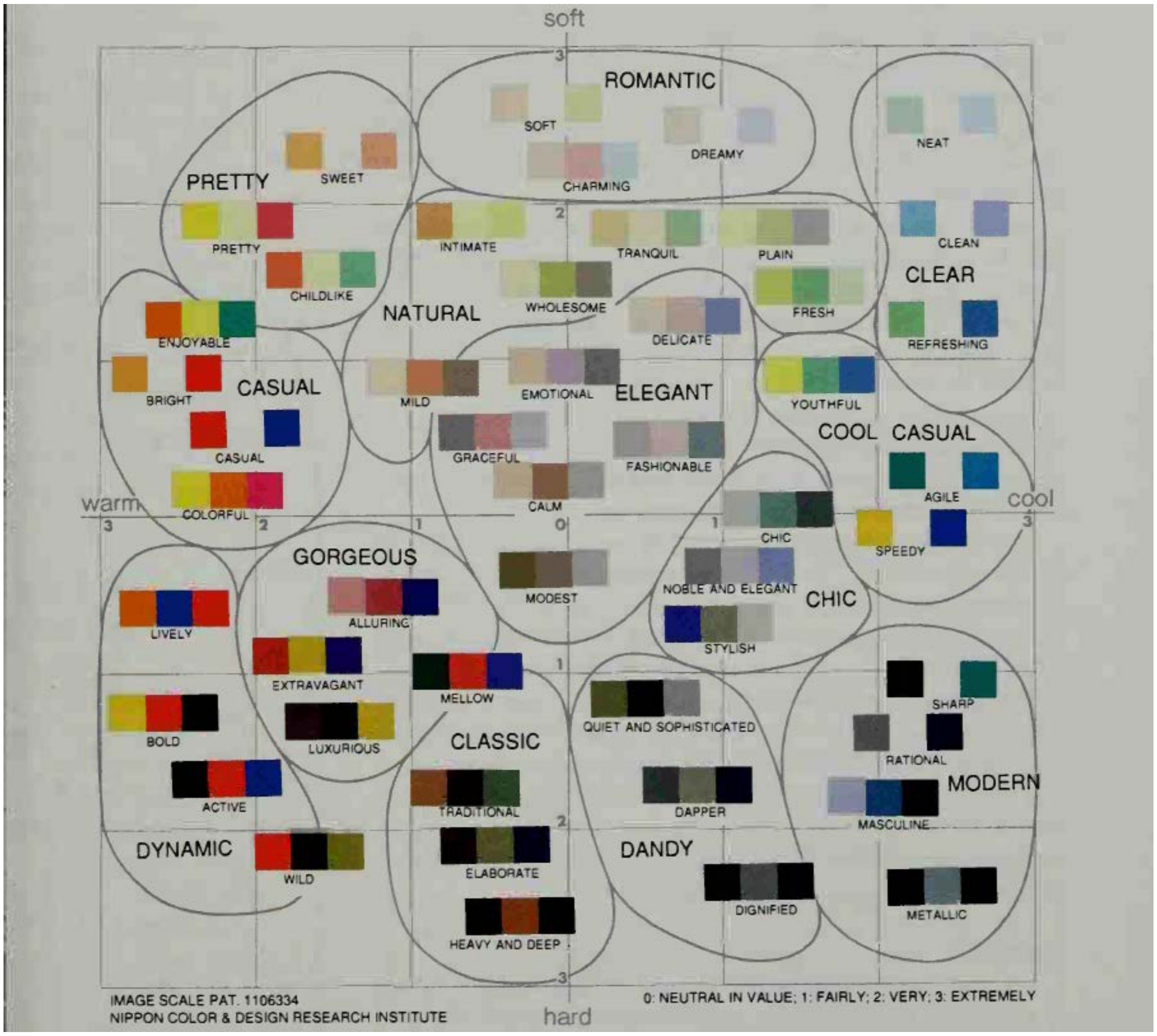


**Figure 2.4 Kobyasachi Color Scale provides color-concept associations as the basis for palette design.**

A lower level of abstraction was identified between the relationship of a color combination and a single word. On the higher level of abstraction, these combinations fit in the 2 dimensional space along the axis representing hard–soft and cool-warm Figure above illustrates the concept. Recent work in computational aesthetics focuses on automatic palette selection algorithms using these concepts of color harmony (Machajdik and Hanbury 2010), perceptual contrast (Kim et al. 2014) and keyword-color scales

(Solli and Lenz 2010). (Cohen-Or et al. 2006) The algorithm developed by Cohen et al. accepts any image with a likely nonharmonic hue distribution (histogram) and next it finds the closest (rotated) harmonic hue template. Then it uses an optimization algorithm to redistribute the hue across the image such that it fits the nearest harmonic template. The algorithm only considers hue, and does not consider the impact of saturation or lightness though higher saturated pixels receive more weight in the template matching procedure due to perceptual saliency.

## 2.5. Palettes in visualization

In Data visualization to convey quantitative information color selection tools are crucial and not used for just an aesthetic choice. When properly selected in data visualization colors communicate the underlying data accurately as compared to many color schemes commonly used in visualization that change relationships between data values. Color is important in visualization to help discriminate between categories, indicate more or less of something or perhaps to serve as a pop out effect. Color palettes are a common part of the design of all forms, including visualization and information design. Good palette design requires attention to basic color perception. At the minimum, colors must be visibly distinct, both with respect to each other and with respect to their background. Even this question of distinctness has some subtlety, as it includes factors like size and background (Stone 2003; Brewer 1994). Properly being able to distinguish different colorings is especially critical in data visualization, where the color indicates a property of the data. Data visualization, there are established rules about color palette properties and the data they label. Categories are expressed by distinct hues, quantities by sequences of related hues. These rules are well expressed in Cynthia Brewer's work in cartography, which are codified in her online tool the ColorBrewer (Brewer 1994). Cynthia Brewer designed an online tool to help users identify appropriate color schemes for maps. A total of 35 color schemes divided into 3 groups, qualitative, sequential and diverging were designed to produce attractive color schemes. For sequential they used lightness steps to imply order. For diverging they varied both hue and lightness. The sets of color schemes were designed using experience. For the qualitative schemes, they provided a small number of colors that are more saturated, darker or lighter than others in the scheme. Perceptual guidelines like differences in luminance and saturation may suggest an ordering in colors and should be avoided for qualitative palettes. However, designers still had to be aware of emphasizing certain colors when using these qualitative sets. This provides designers with practical guidelines for informing color choice based on data type, the number of classes, and perceptual constraints.

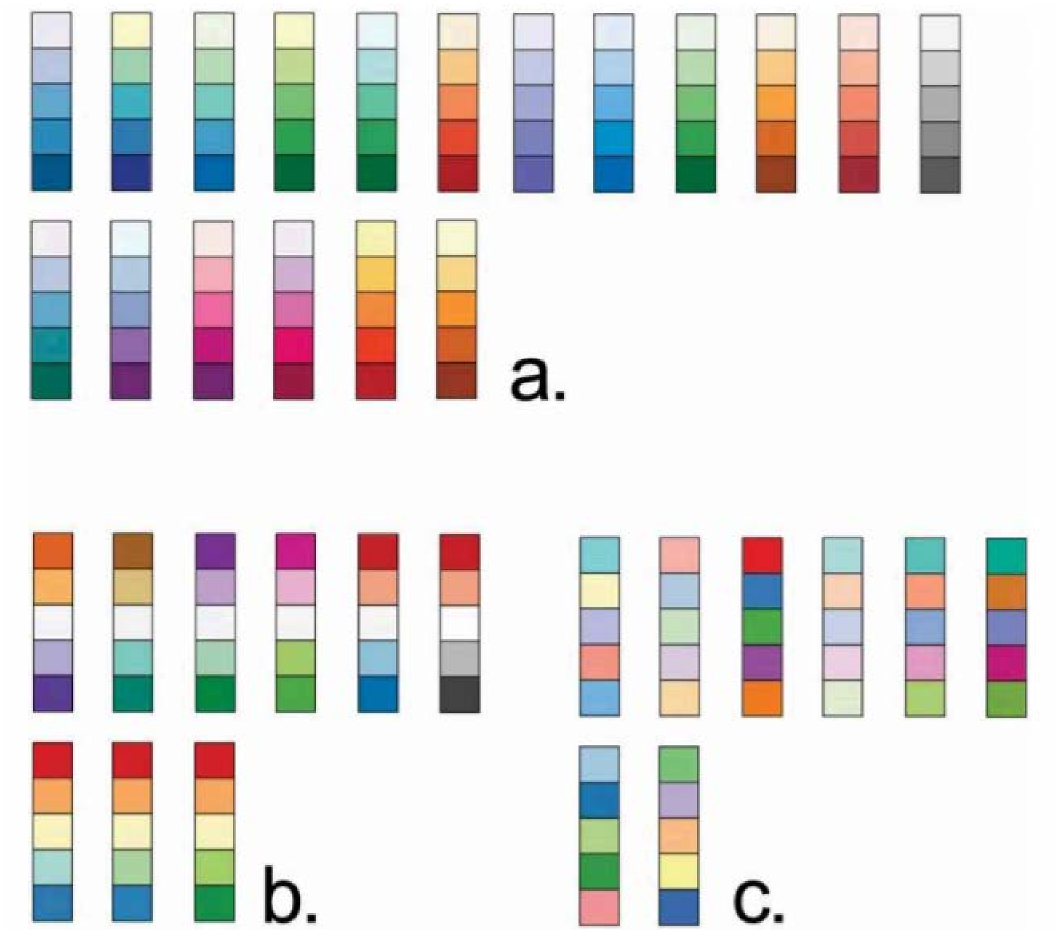


**Figure 2.5 Palettes in visualization have well validated perceptual principles. Color Brewer Palettes a. Sequential b. Diverging c. Categorical.**

Other studies have provided us practical guidelines (Healey 1996) such as colors should be well separated and should not compete with each other. Consecutive informational collections are orchestrated from high to low. Low information qualities are generally spoken to by light hues and high values spoke to by dark hues. Landscape incline classifications or populace densities, for instance, are very much spoken to by sequential palettes. Diverging schemes demonstrate data outward from a basic midpoint of the information extend. A diverging scheme has two different sequential palettes that diverge from a shared lighter color toward dark colors at each end. An example of deviation above and below from the median death rate is well represented by a diverging color scheme. Qualitative schemes use diversity in hue to represent nominal variations or differences in kind. The lightness of the hues used for qualitative categories should be similar but not equal. Allocate the lightest, darkest and the most saturated hues in the design to categories that can emphasize the representation. Data regarding classes or city districts are well represented using qualitative color scheme. User studies of Brewer scales (Harrower and Brewer 2013) explored colored target identification capabilities and found that users did well when the number of colors was 5 or less.

## 2.6. Palette Properties and Evaluation

Color choices are important for setting the right impression in art and design. There are various online communities like Adobe Kuler and ColorLovers.com that allow designers to create and share good color combinations know as themes. In our work we study color preference in creating an affective impression for categorical information which includes a small set of 5 colors. Following Lyn Bartram (Lyn, Abhisekh, and Maureen 2017) we model color preferences using color frequency similar to Lyn et al social network analysis.

Previous studies have used proposed quantitative metrics for evaluating palette quality based on aesthetics (O'Donovan, Agarwala, and Hertzmann 2011) and compared Kuler hue templates with Mastuda Hue templates (figure 2.6), color naming models (Heer and Stone 2012) and palette overlaps and palette distances (Lin and Hanrahan 2013). hen all values of hue angles are identical and highest when they are uniformly spread.

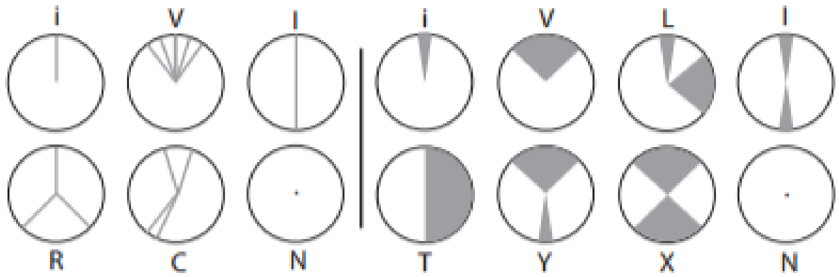


**Figure 2.6 Hue templates implemented in Kuler (left), and those from Mastuda.**

Instead of modelling themes with aesthetic ratings we use hue entropy approaches as O`Donovan to look at color clustering characteristics across affects. (Heer and Stone 2012) Heer et al., Introduced a probabilistic model of color naming that learned from 330 colors in the World Color Survey. Using a distance metric defined between two colors as the distance between the associated name distributions they sought to minimize name overlap and maximize salience. This model was used by Lin et al, (Lin and Hanrahan 2013) as potential predictors for extracting themes from images. They found that color nameability was less effective possibly due to use of less highly nameable colors in photographs. Other metrics proposed by Lin et al, include the distance of colors in themes in CIELAB. Exploring the space of color themes is difficult problem with little or no previous work. We explored hue entropy and distance metrics for themes to find color patterns for hue choices with respect to affect. One simple solution was to look at min and max distance of hues by taking the sum of all the hues in each theme generated in our study. However, the approach does not explain the relationship between colors or why certain color combinations have more preferences. Instead of using color distances Lyn et al developed  social network metric for explaining color preferences in palettes which shows network combinations of which colors are more preferable in designing affective impressions for visualizations.

## 2.7. Semantic Color

Colors augment cognitive abilities due to its physical attributes like name, meaning, and values. A good color design must respond to contextual framing that includes semantic, cultural, and stylistic expectations. It is essential to understand the role of color semantics analysis and synthesis of visual designs in HCI we discuss in the following subsections.

The foundational work that explains linguistic categorization of colors is perhaps the work of Berlin and Kay, noting that color naming is universal and related to evolution (Berlin and Kay 1969). Berlin and Kay work is very influential and continues to be tested by a wide range of studies. The project was aimed to describe a robust method for establishing likely basic color terms of language. As Kay and McDaniel (Heer and Stone 2012) summarize, that in color naming the two main misunderstandings among linguists were that color naming is a matter of cultural relativism and that semantic primes in languages are discrete entities. Berlin and Kay proposed that there is a restricted universal set of color categories that evolve with language. Research shows strong links between color and language, beginning with Berlin and Kay's foundational work in color naming (Berlin and Kay 1969). Their studies showed that all cultures have common concepts of a small set of basic colors and their verbal names mean the same across languages. The binding between color name and comprehension is demonstrated by the Stroop effect: when font color conflicts with the color described by the word, it is harder to name the color of the letters. Heer and Stone used the XKCD color name dataset (the world's largest) to build a probabilistic model of color naming (Heer and Stone 2012), showing how it can map between colors and names and measure color similarity. In recent work, Heer and Stone (Heer and Stone 2012) reviewed statistical color naming models, with the goal of fitting a model to single colors and their associated names. These associations are either from human judgments or retrieved from Internet search engines. They applied this assess and evaluate palette design, where reducing name overlap and increasing salience are important for color comprehension and memorability. In visualization, work by Lin et al (Lin et al. 2013) and expanded by Setlur and Stone (Setlur and Stone 2016) explore the relationship between color palettes and semantics. Lin et al discovered semantically-resonant colors in which a word or term relating to an object or category elicits strong color association (e.g., Green for "money", yellow for "banana") (Setlur and Stone 2016). They apply this concept of semantic color associations to the design of effective categorical color assignments for visualization and found these assignments significantly improved chart reading. This is one of the key things to be aware of that when choosing colors for data visualization it is better to use semantically resonant colors.

More recently, Setlur and Stone (Setlur and Maureen C Stone 2016) developed algorithms to automatically select semantically appropriate color schemes for categorical palettes, based on a measure of colorability that describes how strongly associated a given term or identity is to any of a set of basic color terms. Heer and Stone (Heer and Stone 2012) suggest that using color categorization principles (in the concept of color naming) in user interfaces that model human category judgments, it might demonstrate more meaningful and novel user interactions. They successfully applied this to automatic color assignment for canonical objects and brands. These algorithms explore the rich associations grounded in the concept-color relations of objects and identities, but have not been applied to more nuanced terms of emotion, atmosphere or affect.

Lindner et al (Lindner and Süsstrunk 2013) use Google n grams to generate a large vocabulary of frequently used words and then download 60 images related to the word using Google image. The user described the semantic content and the color extraction algorithm determines the appropriate colors from a pre computed color thesaurus that matches a word to its underlying distribution in HSV. Then they used hue templates to create color palettes associated with that term. In a small user study, they compared their palettes to Adobe Kuler's user generated palettes, and found no significant improvement, concluding that there is a significant influence of personal taste in color palette preferences.

## 2.8. Color Semantics, Emotions and Preferences.

Researchers have attempted to derive color meanings, to understand the emotions and moods evoked by colors and how feelings about colors can influence our performance (e.g. See (Mahlke and Thüring 2007) and (Lin et al. 2013)). From a psychological point of view, for instance, Crozier (Crozier 1996) argues that theories of preference based on innate and learned reactions should be considered while studying color meanings. Crozier summarizes that red, for instance, has the innate mood of the alert signal and also is involved in sexual behavior in many species; or white is learned to be associated with purity in some cultures. Although Crozier acknowledges that the like-dislike bipolar scale in prior studies is a useful measure to investigate color moods, he argues that meanings of individual colors should be considered within the context (syntax, semantics, and culture) in which they are examined, also adding other factors such as age and gender. Later, Ou et al. (Ou et al. 2004) studied color emotions and color preferences to clarify the relations between them. Although their studies agreed with prior work in defining scales of warm/cool, heavy/light, and active/passive, they found notable differences in the like-dislike scale between their two groups of participants, who were Chinese and British. They also found a tendency for their participants to prefer color combinations that hold opposite emotions. Previously little work has used images and image scene categorization like content analysis using affective retrieval and classification of digital media for analysis of the emotional impact of color. (Machajdik and Hanbury 2010) Et al used theory from psychological studies and art to extract image features for emotion recognition in images. They adopted the standardized pleasure-arousal-dominance transforms a color space, image composition features such as low depth of field indicators, colorfulness measure based on EMD, the average contrast of brightness,  contrast of saturation, hue content and spread, low depth of field and proportion of skin pixels in the images. Generally, these studies show that visual feature of an image includes shape, color, composition etc. Among these features, colors have been shown to play an important role in image affective analysis (Machajdik and Hanbury 2010; Kobayashi 1981).

## 2.9. Color metrics

A key element of studying color relates to appropriate frameworks and metrics for computational modeling and evaluation. Perceptually-based color metrics, interpreted as geometries in a three-dimensional color space, expressed as hue, saturation (or chroma), and lightness. Research in this area commonly uses the CIELAB color notation, expressed as Hue, Chroma and Lightness (L*). We are using the cylindrical model of CIELAB space, which uses polar coordinates on the a*, b* plane. C is the radial distance, H is the angle. The CIE notation for this is LCh, but we use H. These describe perceptually uniform scales for distinguishing individual colors. Quantitative measures to represent and to evaluate color combinations (palettes) are more complex. O'Donovan studied palettes of size 5 by exploring color distances in color themes extracted from Adobe Kuler (O'Donovan, Agarwala, and Hertzmann 2011). (O'Donovan, Agarwala, and Hertzmann 2011) Analyzed color palettes where they used color distance metrics to extract distinct palettes from images. These included mean, min and max distances between colors in themes in the CIELAB space. Two quantitative approaches to measuring hue variation (how distinct the colors are in a palette) are entropy (O'Donovan, Agarwala, and Hertzmann 2011) (how distinct the colors are) or saturation-weighted hue (WHD) (Prip and Hanbury 2003), which calculates the angular dispersion between hues along the hue wheel, taking saturation into account (a more accurate measure of distribution in the space).

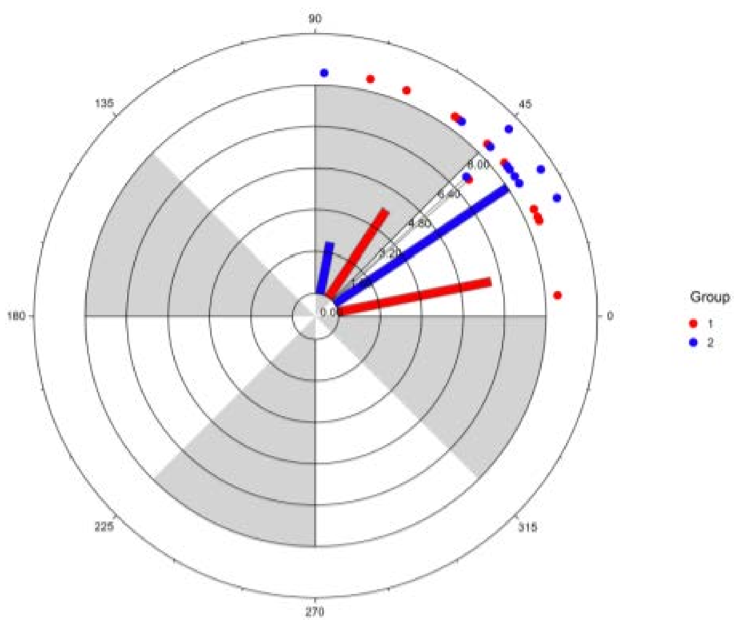


**Figure 2.7 Example of Circular statistics (Fisher 1995)**

Finally, methods such as k-means clustering is commonly used to model color associations (Lin et al. 2013). Designers also approach the problem of reducing complex visual by varying visual parameters such as transparency (Lyn Bartram, Cheung, and Stone 2011). Lyn et al established an range of alpha for overlaid grids in visualization that are strong enough to reduce the visual clutter. These experiments point that alpha is an important visual element that has been used in showing uncertainty by making unclear objects less opaque.

## 2.10. Measuring and Evaluating Perceptual properties

Scanning visually for cognitive processing are two fundamental components of working with any visualization. Researchers in perceptual studies have used gaze-based techniques which focus on information visualization where the user's main task is to compare and visualization and perform lookup operations.

Lyn et.al (Bartram, Cheung, and Stone 2011) used visualization design task where users were required to adjust grids transparency over images to measure perception and visual working memory activities. Using artists and designers, they attempted to define a metric "just attainable difference" that draws equally from perceptual methods and design practices. Lyn et.al, used a standard LCD computer monitor and presented users with a series of images which users would adjust the grid transparency as per their satisfaction. These studies borrow from artist and designers tasks who manipulate visual cues to quantify structures which are otherwise challenging to quantify in an applied context. Lyn et al. carefully attempted to measure levels of legibility in overlaid grids using an empirical study that borrows from perceptual methods and design practice of artists and designers on the other. Recently, it was also found that it is also important to consider the judgment of visual experts such as artists, graphic designer or illustrators and can be used in combination with techniques such as sketching or designing (Acevedo et al. 2008). They created a framework for evaluating visualization methods for a given scientific challenge through feedback from expert visual designers and art experts. For measuring the effect of visual cues in the visual representation of single-valued data visual designers evaluated a set of design factors which were collected to build a model of effective visualization methods. Recently Lyn et.al (Lyn, Abhisekh, and Maureen 2017) developed color-affect preference models using social network analysis to (Lyn et al. to) provided us with an effective means to improve affective impressions in visualizations. These models were drawn from the results of studies using perceptual design task which were statistically validated.

Reporting the subjective experiences such as preferences or emotion via rank based studies have been used in psychology and affective computing (Yannakakis and Martínez 2015). Previous studies in affective computing have shown the advantages of rank based emotion studies and recommend that for self-reporting it is suggested that subjects should provide ranks for the contents they experience. Ranking based emotion builds on studies by (Yannakakis and Martínez 2015) which have shown that there are limitations when using ratings for subjective assessment and provide empirical evidence for the superiority of rank-based questionnaire schemes for subjective experience.

# Chapter 3.

# Goals and Approach

As Bartram et al point out (Lyn, Abhisekh, and Maureen 2017), while there is a long history of research and practice in how certain visual elements relates to affect, there is as yet no comprehensive framework grounding visualization principles for affective representations. Previous studies by other researchers in the fields of color in the arts, psychology, and digital communication, as described in Chapter two, have suggested that color can be highly useful in both effective cognitive interpretation and also in a communication of affect in different.

In this research, we focus on understanding whether affect influences the choices of colors in a five color categorical palette in information visualization. These color choices relate to the overall impression the visualization designer wishes the viewer to get. While most color- semantic associations are based on mapping color with semantic space, we explore whether color associations along valence and arousal dimensions of the PAD space can be mapped to color properties. We identified eight affects of interests. The four cores affects Calm, Exciting and Positive, Negative representing the valence and arousal dimension of the PAD model. To further explore whether certain affects reflect the relative influence of core affects we selected four pragmatic affects. Considering the importance of impressions important to narratives tones in visualization, we selected: Serious, Playful, Trustworthy and Disturbing. By conducting an experimental study base, we sought to develop a link between affect and color that can be computationally defined and visualized in the context of visualization. The motivating goal of our research was to examine the affective capacity of visual features such as color as part of this emerging framework and lay the guidelines for the use of colors in evoking affect in information visualization.

## 3.1. Research Goals and approach

Our research focuses on the expressive capacity of color to convey or enhance affect in visualization, and more specifically on whether we can define affective palettes for categorical data visualization that reliably reproduce results from psychological and design experience.

Our initial research questions are whether people choose distinct color and palette properties to convey different affective impressions, and how these choices may apply to categorical palettes in information visualization design. We are interested in both aggregate perceptual properties (such as lightness or chroma) and what we think of as palette characteristics (color dispersion, clusters). Our Second research question was what might this mean operationally for the design of affective color palettes that are useful in designing categorical information visualization? Can we derive guidelines for how color can be manipulated to enhance a desired affective impact or minimize an unintended one? We conducted three studies to explore these questions: an analysis of creative imagery tagged with relevant affective terms, and three subsequent user experiments in which participants selected color palettes for simple information visualizations to communicate certain affect and later ranking palettes derived from the results of previous user studies. We detail these color–affect relations in the following three studies.

### 3.1.1. Determining key affects for analysis

To explore the first research question we select a limited set of 8 affects from the PAD model. In the PAD model, basic emotions as identified by research in emotion includes anger, disgust, fear, sadness, sensory pleasure, surprise, courage, joy, worry, disgust, pride, shame and guilt. For the study in this thesis, we had to identify affect within the PAD dimension that would fit into the communicative scope for information visualization. As suggested by Lyn et al (Lyn, Abhisekh, and Maureen 2017) it is a challenge to identify the specific emotions for communicative context as feelings may be highly contextualized is difficult. For the purpose of this thesis as suggested by Dr. Lyn Bartram, we expand our operational definition of affect to an experience or feeling due to a visual impression that may be of interest to visualization community.  Rather than attempting to define a much finer-grained representation of emotions like the happy or sad following (Lockyer, Lyn Bartram, and Riecke 2011) we looked at four core affects valence (positive/negative), arousal (calm/exciting). We were interested to see how the color palette maps along the valence and arousal axis. They are also interesting representations of affects that designers of visualization are interested in creating. Further as suggested by Lyn Bartram  (Lyn, Abhisekh, and Maureen 2017) we were interested to see how the color grouping would overlap when we have affects that can be a combination of our four core affects.  Following this, we added four more pragmatic affects: Serious, Playful, Trustworthy and Disturbing. These affects can be considered as combinations of the core affects. Disturbing is Exciting+Negative; Playful is Exciting+Positive; Trustworthy is Calm+Positive; Serious is Calm+Negative. Disturbing and Playful are affects of interest in visualization design for narratives and storytelling while Serious and Trustworthy affects that may be of importance for visual design in business communication.

### 3.1.2. Determine the key factors that group affective images

In this research, we were initially interested in evaluating sets of abstract and artistic images that were designed by artist and designers. The goal was to understand how designers and artists use color to convey affective impressions in images. We began our inquiry into color palettes by analyzing images in two large social network databases, Flickr™ and deviantArt. People including designers, artists and photographers share a lot of content in the form of images which are personal or everyday scenes, visual designs or simply abstract art.  These images are very different from one another and still depict the same emotions as tagged by users. Analyzing the content of such images can give insights into general patterns of design that can evoke emotions. Our goal was to find significant differences in the lightness, chromaticity and hue range of images associated with each of our affect.  As previous research has shown that human faces in images can powerfully draw attention and the expression of the human face is also responsible for setting the mood of the picture, we tried to avoid images with human content in it. We decided to mine for abstract images and images that depicted natural scenes where designers amplify visual cues to set the mood of the scene. Like Flickr, deviantArt is another online design sharing platform where designers share visual designs and are subsequently rated and tagged by users. We used Flickr's API services to query for images using the keywords generated. We then store the results which are first sorted by the interestingness to make sure we have images that were relevant to the emotional keywords and retrieved on priority. We finalized the emotional categories and then we search for images using the affective keywords and synonyms of the keywords. Similar to Flickr devianArt provides an API to mine their database for images. Dr. Gornik from devianArt helped us mining the image database by developing queries for collecting image data relevant to our affective keywords. The approach was based on the speculation that some affects might be similar in chroma and lightness and we may see differences in hue distances. Prior research has shown that color, features become much more important features for the artistic and abstract photos (Machajdik and Hanbury 2010). Second, we were interested in extending semantically resonant palette design to affective concepts (Lin et al. 2013).

### 3.1.3. Determine Color preferences and patterns

We believe that there are identifiable color attributes (lightness, chromaticity, and hue) in images that are manipulated by designers to convey a certain meaning and impressions. The goal of the second and third design studies focuses on understanding the choice of color attributes in information visualization influences the impression people get from the visualization. We measured this with two types of screen-based design experiments. We asked designers to select five colors for visualizations to create an affective impression that was intended to communicate and how well the color palette helped in perceiving it. In a later study with crowd sourced nondesigners participants, we ran a similar experiment to study how their color choices correlate with colors identified by designers to encode affect. After this, we generated palettes considering the computational models developed using features extracted from the user study and validated them through online studies. Our motivation was to understand and characterize the dominant patterns that might enable us to develop operational features for automatic recommendations of color combinations for the affective communicative intent and algorithmic manipulations of perceptual properties to enhance affect.

## 3.2. Overview

Chapter 4 covers the image analysis study, and the Chapter 5 covers the color palette study. A Total of 3 experiments and one image mining done through studies which are organized as follows:

- Image Mining
  - Image Data Analysis
- User Selected Palettes
  - Experiment 1 with designers
  - Experiment 2 with non-designers
- User Ranked Palettes
  - Experiment 3 with users ranking palettes

## 3.3. Image Data Collection and Analysis

In an initial image analysis of 12,000 images from Flickr and deviantArt.com, mostly abstract, we ran a statistical analysis to find distinct differences for color properties across our affective tags. Our dataset of the image covers includes 8608 images from Flickr and DeviantArt. We collected approximately 1076 images for each affect category. We attempted to collect eight different affective categories. We expanded our search queries by using synonyms of the affect and assumed that since most of the designs are rated and tagged by users, it will help us diversify the type of images. To avoid conflation with content in the images, such as human faces, we selected abstract images for approximately 2/3 of the set. We used the results identified from this study, which includes lightness and chroma to the development of color palettes for subsequent user studies.

## 3.4. User Selected Palettes Study

In this research, we were interested in evaluating whether users would consistently select different color sets for our eight affective categories in the visualization design study. Based on our image analysis, we developed affective color palette consisting 36 colors for the first design study and 41 colors for the second design study. The palettes were developed by a visualization color expert. The palettes are used in the two web-based user studies, first with designers and second with non-designers. We analyzed the results further to determine whether certain kinds of palettes (sets of colors) are more likely to be chosen to convey affective impressions. Each study used the same method and metrics and explained in detail in chapter four. We captured color choices made by users for representing affective impressions on simple visualizations. In our first user study, users were designers or had some design background selected from design schools and the community. After the first study, we realized that our palette was missing some dark colors. Hence we added additional five colors to make a total of 41 color palettes for a second study. Users in our second study were mostly non-designers. For the color choices made we analyze the properties identified from images study, which includes lightness and chroma. We also analyze patterns across palettes by looking at the features of hue dispersion and analyze hue clusters for a given affect. These color properties have been discussed in the next section.

## 3.5. Color Properties for Investigation

Determining the emotional elements of colors requires understanding our eight affective categories and the context in which they carry messages. Studies have shown that use saturated colors elicit physiologically arousing emotions (Valdez and Mehrabian 1994). Cool colors are considered calm and soothing. Findings revealed that brighter colors like whites and light grays and light colors are more pleasant, less arousing and less dominance inducing. We believed designer might vary saturation to regulate arousal and while lighter colors used for controlling valence. Another generalization from previous studies included that darker and more saturated colors are likely choices for eliciting displeasure and high arousal (Labrecque and Milne 2012) (Mehta and Zhu 2009). Features like brightness, saturation and hue spread and histograms have been found to be effective in determining affective patterns for artistic and abstract images (Machajdik and Hanbury 2010).

However, these are not the only factors that influence designer color choices the hues and combination of hues also matter (Cyr, Head, and Larios 2010). We were interested to know what colors are preferred and how colors combined by designers would translate into multi-hued palettes in visualization. We were curious to learn and how the colors would combine for our pragmatic affects where we expected core affects to combine. For example, Disturbing and Negative both being closer in the emotional space the colors chosen to convey this affect might be similar and for example may use dark colors to convey the context so similar in lightness. But it might be a different approach when it comes to using hues where a designer can vary the saturation levels for the colors when making for disturbing where it is more in the dimension of dominance as compared to negative. Conversely, for high arousal affects like Exciting designers may prefer certain hues and which are highly saturated. Hue dispersions and how far the colors are in the CIELAB space may suggest hue preferences and patterns. Hue is measured in a circular way (in degrees), vector-based, circular statistics were used to compute measurements like hue spread (Prip and Hanbury 2003). But the general hue is difficult to measure, and there are very metrics available to measure and access hue preferences or combinations. To analyze hue clusters and hue preference, Dr. Lyn Bartram in collaboration with Maureen Stone developed (Lyn, Abhisekh, and Maureen 2017) network graph metrics that were used to model hue preferences. Since we were also interested to see whether affect would actually affect transparency choices we considered tracking transparency by collecting the alpha manipulation.

Therefore, we considered the following properties in our study to analyze images and palettes from user research.

- Lightness
- Chromaticity
- Hue Dispersion
- Alpha
- Hue Clusters

## 3.6. User Ranked Palettes

In a final study we validated our findings by generating palettes and asking users to provide us with the best and worst rated palettes for each affective category. For each affective category palettes were generated using insights from the user studies. The palettes designed were weighted using color frequency metric derived from online design study. We then asked users to rank palettes of different weights as to how well they were effective in generating the affective impression over simple visualizations. In the rank based scheme we ask participants to compare 5 palettes over a set of 5 charts for each affect. Reporting about subjective constructs such as a feeling, experience, preference or emotion via rank based questionnaires has recently attracted the interests of researchers in psychology (Yannakakis and Martínez 2015).

In this experiment, we were interested in evaluating how effective were the affective color features in conveying impressions. The study has been discussed in details in chapter 6.

# Chapter 4.

# Image Analysis

Following the work of Lin et al. (Lin et al. 2013), we analyzed images in two large social network databases, Flickr™ and deviantArt.com, to explore whether there were noticeable differences in the color palettes of images associated with our affective terms of interest. The semantic content of the image has the greatest impact on the emotional influence of any picture. Human faces in a picture strongly draw the attention of human observers. We used abstract images to avoid conflation with depictions of content in the pictures, such as human faces or scenes typically associated with emotions (a beach, a war scene). To avoid conflation with content in the images, such as human faces, we selected abstract images for approximately 2/3 of the set. We had two objectives:

- To determine if there were consistent color and palette properties associated with tags, names or comments relating to our affect terms; and
- If there were consistent patterns of color use, to apply these to the development of color palettes for further user studies.

Lightness and Chromaticity statistics were computed because prior studies have shown that the axes of the emotional space pleasure, arousal and dominance are influenced by saturation and brightness (Valdez and Mehrabian 1994). Hue statistics are also computed, as the tone of the image is important.

**Figure 4.1 These are sample abstract images for Calm. (Herrmann 2014; Robinson 2013; Andreas-photography 2008)**

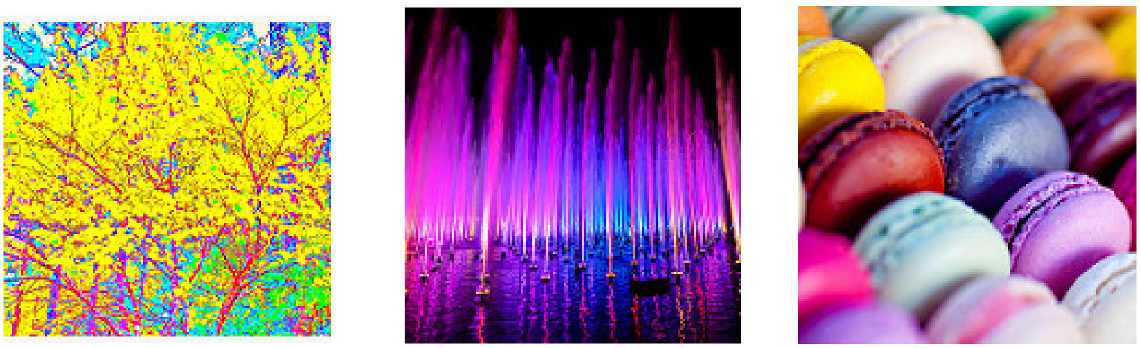

**Figure 4.2 These are sample abstract images for Exciting. (Lefferts 2015; CetusCetus 2013; haler 2010)**

## 4.1. Method, Metrics and Analysis

We analyzed 8608 images, approximately 1076 images tagged for each of the eight affect categories. We expanded queries by using synonyms for the affective words to build an image dataset. We roughly selected five to six synonyms using Thesaurus (Roget's 21st Century Thesaurus, Third Edition 2017) for each our eight affective categories. We crawled the images from Flickr using the publicly available Flickr api. We used the api to pullout images which has associated textual information related to our search terms. These images were also sorted in descending order by their rating. We did a similar exercise with another publicly available api provided by Devianart. We used the Devianart api to form querys that allowed us to mine abstract and fractal artworks that were associated with the search terms we used.

We calculated all color properties using CIELAB. For each image we calculated aggregate mean L* (lightness) and chroma. We then computed distribution of those by using histograms with a bin size of 10 for each, calculating the percentage of pixels in the image that was in the lightness or chroma range of the bin. Finally, based on (Lin et al. 2013) techniques and using k-means clustering, we select the most commonly used colors in each of the affective image sets. We discuss each in turn

## 4.2. Results

**Table 4.1. Significant Effects (Image Analysis)**

| Study | Lightness | Chroma |
|---|---|---|
| Images | $X^2$ (7, 8607) =199.6250, p<.0001 | $X^2$ (7, 8607) =387.7106, p<.0001 |

Our data was not normally distributed. We used a Kolmogorov-Smirnov normality test and the observed value for Mean Chroma of images was D=0.156953, p<.0100* and mean Lightness of the images was D=0.066154, p<.0100* . A Levene's test for homogeneity in variance showed that the assumption of homogeneity in variance was violated for Chroma F(7,8600)=21.3530, p<.0001* and for Lightness F(7,8600)=9.6653,p<.0001*.

As our data distribution was marginally non-normal, we used a nonparametric Kruskal-Wallis test for significance. Table 4.1 show the results.

### 4.2.1. Lightness (L*)

A non-parametric Kruskal-Wallis test showed significant effect of affect on mean lightness $X^2$ (7, 8607) =199.6250, p<.0001. A post-hoc pairwise comparison showed the most difference was significant, except between **Seriously: Negative, Playful: Calm, Positive: Trustworthy, Exciting: Calm, Positive: Exciting,** and **Trustworthy: Exciting.**

### 4.2.2. Chroma

A non-parametric Kruskal-Wallis test showed significant effect of affect on mean chroma $X^2$ (7, 8607) =387.7106, p<.0001. A post-hoc pairwise comparison showed the most difference was significant, except **Trustworthy: Calm, Serious: Positive, Trustworthy: Positive, Serious: Disturbing, Positive: Disturbing,** and **Trustworthy: Serious**.

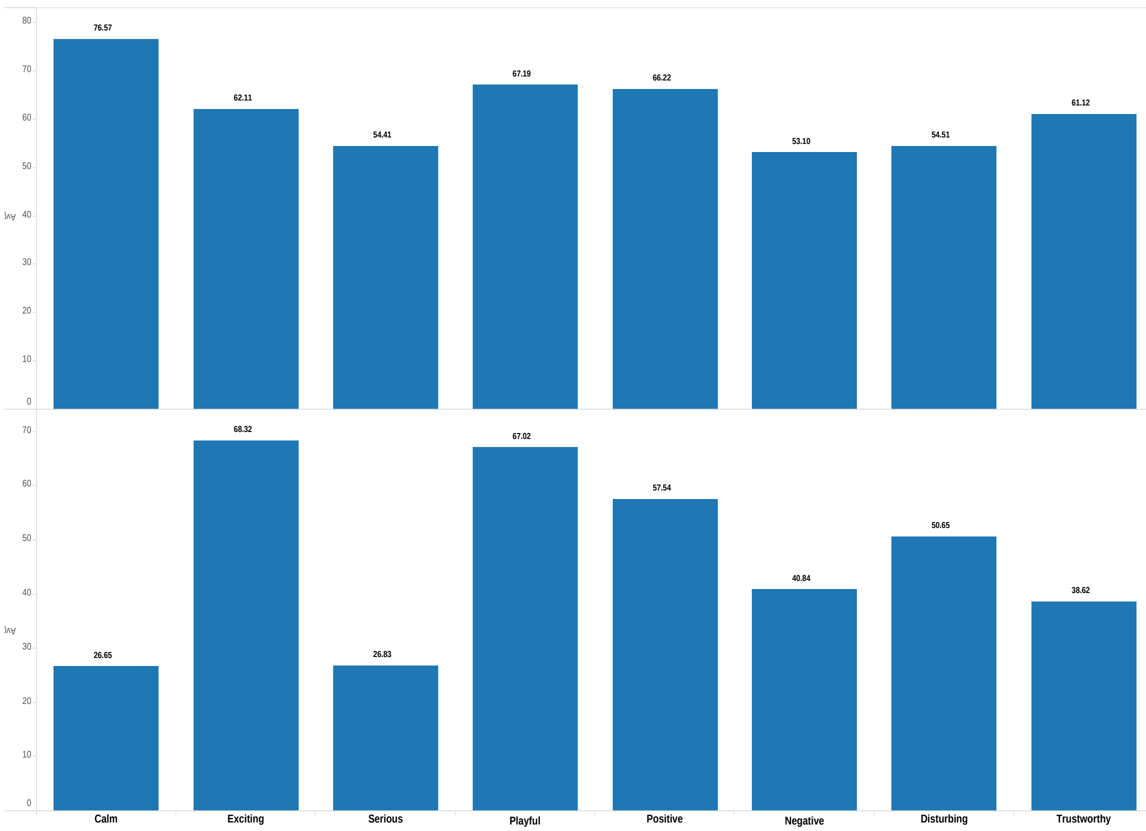


**Figure 4.3 The above bar chart shows the Avg Lightness (L*) and the below chart shows the average Chroma of the images.**

### 4.2.3. Interaction

We binned percentage of pixels into bins ranging from 0-9 for L* and Chroma and then looked at the interaction across the percentage of pixels in each bin and affect. It shows us that there is significant interaction across bins for each affect F (27, 43860) =10.1483, p=.0001*. The below figure 4.4 illustrates the interaction of L* and

Chromaticity across images grouped by the affect. It shows us that there is significant interaction across bins for each affect F (79, 87840) =207.524, p=.0001*.

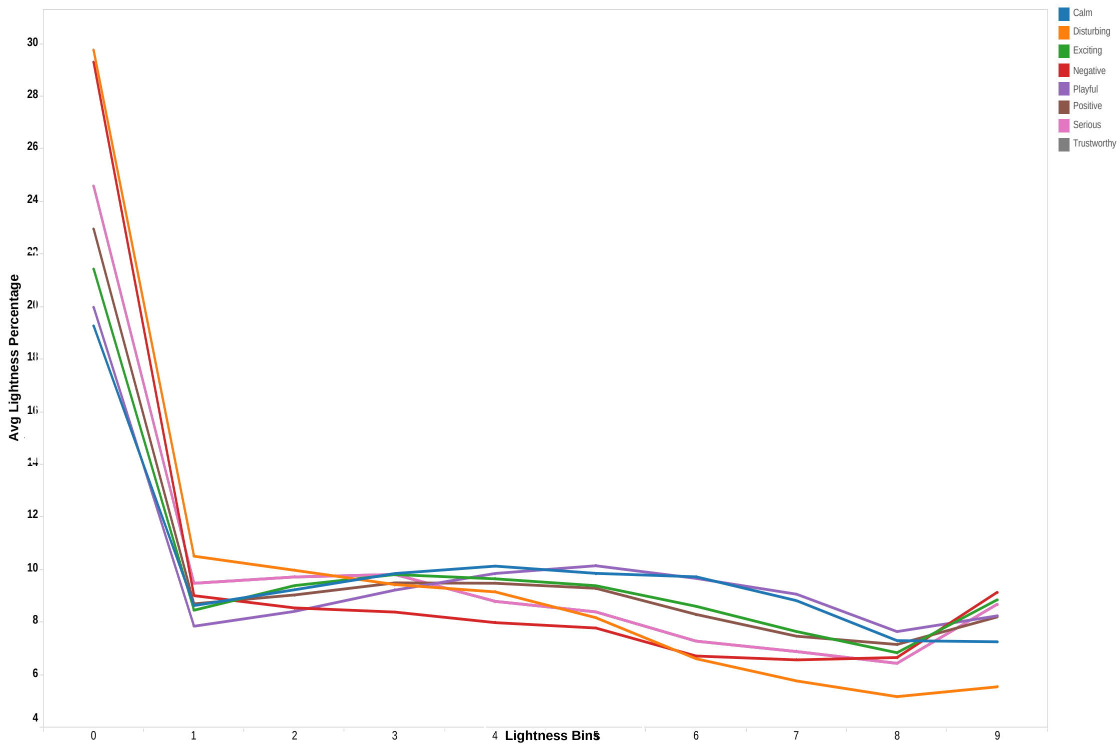


**Figure 4.4** **The chart shows the Lightness distribution of the images. The y axis shows the percentage of the pixels in the images. The x axis shows the lightness bins. Bin 0 are darker and Bin 9 are the lighter colors.**

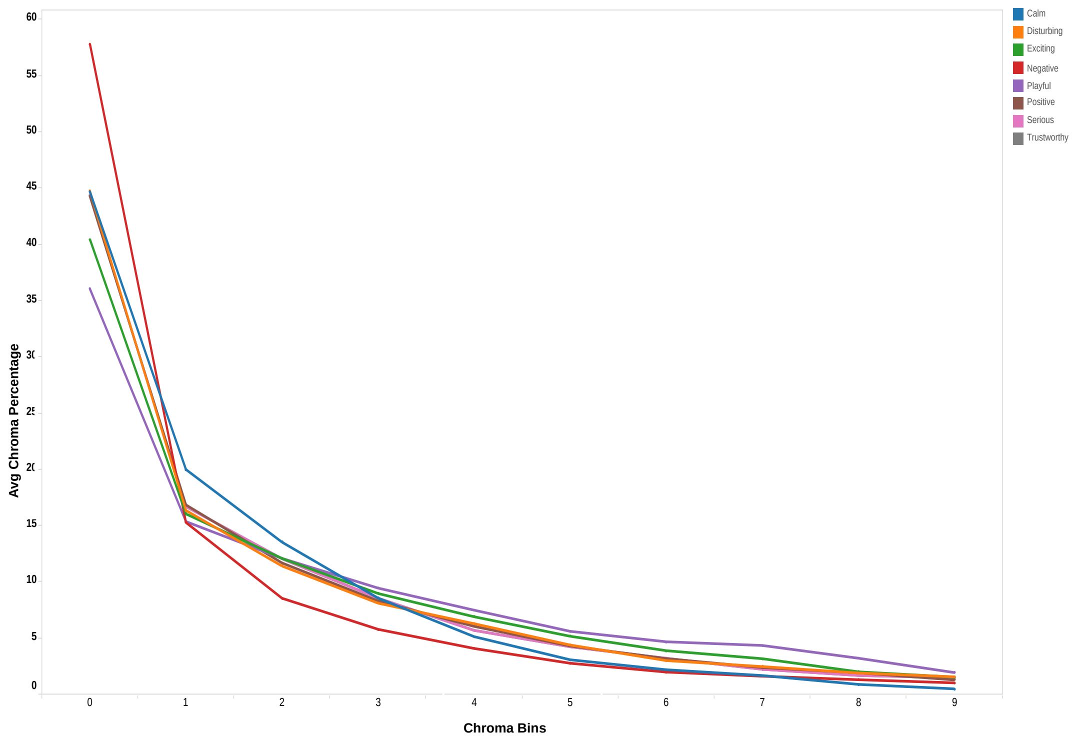


**Figure 4.5** **The chart shows the Chroma distribution of the images. The y axis shows the percentage of the pixels in the images. The x axis shows the Chroma bins. Bin 0 are less chromatic and Bin 9 are the most chromatic colors.**

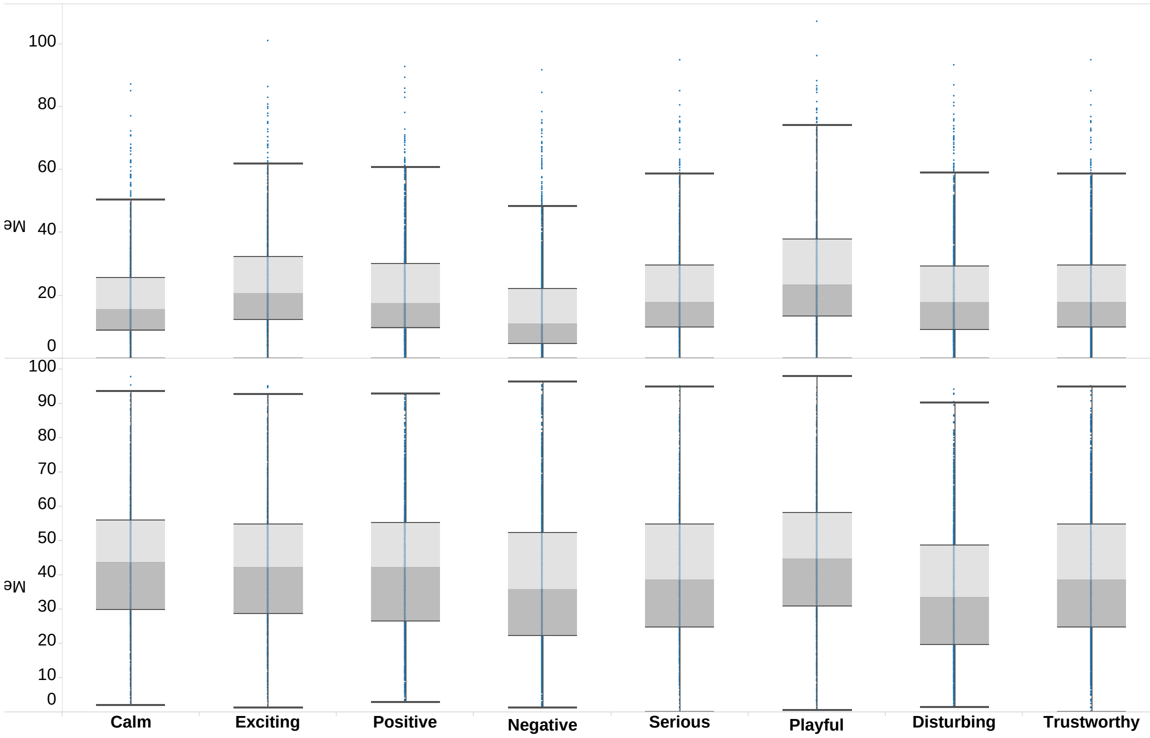


**Figure 4.6 This figure shows the distribution of mean lightness and chroma of all images. The box plots in the first chart suggest that Calm, Negative and Serious are less chromatic as compared to Exciting and Playful. The box plots in the second charts suggest that Calm, Exciting and Playful are lighter than Negative, Disturbing and Serious.**

### 4.2.4. Hue

Large areas of background influenced both lightness and chroma. We considered hue distribution using Lin's algorithm (Lin et al. 2013) to generate weighted hues. The algorithm by Lin et al takes care to remove the effects of background by removes the white or solid back grounds. The algorithm considers an image to have a black or white background if 75% of the image border is within 3 CIELAB units. We created eight sets of forty distinct hues, each using k-means clustering. We used the Medialab tool (iWantHue n.d.) to create distinct hues for the lightness and chromaticity ranges from the image analysis as shown in the figure 4.6. We picked the lightness and chroma range between the upper and lower whisker of the box plot in figure 4.6. For each of this eight sets of forty hues we calculate the conditional probability of how likely the hues were used in the images. For an affect and a candidate color c from the corresponding set, we calculate image histogram T corresponding to the images in that affect. Then the algorithm applies kernel density estimation (KDE) to the histogram (Lin et al. 2013) to find the probability of color c across all the images. The algorithm weights the probability based on the saturation of the candidate color and provides the contribution each histogram type makes towards the final color distribution of that candidate color. We calculated the weights of hue against the set of different images that were categorized by affect and select the most weighted and distinct colors to fit across affects.

$$p(c|v,T) \propto \sum_{\substack{b \in T \\ ||b - white||_2 \geq w_t}} T(b) \exp\left(-\frac{1}{2}\left(\frac{dist(b,c)}{\sigma}\right)^2\right) \quad (1)$$

**Figure 4.7 Equation from Lin's algorithm that was used to find the hue weights.**

In Equation 1, wt is the distance threshold from white, and dist(b, c) is a color distance metric. We use color name cosine distance. The formulation weights the probability based on the saturation of the candidate color. The collected data provides us with a weighted set of hues that gives us an understanding of the color preferences for hues among designers for the different affect. The below image shows the results for weighted hues gathered from Flickr and Devianart images.

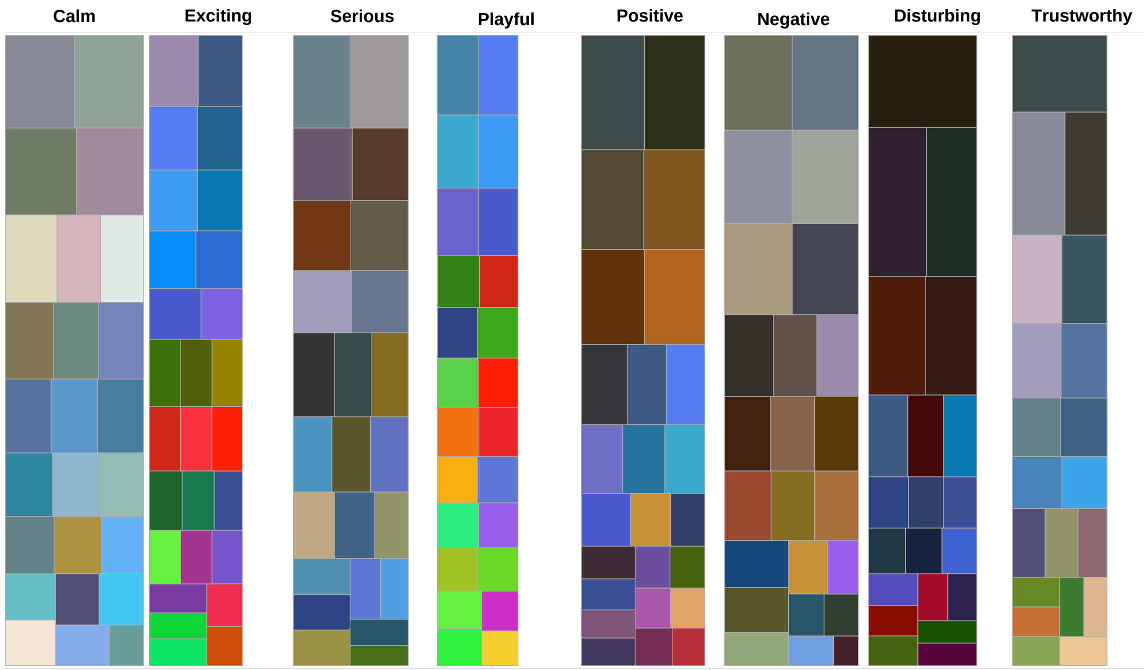


**Figure 4.8 The figure shows the hue frequency obtained using Lin's algorithm.**

## 4.3. Discussion

The analysis performed in collaboration with Dr. Lyn Bartram and Maureen Stone identified strategies that designers used to choose colours for design in graphics. The figure 4.9 shows the distribution of the mean lightness and mean chroma of all the images by affect. The figure 4.10 developed by Maureen Stone using the image analysis from figure 4.9 results shows us the distinctions between each of the affects and their aggregated lightness and chromatic properties. These are the aggregated centroids of the distribution shown in figure 4.9. Calm, Playful and Exciting images are lighter than Disturbing, Serious and Negative. The post hoc pairwise comparison showed strong differences in lightness: the major ones are Playful: Disturbing, Exciting: Disturbing, Negative: Calm and Disturbing: Calm. There was a less significant difference between Exciting, Trustworthy and Positive affect. We were surprised by the amount of darker browns and blues in Positive; this did not correspond to what color psychology suggests. The results tell us that affect was significant for lightness and that a designer would use lighter colors for Calm and darker colors for Negative. Negative and Calm are less colorful (chromatic) than Playful and Exciting whereas Disturbing, Serious and trustworthy were less and similar in chroma. While the differences are significant, the effect sizes are smaller.

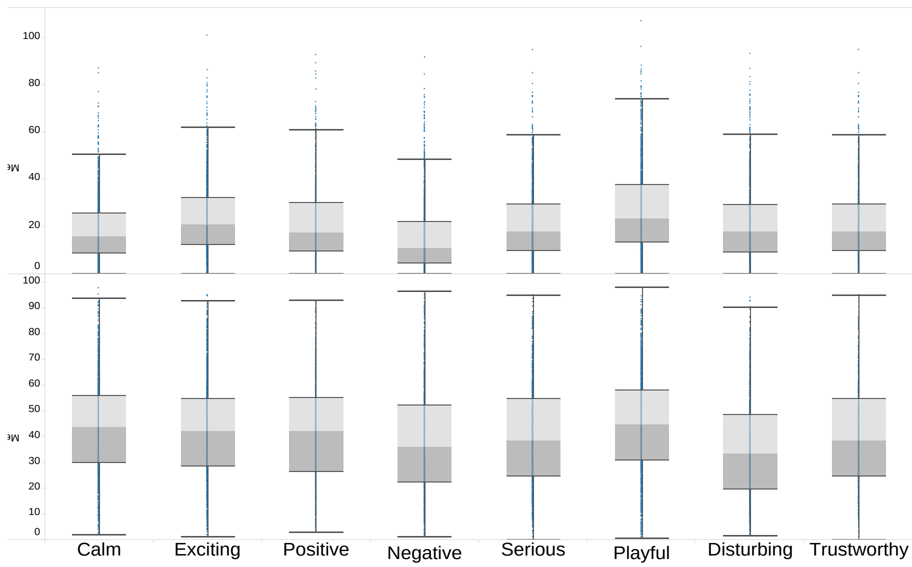


**Figure 4.9 Distribution of Image Chroma and Lightness values.**

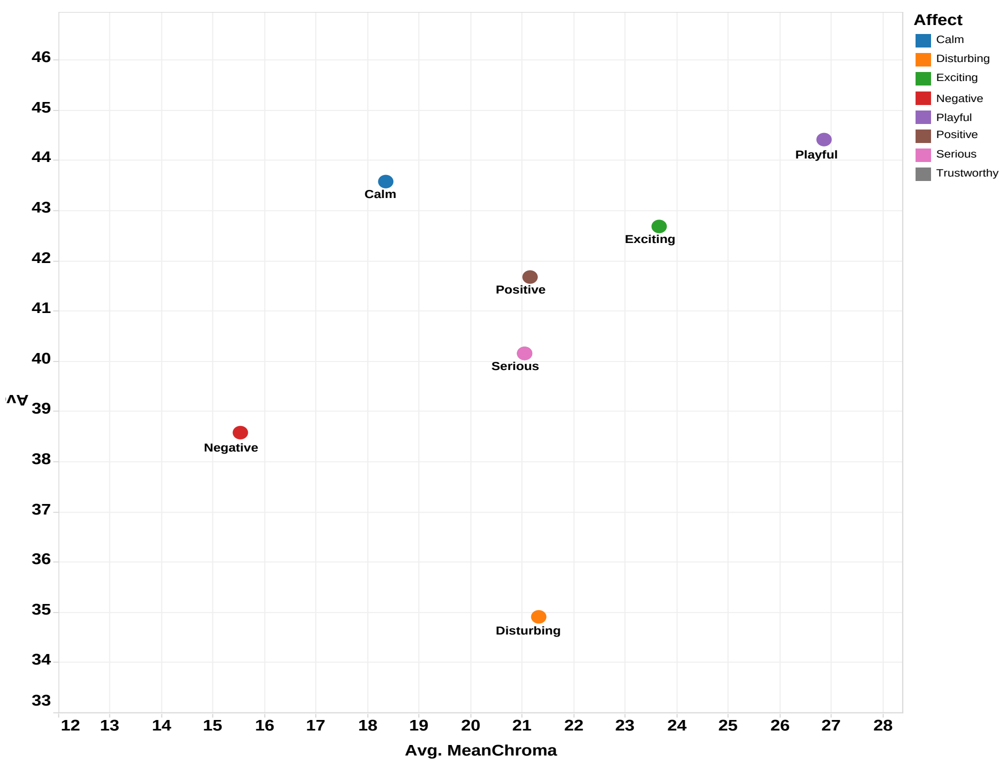


**Figure 4.10. This figure shows the aggregated mean Lightness and mean Chroma distribution of the Images grouped by Affect.**

We assume this is due to the dark, gray and brown background colors. A post hoc analysis showed major differences between: Playful: Negative, Positive: Negative, Negative: Exciting and Negative: Calm. The results indicate that designers linked arousal with higher chroma colors.

Figure 4.8 of weighted hues by affect, we see patterns between Calm palettes containing a larger concentration of light and desaturated blues and greens. Trustworthy also has shades of blues, purples and some greens. Blue and green relating to the skies, sea, nature and are pleasing to the senses, but research (Labrecque and Milne 2012; Mehta and Zhu 2009) has also shown that is associated with words sad, unhappy and along with secure and pleased. Playful and Exciting are used for a fun providing the environment and have highly saturated colors like reds, vibrant greens and blues with Exciting having relatively darker reds and most of these colors are arousal seeking. Disturbing has a larger distribution of dark browns, blues, reds and black. Negative used more gray and muted browns while the variation in hue was lesser compared to other affects. These results mirror what color psychology would predict.

Our results suggested that there are consistent color properties and hue patterns associated with affective tags. We wanted to know whether these results would transfer to visualization contexts, so we ran further experiments using color palettes derived from this analysis.

# Chapter 5.

# User Selected Palettes

We used the image analysis results to design, colors for our user studies. The weighted hues were further provided to Maureen Stone an expert in visualization, color design who refined colors by clustering to optimize saliency and distinctiveness. We build a set of candidate colors (as shown in the image below) that captured the range in Study 1. The goal of our study was to see whether users would consistently assign different color palettes for each of our eight affective categories in simple visualization tasks. We conducted two web-based user studies, first with designers and second with non-designers. Each used the same method and metrics.

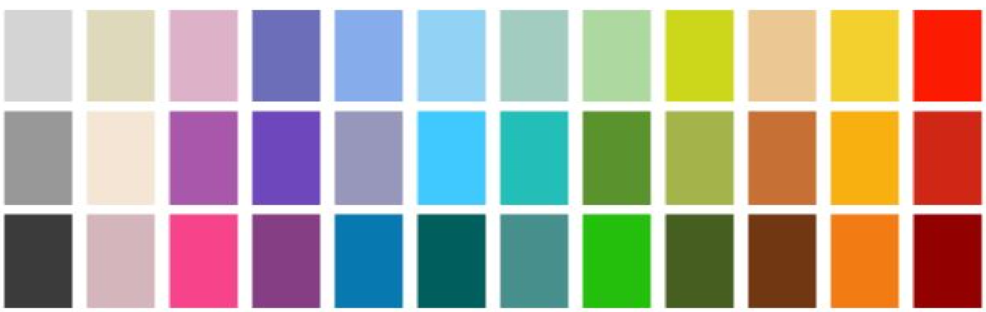

**Figure 5.1 This figure shows the Color palette developed by a visualization color expert for the user study 1.**

## 5.1. Method

Participants completed a series of coloring assignments for two simple visualizations (bar chart or map) and one primary data type (Categorical) using the interface shown in Figure 5.2. We chose a map and a bar chart as they are one of the most popular and efficient visualization techniques. As we were interested in categorical type data, they selected five colors. We asked participants to select colors to convey the communicative intent of each of our eight affective categories. No information of what the data represented provided other than affective impression required for designing. The participants saw the charts on a gray background and also the charts initially colored gray. A basic color picker allowed them to select colors from the overall set. Participants could only color the charts and not the background. They could modify their palette by adjusting a slider to control alpha. The alpha value was set to 1 when the participants started  the task. We were interested to see if affect would have significant impact on alpha. When the participant finished with the color selection, s/he rated satisfaction using a slider between 0 and 10 to indicate how successfully s/he felt the colors expressed the concept. All charts have alpha one at the beginning of each trial, and the colored in neutral gray.

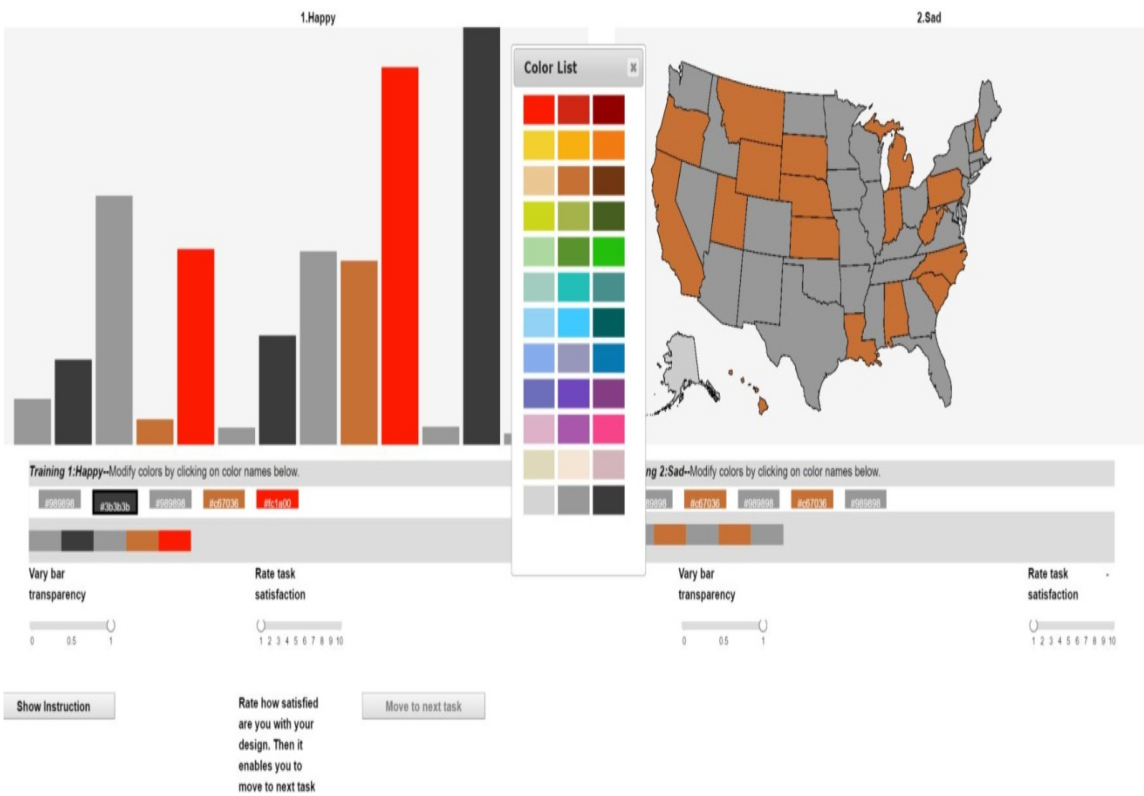


**Figure 5.2** **This figure shows the web interface for user study 1. Participants had to convey the communicative intent of each afeective category using the palette provided.**

We were interested in the relative locations of color preferences across the PAD space, and hence we paired the affects for comparison ease (Calm: Exciting; Positive:

Negative; Serious: Playful), following suggestions from a small pilot study. However, because Trustworthy and Disturbing are not symmetrically opposite, we presented them singly.

The experiment began with a training task in which participants designed for "Happy" and "Sad" impressions. They were provided with a bar and a map, chart and were required to select 5 colors for each of the designs. Participants had no time limit on training; participants proceeded to the main study when ready. During the experiment, participants could stop at any time, and login to the system later to complete the study: the system retained state. We report only on results for tasks completed.

## 5.2. Factors and metrics

We had three independent variables (factors): Affect (8); Visualization (2: bar chart, US map) and Data Type (Categorical: 5 colors). Our dependent variables were color metrics, alpha and satisfaction ratings. Color metrics were perceptual properties of aggregate lightness (L*) and chroma across the selected palette; and palette properties of hue clustering and color. We measured hue dispersion with saturation-weighted hue distribution (Prip and Hanbury 2003) (henceforth WHD). WHD was chosen over entropy as a more accurate model of hue dispersion. When WHD is higher, hues are more concentrated (less dispersed).

## 5.3. Hypothesis

We had the following hypotheses.

- **H1**. Affect will have a significant effect on L*. We expect Calm colors to be lighter.
- **H2**. Affect will have a significant effect on chroma. We expect high arousal affects to be more saturated.
- **H3**. Affect will influence hue choice. Cooler colors will be used for low arousal Calm, Serious and Trustworthy. High arousal or negative valence affects Exciting, Negative; Disturbing will use more reds, browns, oranges and yellows.

## 5.4. Experiment 1: Designer Study

Our first experiment involved people with some design experience. We used a 1 way within-subjects design split by Data Type: They did Categorical coloring on the two visualizations and a 2 (Vis) × 8 (Affect) factorial designs yielded 16 experimental conditions. Trial ordering was randomized and block ordering was counterbalanced.

### 5.4.1. Participants

49 participants recruited from online social media with a design background which included 26 males and 23 females participated. All participants said they had some design background, but levels varied from some experience to professional practitioner and all had normal or corrected to normal vision. Participants were entered into a draw for potential reimbursement.

### 5.4.2. Results

**Table 5.1. Significant Effects (Study 1)**

| Study | Lightness | Chroma | Alpha | Rating | WHD |
|---|---|---|---|---|---|
| Designer | X2 (7, 1032) =182.4576, p<.0001 | X2 (7, 1032) =233.2628, p<.0001 | Not Significant | Not Significant | X2 (7, 344) =63.5393 p<.0001 |

We removed all palettes that did not have 5 distinct colors giving us 403 palettes. We then did both visual and statistical analysis. The data was not normally distributed and the figure 5.3 below shows the data plot for normality test. We used a Shapiro-Wilk normality test and the observed value for Chroma was W=0.942246, p<.0001* and Lightness was W=0.937419, p<.0001* . A Levene's test for homogeneity in variance showed that the assumption of homogeneity in variance was violated for Chroma F(7,1837)=27.7378, p<.0001* and for Lightness F(7,1837)=31.6542,p<.0001*.

We used non-parametric Kruskal-Wallis tests because the data were marginally not normally distributed. We did not find a significant effect of affect on Visualization Type. We report only significant effects.

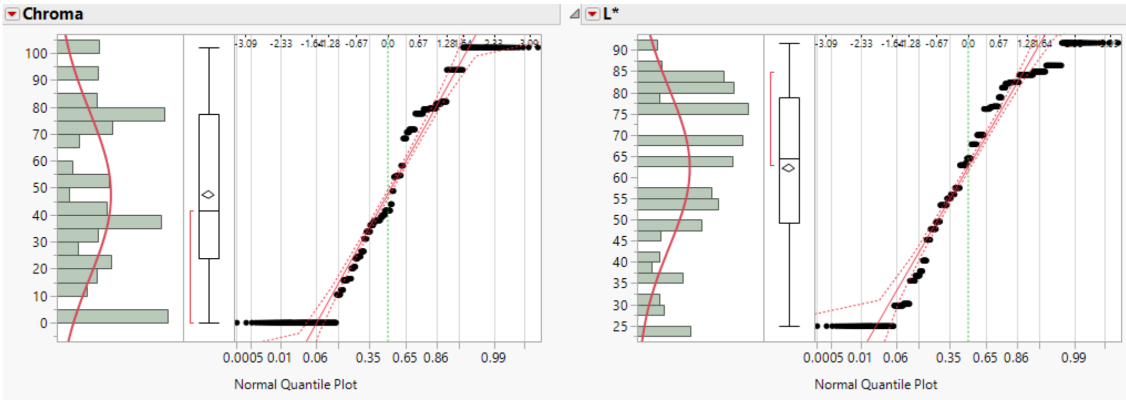


**Figure 5.3 The figure shows the plot for Normality Test for Chroma and Lightness (L*) for the color choices made by participants.**

### 5.4.3. Lightness (L*)

We see a significant effect of affect on lightness $X^2$ (7, 859) =178.8017, p<.0001. A pairwise comparison showed significant differences except for Positive: Playful and Trustworthy: Exciting. The most significant difference was between **Playful: Negative, Positive: Negative, Playful: Dusturbing, Positive: Disturbing, Exciting: Calm, Serious: Calm, and Disturbing: Calm.** This confirmed H1, although we had expected Disturbing, Serious and Negative to be much darker. Positive Valence affects is lighter while negative valence is darker The figure 5.4 shows the average lightness of all the colors selected by participants across the affects in the design tasks. The figure 5.5 shows the distribution of lightness of all the colors selected across each affect.

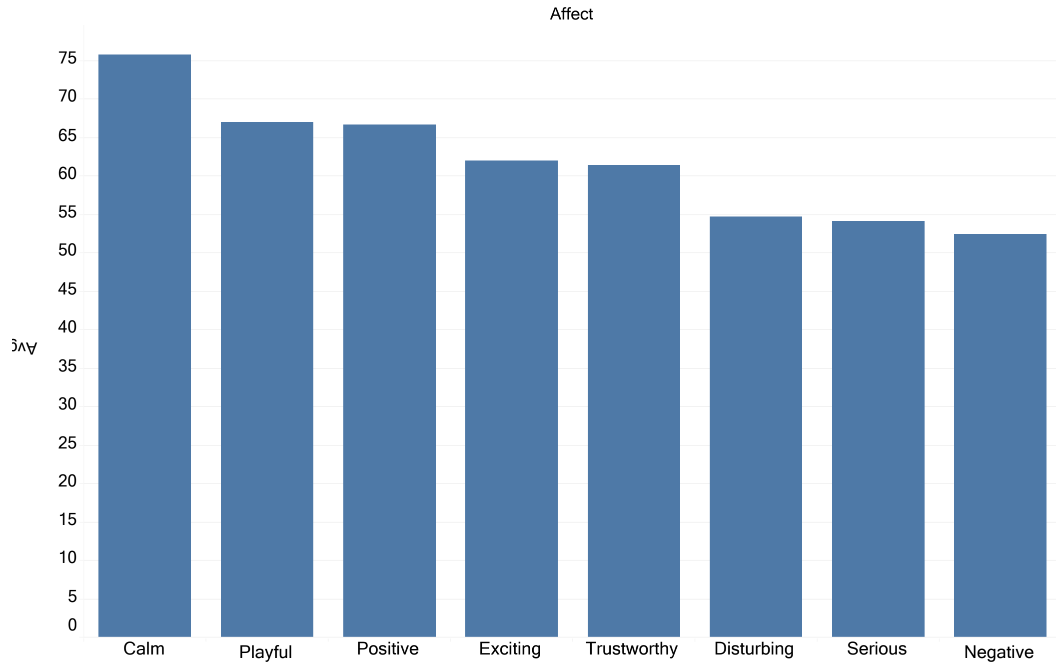


**Figure 5.4** **The figure shows the affects sorted by Average Lightness(L*) for the color selected by participants.**

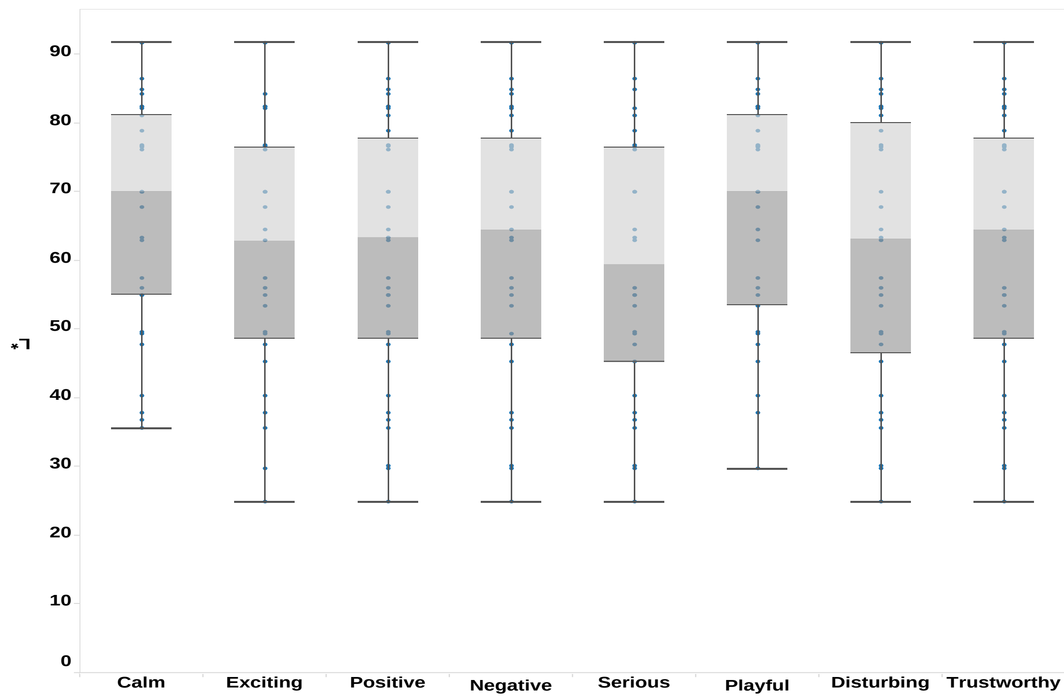


**Figure 5.5** **The figure shows the box plots of the Lightness(L*) values for the color selected by participants.**

### 5.4.4. Chroma

Results showed a significant effect of affect of chroma $X^2$ (7, 859) =238.0539, $p<.0001$ A pairwise comparison showed all significant differences except Trustworthy:Negative, Playful:Exciting and Serious:Calm. The most significant difference was between Playful: Calm, Exciting: Calm, Positive: Calm, Playful: Negative, Serious: Playful, Serious: Exciting, Trustworthy: Exciting, Trustworthy: Playful, Serious: Positive, Negative: Exciting and Serious: Disturbing. This confirms H2: Exciting and Playful had higher chroma, but Disturbing, which might be considered both high arousal and high negative valence, was not high in chroma as we expected. The figure 5.6 shows the average chroma of all the colors selected by participants across the affects in the design tasks sorted by average chromaticity. Figure 5.7 shows the distribution of chromatity of all the colors selected across each affect.

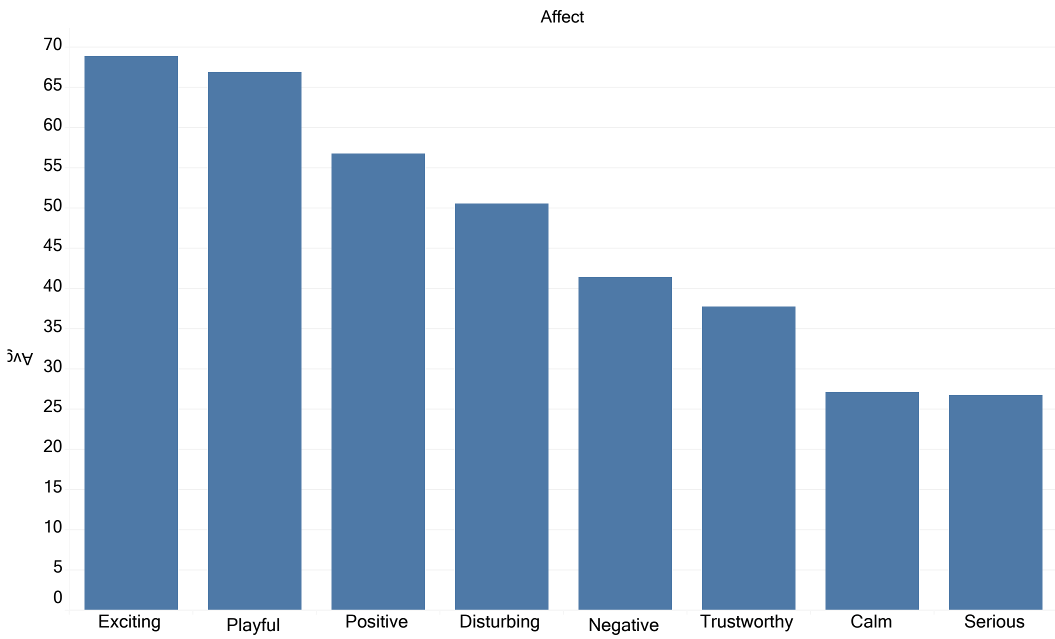


**Figure 5.6 The figure shows the affects sorted by Average Chroma for the color selected by participants.**

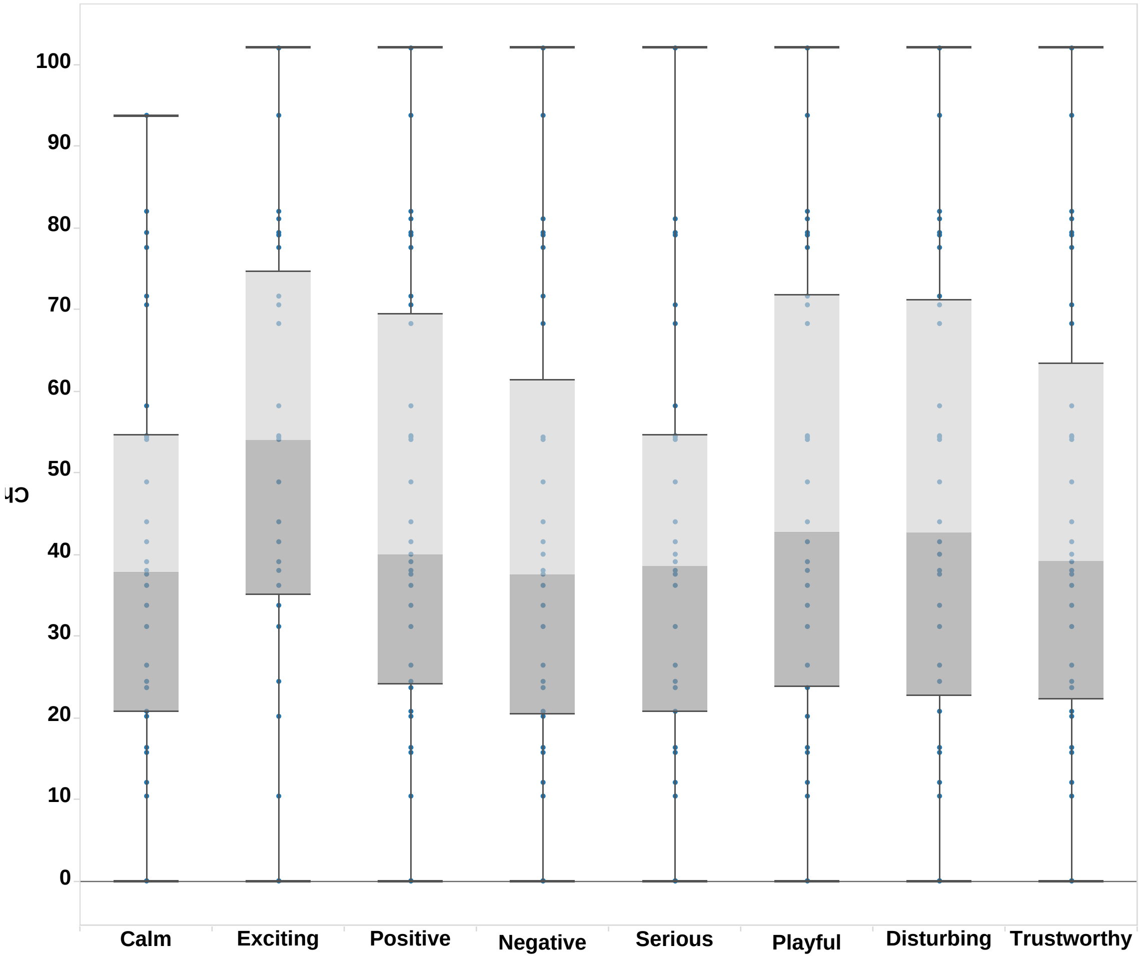


**Figure 5.7 The figure shows the box plots of the Chroma values for the color selected by participants.**

### 5.4.5. Alpha: Transparency

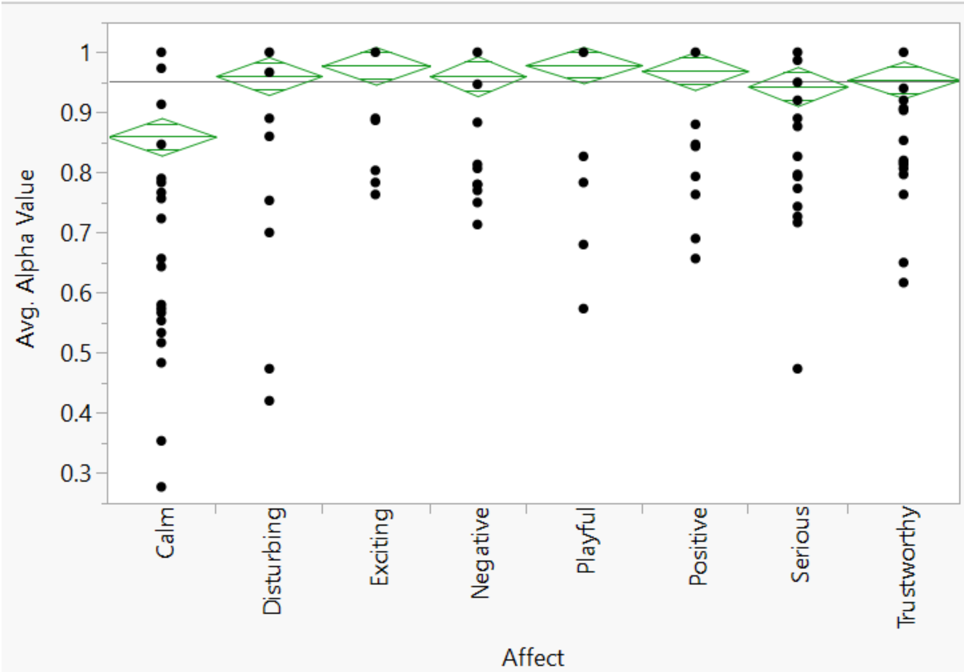


**Figure 5.8 Alpha distribution across affect.**

Results showed a significant effect of affect on alpha X2 (7, 394) =5.92, p<.0.0001* and a paired comparison indicated alpha was only significant with respect to Calm, where it was lower.

### 5.4.6. Rating

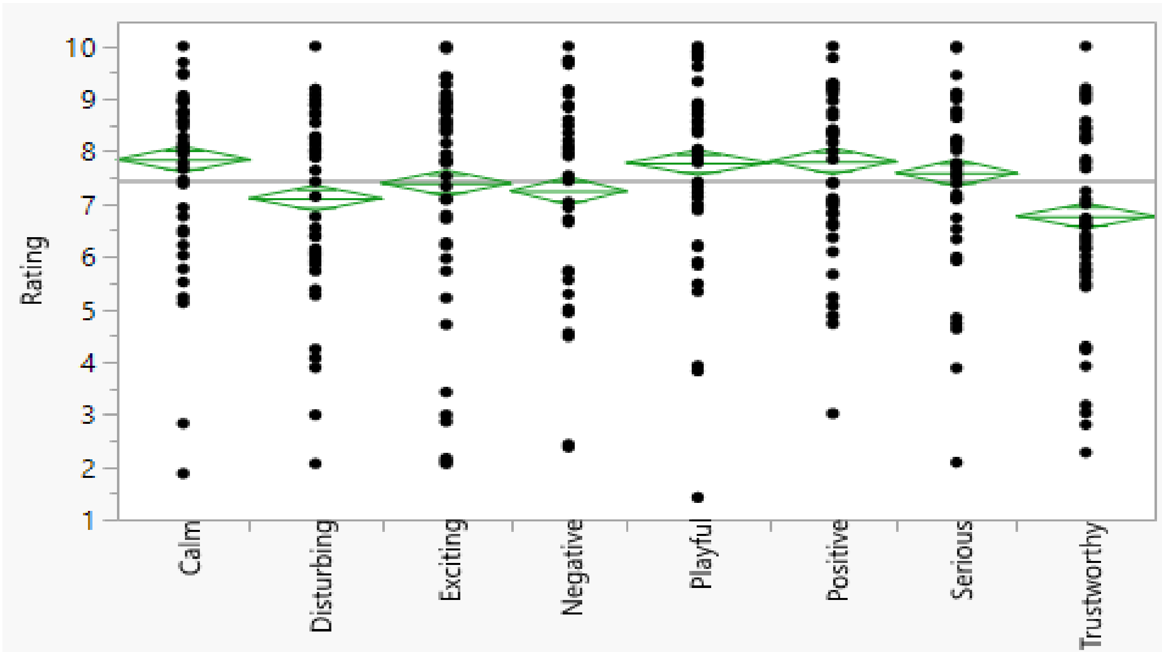


**Figure 5.9 These are the distribution of rating across each affect.**

Mean ratings was not significant. Overall mean ratings as shown in figure 5.9 revealed that designers rated satisfaction relatively high except for Trustworthy (M=6.8) and Disturbing (M=7.1).

### 5.4.7. Hue

Affect has highly significant effect on hue: $X^2(7, 2002) = 26.93$, p<.0.0001*. A pairwise comparison showed significant difference between Playful: Negative, Positive: Negative, Playful: Disturbing, Trustworthy: Negative, Negative: Calm, Serious, Playful, Serious Calm and Negative: Exciting. The difference was least between Serious:Negative, Trustworthy:Positive, Trustworthy:Exciting and Playful:Calm. We also calculated the angular dispersion for each palette using WHD. affect was highly significant for WHD: $X^2(7, 394) = 3.5151$, p<.0.0011*. Thought the effect size was small a paired wise comparison showed that the most significant difference was between Positive:Calm, Playful:Calm, Disturbing:Calm, Serious:Playful, Serious:Positive, Serious:Disturbing. The figure 5.10 shows the hue distribution for the palettes. Each palette is represented as a convex hull over the hue wheel. The less saturated colors are closer to the origin and more saturated colors are closer to the periphery of the circle.

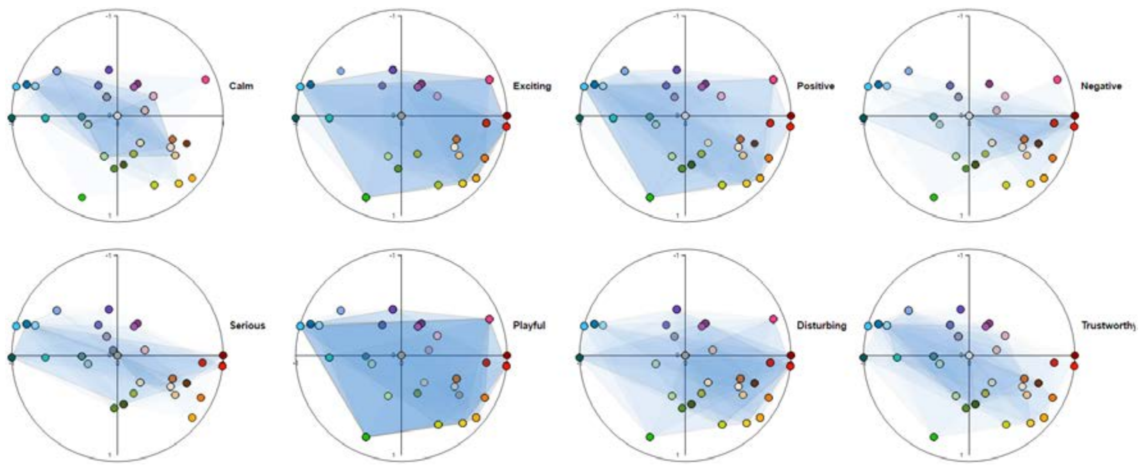


**Figure 5.10 Hue distribution of colors selected in Palette. Each palette is represented as a convex hull over the circular hue wheel. Radius is the saturation ranging from 0-1.**

### 5.4.8. Discussion

The analysis was done in collaboration with Dr. Lyn Bartram and Maureen Stone. The figure 5.11 developed by Maureen Stone using the results from the study show resulting palette frequency. Each bubble represents how frequently the color was used. We clearly see that the colors and color characteristics varied by affect. Calm, Playful and Positive were much lighter than Disturbing, Serious and Negative. Calm was the least saturated of all the affects; Figure 5.12 shows the affects sorted by lightness.

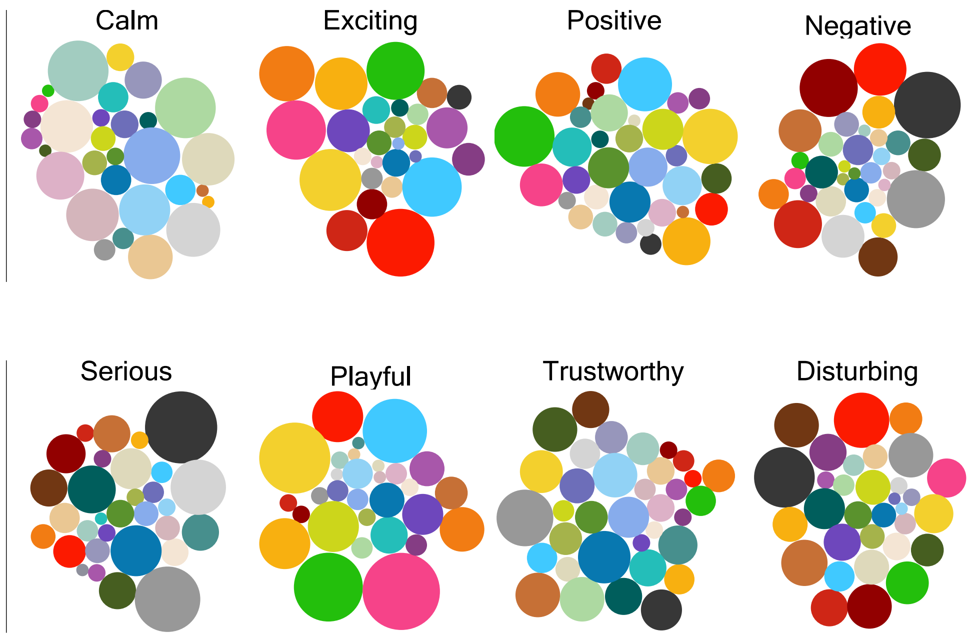


**Figure 5.11** **This is a bubble chart where each bubble represents the color used and is scaled by its frequency of use in each affect. The bubble sizes are absolute.**


**Figure 5.12** **Here the affects are Sorted by Lightness: Calm Lightest-Negative Darkest.**

Figure 5.13 shows the bubbles binned into 4 groups by the chroma values and the affects are sorted by lightness. The left bins are lower chroma colors while the right bins are higher chroma colors. Exciting, Playful and Positive the most colorful (chromatic). Core affects Calm and Exciting have very clear, distinct chromaticity variations. Calm palettes which are lower arousal have less chromatic colors compare to higher arousal Exciting palettes. Calm and Exciting show very strong hue patterns.

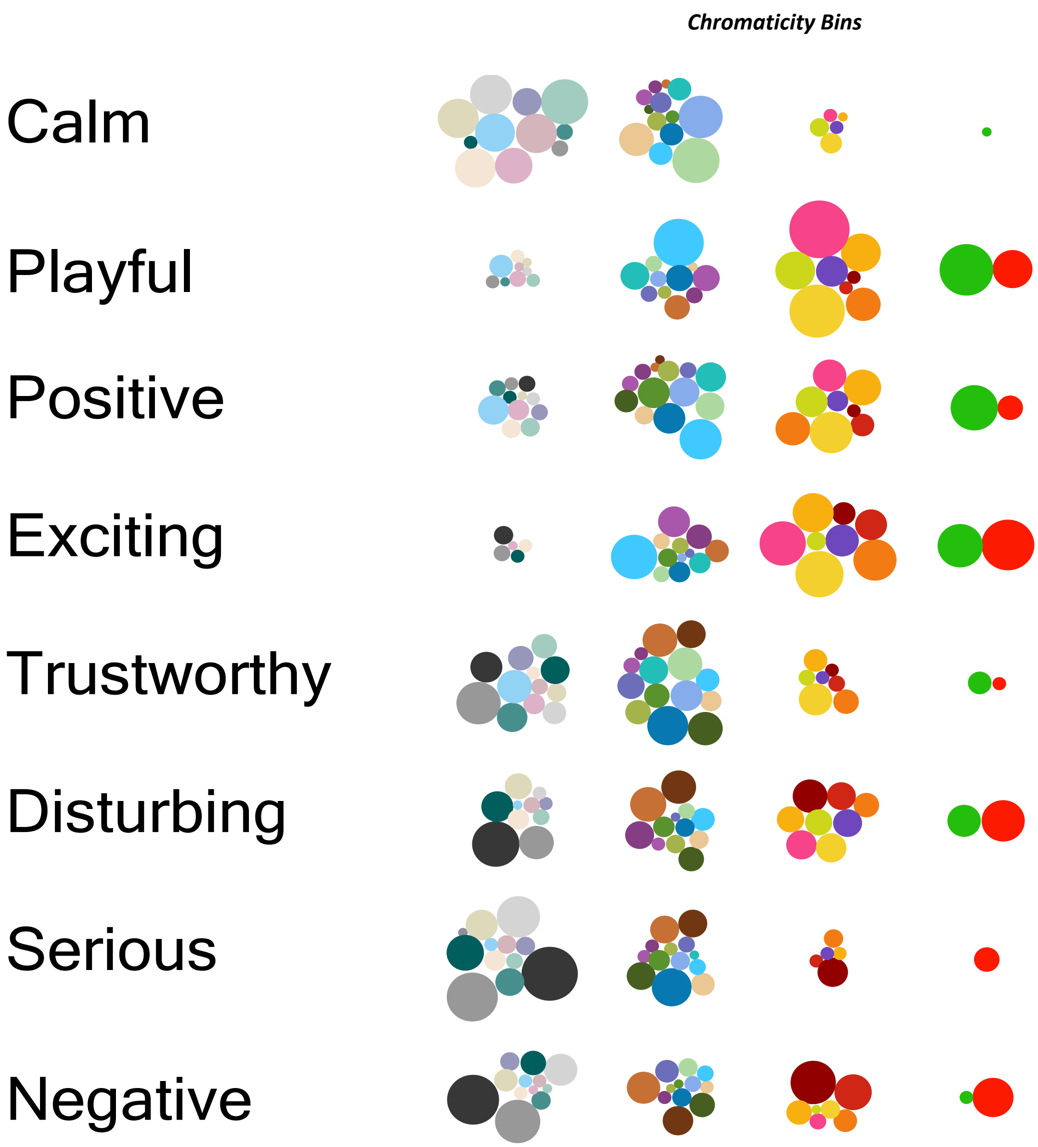


**Figure 5.13 Here the bubbles are split by Chroma. The bubbles are binned by Chroma values:Left are lower chroma colors and the right bins are higher chroma colors.**

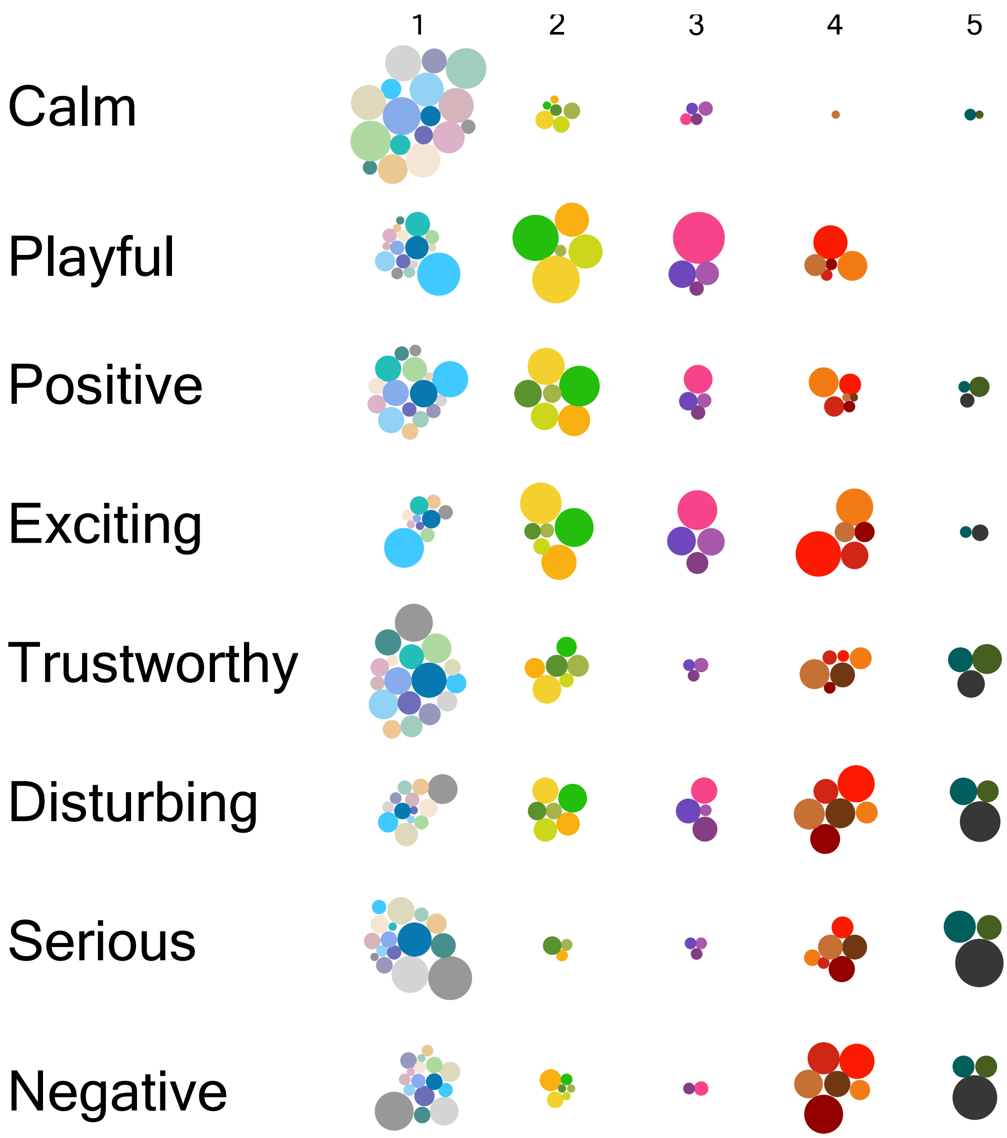


**Figure 5.14 In this figure the bubbles are clustered using the LAB values in the CIELAB space. i.e how close they are in the CIELAB space.**

The figure 5. 14 shows in CIELAB space 5 clusters using hierarchical clustering. We used the LAB values to cluster them in the LAB space. In Calm, we see very strong colors, mostly coolers blues and green hues and are of equal weight. These groups of colors appear in most of the palettes with the pale pinks and creams being used. High arousal affects (Exciting, Playful, and Disturbing) uses more reds and yellows. In Exciting along with Oranges, Reds, Yellows and Pinks, we see bright Green is commonly used with all of them. The other less weighted teal, purples, maroons and browns were used in combination with oranges. Both Trustworthy and Calm make more use of cool colors (blue and greens). Positive valence has strong green similar to the Trustworthy and yellow clusters. Negative uses darker reds, grays and browns. And less weighted dark pale blues and greens. These patterns reinforce predictions from color psychology and confirm H3. However, we anticipated darker blues, reds and browns in Disturbing (from the image analysis results). While these results showed us clearly that there are patterns of color they provided few insights as how these colors were combined in these palettes. Figure 5.10 shows very distinct hue distribution patters across the affects. Calm palettes hues which are denser near the origin and also pick colors like light cream and pink colors from the warm regions. Exciting is more dense near the warm regions and Positive also to a lesser extent but includes more greens and yellows. Negative is denser near the origin but also has the darker warm colors like reds and browns. Playful is clearly more dense near the primary regions of the colors which includes he bright reds, greens and blues. While the hue dispersion measure and hue frequency statistics highlighted aggregated differences among palettes they were less informative about explaining the color combinations.

## 5.5. Experiment 2: Non Designer Study

We refined our design of a subsequent experiment. First, because we were concerned that the palette in the previous experiment was not expressive enough, lacking in darker colors, our color expert redesigned it and added additional colors to a total of 41 colors as shown in figure 5.15. Figure 5.16 shows the distribution of the colors in the palette for study 1 and study 2. The distribution is shown in the a*b* plane which are the polar coordinates.

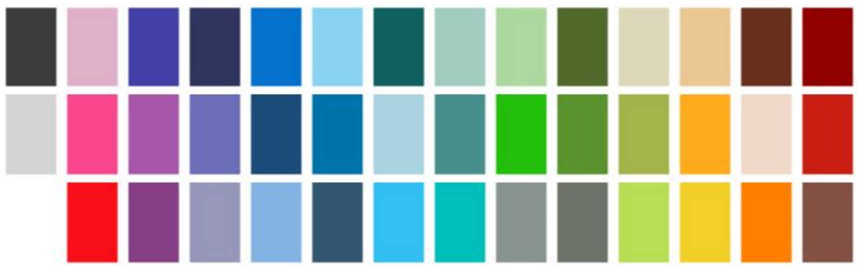

**Figure 5.15 The figure shows the new Palettes used in Study 2. We added additional dark colors.**

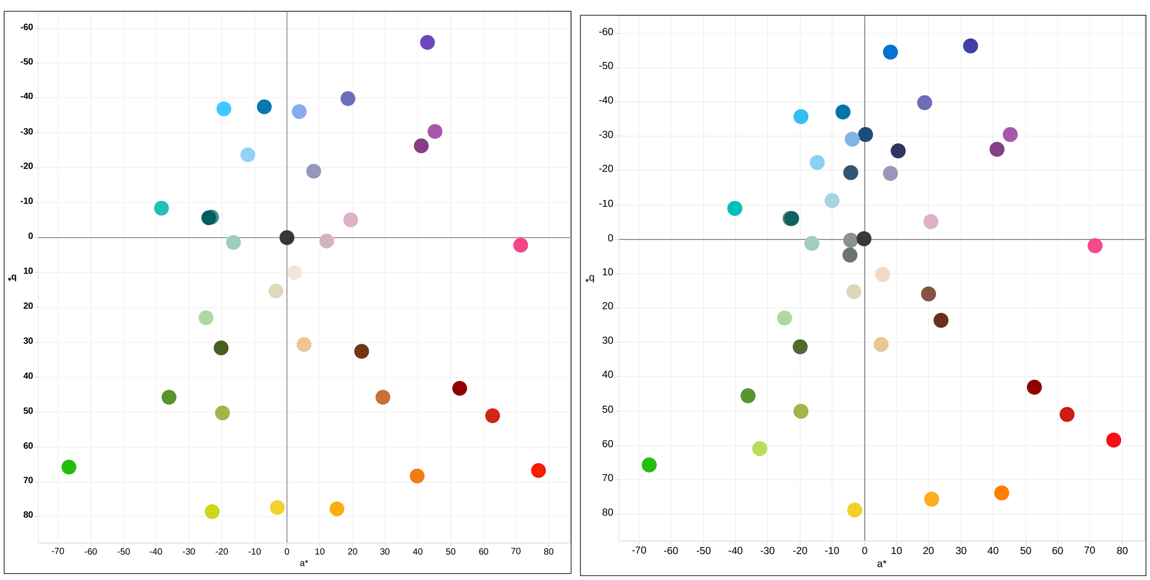


**Figure 5.16 This figure shows the Color Distribution in Palette for Study 1 in Left and Study 2 in Right. The distribution is hsown across the a*b* plane.**

A visualization color expert added additional dark colors and tuned our palette for the second study. As participants complained that the previous study took too long, we used a 2-way between-subjects design: a 8 (Affect type) x 1 (Visualization) producing 8 experimental conditions. Trial ordering was randomized and block ordering was counterbalanced.

### 5.5.1. Participants

76 participants, 48 females and 28 males, with normal or corrected-to-normal vision were paid to undertake the experiment. They were randomly assigned to either of the visualization types.

### 5.5.2. Results

The figure 5.17 below shows the normality plot of the data and it was not normally distributed. We used a Kolmogorov-Smirnov normality test and the observed value for Chroma was D=0.120094, p<.0001* and Lightness was D=0.130673, p<.0001*. A Levene's test for variance revealed that homogeneity of variance was violated for Chroma F(7,2457)=35.4038, p<.0001* and for Lightness F(7,2457)=30.7781,p<.0001*.

Again, we used Kruskal-Wallis test because the data were marginally normally distributed. Table 5.2 shows the significant effects details.

**Table 5.2. Significant Effects (Study 2)**

| Study | Lightness | Chroma | Alpha | Rating | WHD |
|---|---|---|---|---|---|
| Designer | $X^2$ (7, 1216) =426.7211, p<.0001 | $X^2$ (7, 1216) =481.8955, p<.0001 | $X^2$ (7, 1216) =93.4, p<.0001 | Not Significant | X2 (7, 1216) =88.21, p<.0001 |

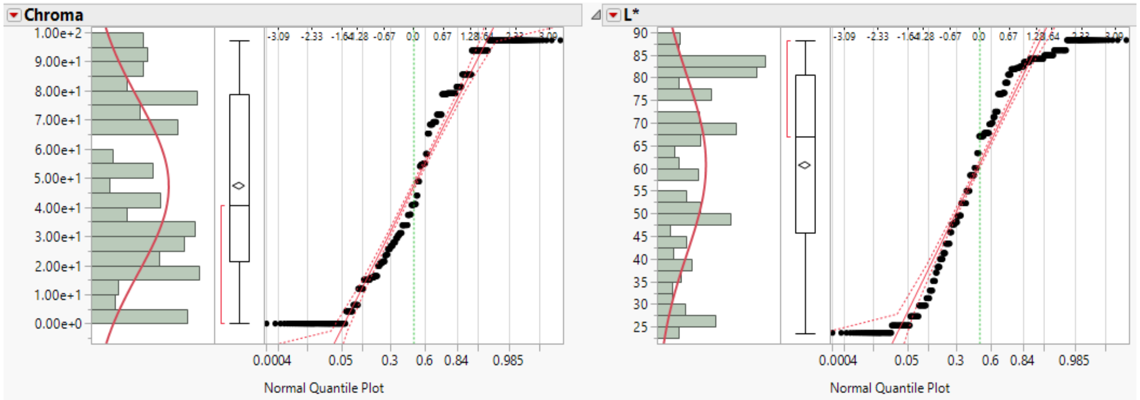


**Figure 5.17 The figure shows the plot for Normality Test for Chroma and Lightness (L*) for the color choices made by participants.**

## 5.5.3. Lightness (L*)

Results showed a significant effect of affect on lightness $X^2$ (7, 1216) =426.7211, p<.0001. A post-hoc pairwise comparison showed the most differences were significant, with exceptions Negative: Calm, Trustworthy: Disturbing, Seriously: Negative and Serious: Calm. Calm, Playful and Positive were much lighter than Disturbing, Serious and Negative Figure 5.18 shows the affects sorted by overall average lightness of all the colors selected. Figure 5.19 shows the distribution of all the colors selected across each affect.

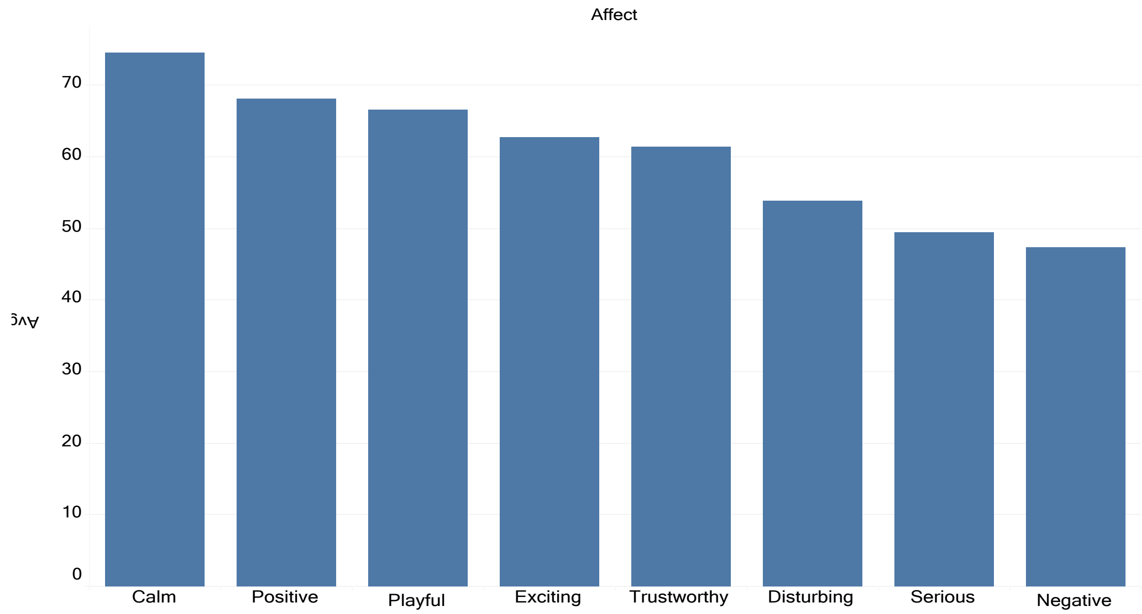


**Figure 5.18** **The figure shows the affects sorted by Average Lightness(L*) for the color selected by participants.**

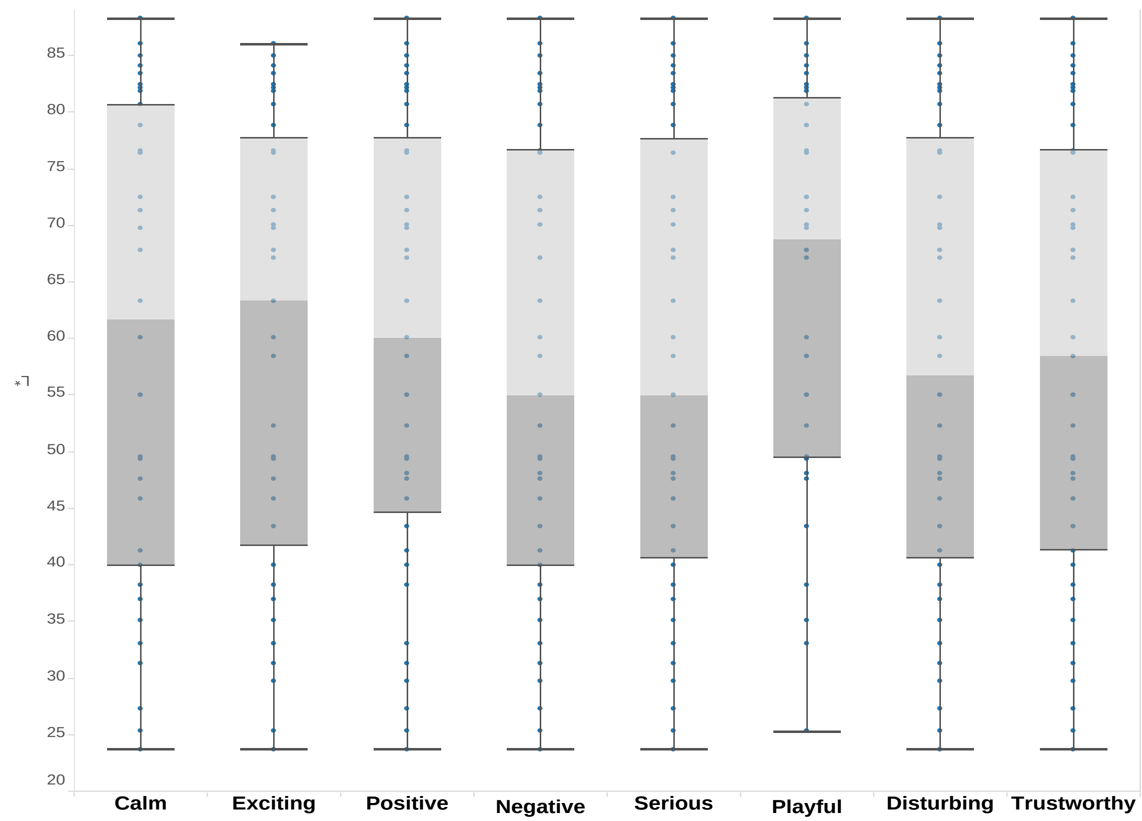


**Figure 5.19** **The figure shows the box plots of the Lightness(L*) values for the color selected by participants .**

### 5.5.4. Chroma

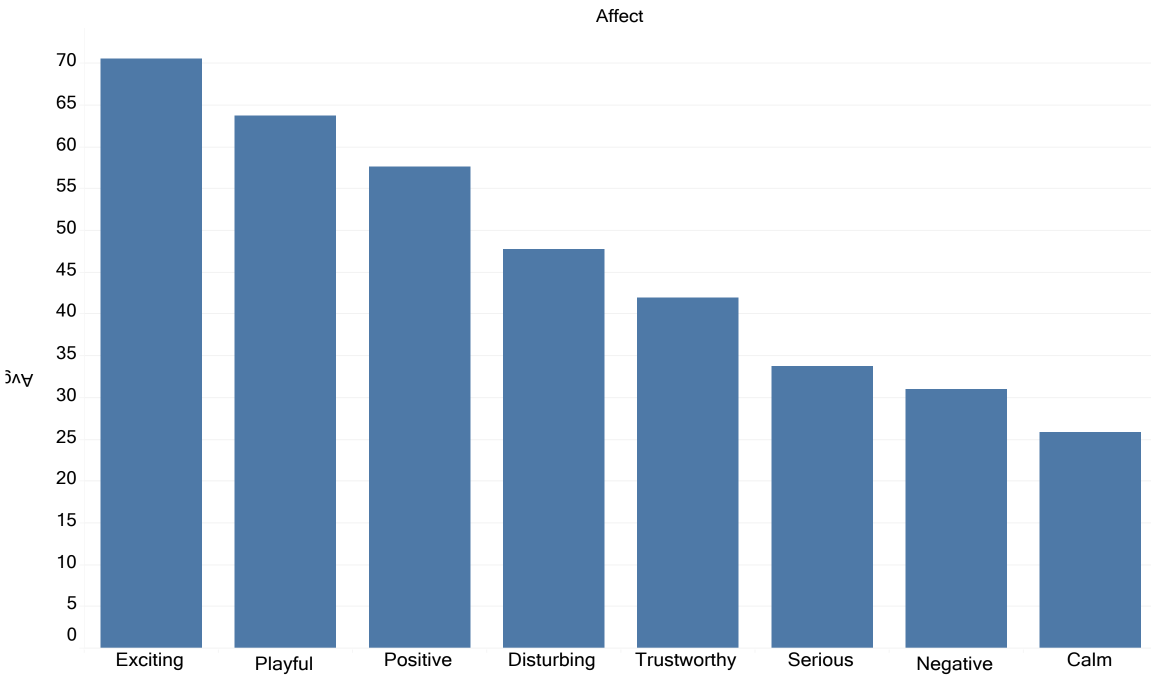


**Figure 5.20 The figure shows the affects sorted by Average Chroma for the color selected by participants.**

Results showed a significant effect of affect on chroma $X^2$ (7, 1216) =481.8955, p<.0001. A post-hoc pairwise showed significant differences except Negative:Calm, Trustworthy:Disturbing Serious:Negative and Serious:Calm. Calm was the least saturated of the affects; Exciting, Playful and Positive the most colorful (chromatic). Figure 5.20 shows the average chroma of all the colors selected across each affect. The chart is sorted by average chroma values. Exciting is higher in chroma while calm uses less chromatic colors. Figure 5.21 shows the distribution of the chroma values for all the colors selected across each affect.

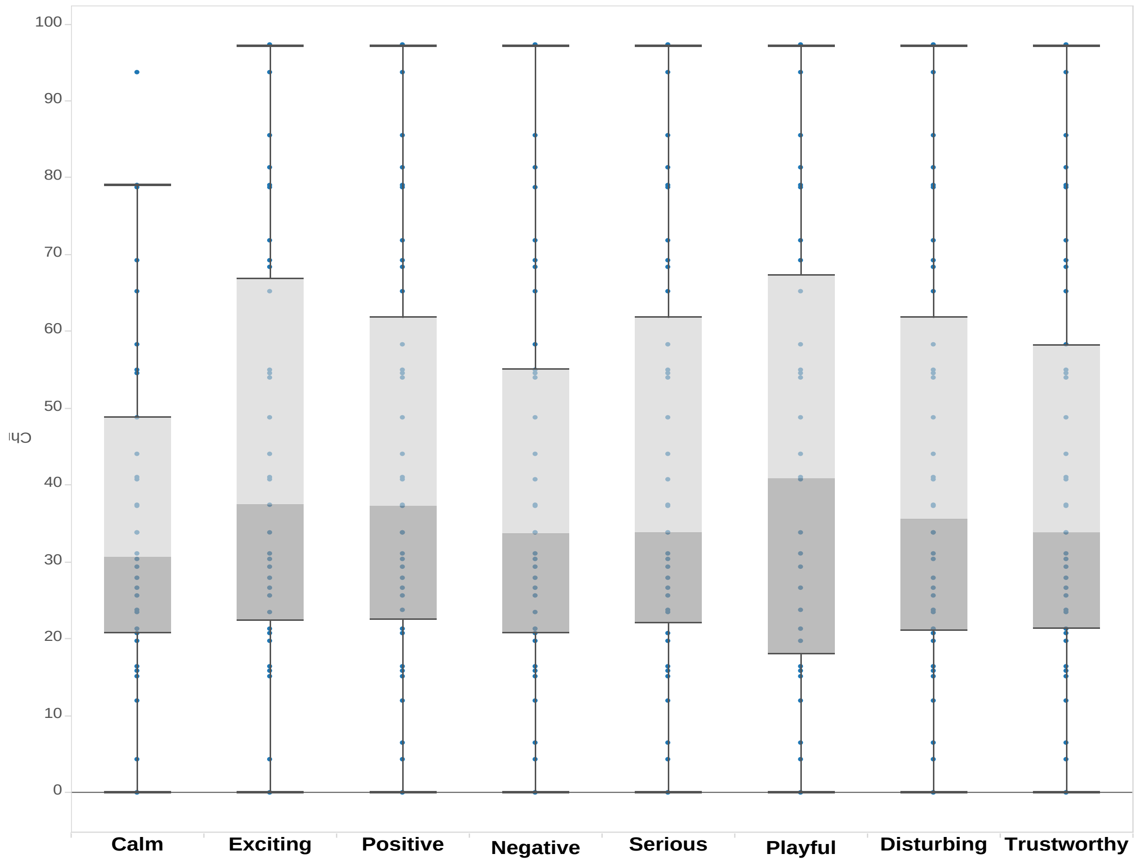


**Figure 5.21 The figure shows the box plots of the Chroma values for the color selected by participants.**

## 5.5.5. Alpha

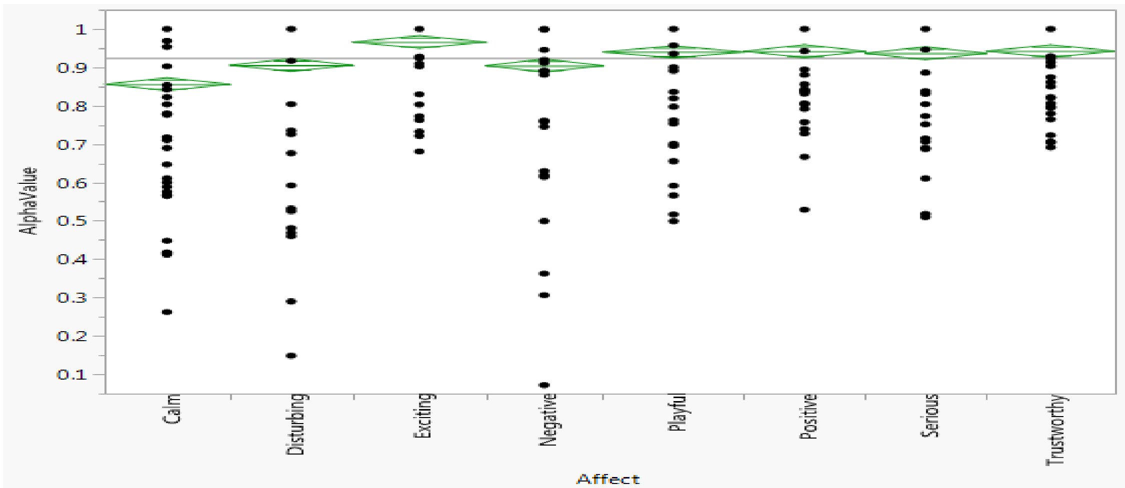


**Figure 5.22 Distribution of Alpha choices across each affect.**

Results showed a significant effect of affect on alpha $X^2$ (7, 1216) =93.4, p<.0.0001* and a paired comparison indicated alpha was only significant with respect to Calm, where it was lower as shown in figure 5.22.

### 5.5.6. Rating

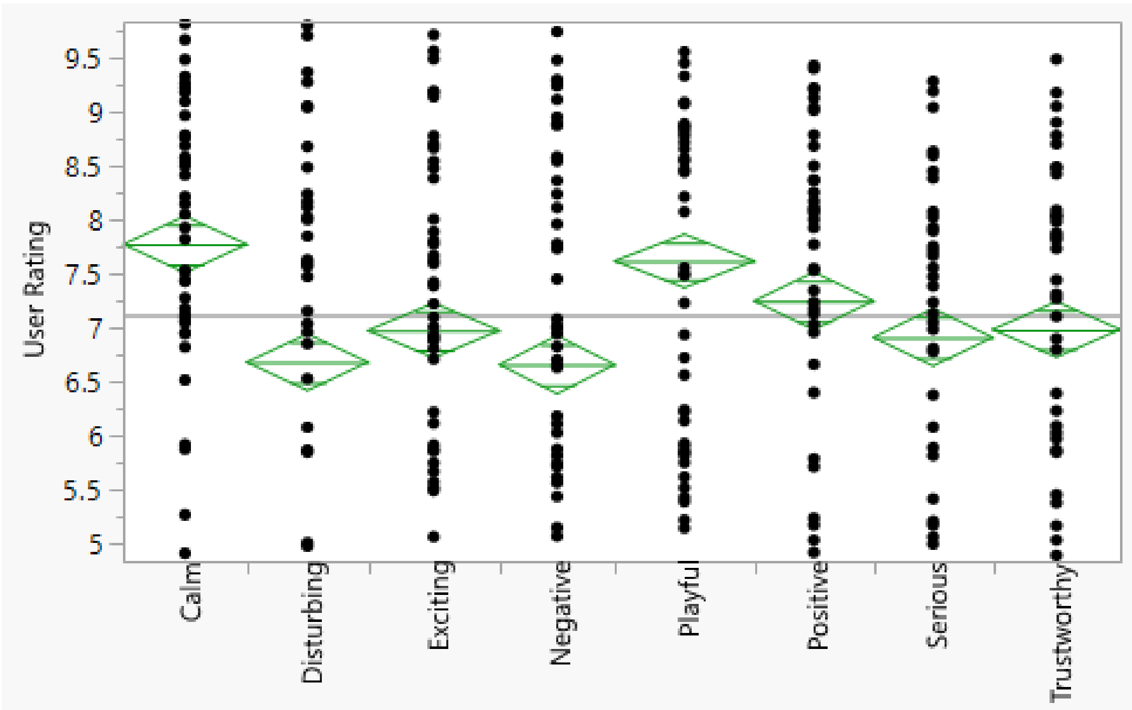


**Figure 5.23 Distribution of ratings across each affect.**

A non-parametric test of rating shows that affect had significant effect on rating across tasks and mean ratings were between 7 and 6 for all affects.

### 5.5.7. Hue

Table 5.1 show affect had a significant effect on hue and WHD. A non-parametric comparison revealed that most significant effects of WHD was among Exciting with Serious, Negative, Calm; Negative: Playful, and Calm: Playful. Figure 5.17 shows the color distribution across the hue wheel. Each palette is representing a convex hull in the hue circle. The radius of the circle is mapped to the saturation. Colors farther away from the center are more saturated. Calm, Serious and Negative palettes are denser near the origin while Playful, Exciting and Positive are denser towards the warmer hues. We cluster the hues in CIELAB space in 5 clusters using hierarchical clustering and also create 5 bins for chromaticity (Figure 5.12

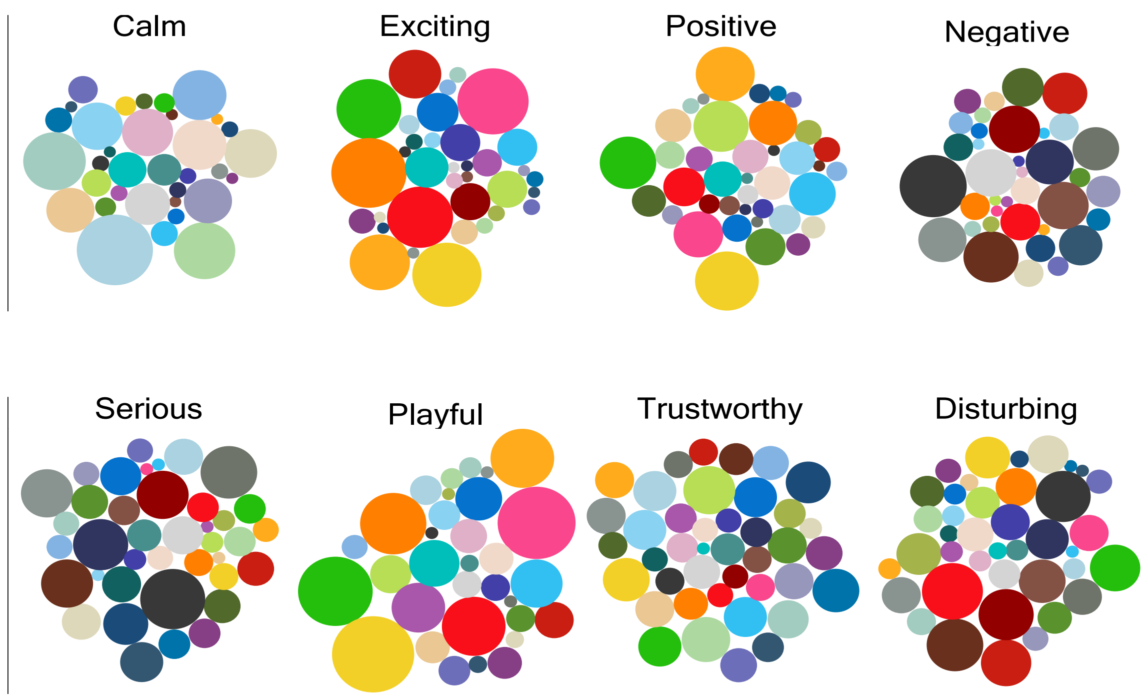


**Figure 5.24 This is a bubble chart where each bubble represents the color used and is scaled by its frequency of use in each affect. The bubble sizes are absolute.**

Similar to previous experiment, high arousal affects (Exciting, Playful, and Disturbing) uses higher chroma reds and yellows and maroons as shown in figure 5.25. . Exciting has more reds than playful while playful has more pinks. In figure 5.25 the CIELAB hue clusters show very strong hue patterns. Calm uses more blues and green and cream hues of similar weights and is overall high lightness and low saturation. Exciting prominently uses warmer colors: more reds and oranges. Positive, like Exciting, uses strongly saturated hues, but incorporates more green. Negative, as anticipated, has more browns, dark reds, and grays. Exciting, Playful and Positive is more spread out in the CIELAB space, Positive a little. Serious and Negative has more grays while Serious had more blues, Negative had more grays; Disturbing, has more browns and grays and also reds and yellows. Calm, Serious and Negative palettes were more tightly clustered in the CIELAB space. These patterns combine in interesting ways when we consider the *pragmatic affects*. Playful is similar to both Exciting and Positive has hue clusters using more greens and yellows and less reds than Exciting. These findings confirm H1: Affect clearly influenced color choice. Figure 5.25 shows all the affects sorted by lightness, binned by chromaticity and clustered by LAB in CEILAB space.

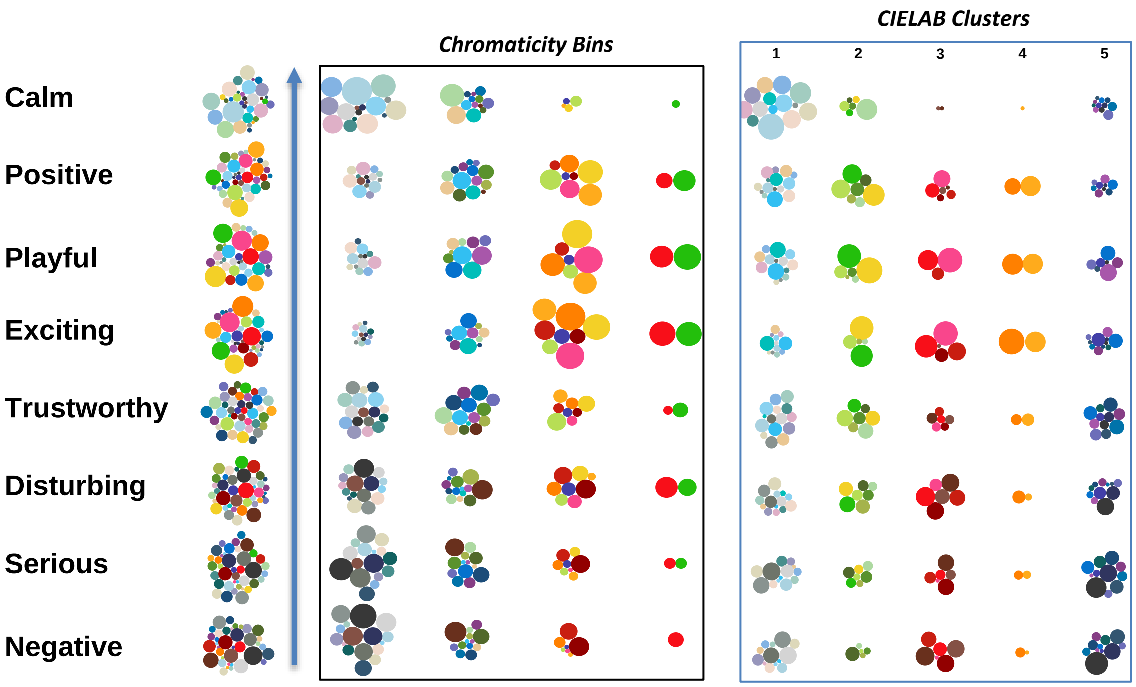


**Figure 5.25 Frequency distribution of colors sorted by L*: Calm lightest-Negative darkest.**

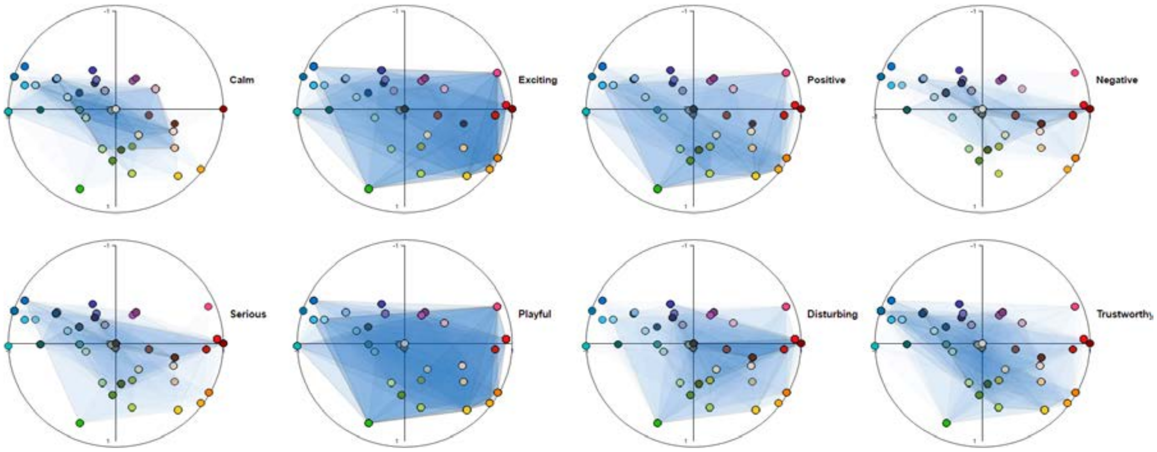


**Figure 5.26 Hue distribution of colors selected in Palette. Each palette is represented as a convex hull over the circular hue wheel. Radius is the saturation ranging from 0-1.**

## 5.6. Discussion

We see differences in both particular hues chosen for affect and how dispersed the colors are in the resulting palettes. We see consistent patterns in lightness related to affect across all studies. Figures 5.25 shows examples from our result that highlight some of the significant differences. Calm, Playful, Positive and to a lesser extent Trustworthy are lightest, while Serious, Disturbing and Negative use more dark colors, confirming H1. Similarly, we also saw the consistent use of higher chroma colors for Playful, Exciting, Positive and Disturbing: where Calm, Serious and to a lesser extent Trustworthy were less saturated. These comparisons are significant and reflect what we would expect from color psychology, confirming H1 and H2. It indicates that any color set intended for use in expressing these affects must provide enough variation in both lightness and chroma.

We also see trends in both what hues chosen for affect and how dispersed the colors were in the resulting palettes. Figure 5.26 highlights some of this patterns in the palette compositions.Similar to study 1 each palette in study 2 is represented as a convex hull over the hue wheel. The radius is mapped to the saturation of the color. Calm and Trustworthy palettes used more blues compared to others, reflecting evidence that these hues relate to peace, competence, and trust (Valdez and Mehrabian 1994). At the same time, hue dispersion is greater in these palettes, meaning that there was a wider spread (a broader selection of other hues), compared to Exciting and Playful that have a larger concentration of warmer hues (closer to each other in the color space). Unlike studies from marketing, we did not see a trend of yellows used in negative valence affects.

Previous studies have shown that yellow is considered exciting. Yellow hues figured in the affects related to positive valence and higher arousal (Positive, Exciting, and Playful), indicating that while it may not be a hue that conveys a professional or serious impression; it does contribute to the above affects. Green was more pronounced in Positive palettes (Playful); studies have shown green to a lesser extent has positive links and are associated with positive content. As expected, Negative, Serious and Disturbing palettes contained more dark reds, browns, black and dark blues. Disturbing palettes had a higher concentration of dark, saturated, warm colors. Negative and Disturbing palettes used more reds, browns and while Disturbing include one or two light colors we resume for contrast. Prior studies also associate brown with “sad” and “stale” ratings while black is considered negative and dominant. Serious used more blue hues. Exciting and Playful those have a larger concentration of warmer hues (closer to each other in the color space). Negative, on the other hand, is similar to Disturbing in lightness; both use browns and dark reds. Similarly, though Playful and Positive have similar chroma and lightness, we see differences in hue distance and dispersion. Playful hues are more distributed in the space than Positive, which has a higher concentration of greens and yellows. These are subtle differences, but they suggest that palettes that want to distinguish between these affects and otherwise close in perceptual properties can vary hue dispersion as one manipulation. The difference in saturation between the more exciting affects of Playful and Disturbing and the less aroused of Calm and Trustworthy indicates that chroma relates strongly to these impressions. The strong difference in lightness between Calm and Disturbing shows that lightness also influences the impression of intensity. This suggests that palettes with predefined hues (such as used in branding) for affects can vary these properties to tune affect. Hue dispersion, and the types of predominant color family, on the other hand, relate more strongly to valence: the more negative affects used proportionally more browns, dark reds and dark grays, and less yellows and greens.

Analyzing the color associations along the valance and arousal dimension we see interesting patterns in figure 5.27 that emerge when we combine core affects with pragmatic ones. Playful is both Exciting and Positive in affect: its colors are similar to Exciting, but included more greens and yellows and fewer reds than Exciting. Serious shared the grays of Negative but used more blue; we would expect that it has aspects of low arousal and Calm. Notably, Serious, which might be considered both calmer than Disturbing and less Negative, used less red and yellow hues. Disturbing, which is clearly Exciting and Negative, reflects the browns and grays of Negative but incorporates more of the reds and yellows of Exciting. Calm and Negative palettes were the most tightly clustered. Finally, the ratings were uniformly high, except for one case in the first experiment where designers were less satisfied with Trustworthy. These findings inform possible operational features for automatic recommendations of particular colors for different affective communicative intent, and how to manipulate their perceptual properties to enhance that affect algorithmically.

The resulting network models by Dr. Lyn Bartram and Maureen Stone provide distinctive network features that give us insights into palette structures and color groupings (Lyn, Abhisekh, and d Maureen 2017).

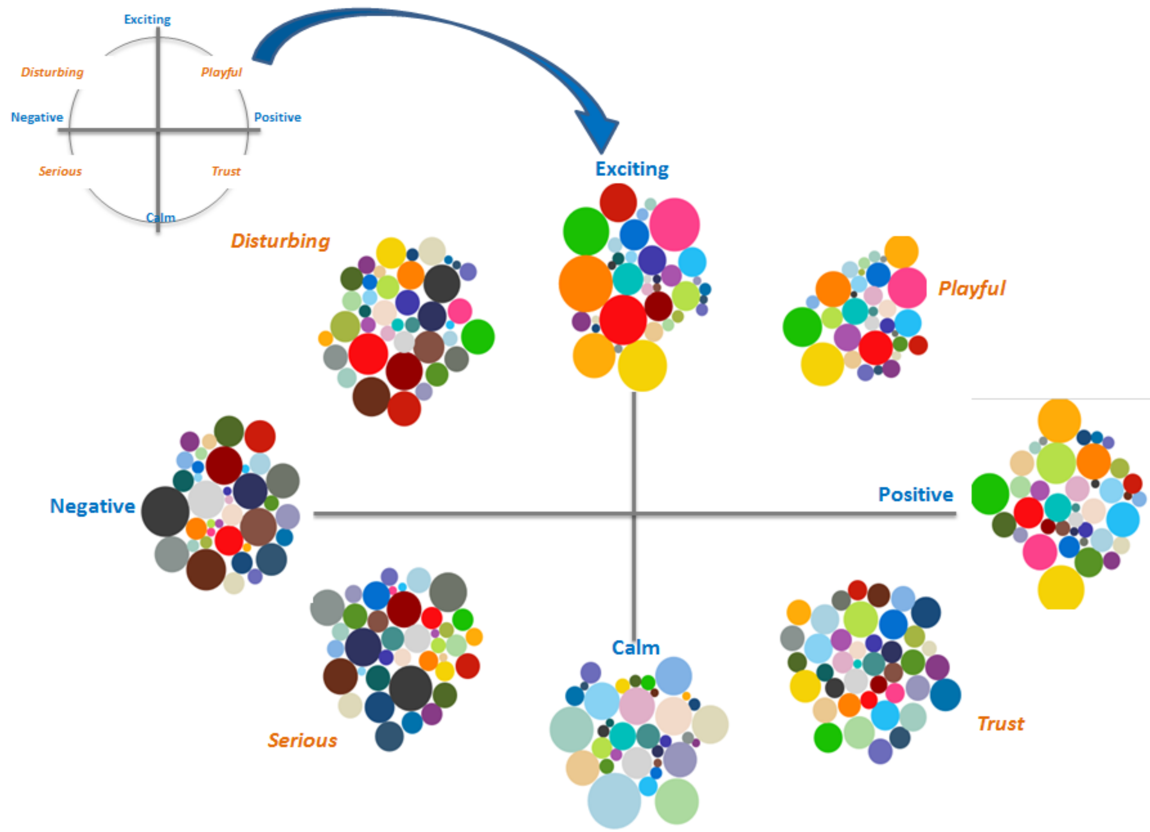


**Figure 5.27 Affect Mapping : This figure shows that in our affect space the Pragmatic affects share elements from Core affects.**

# Chapter 6.

# Palette Ranking Study

Finally, we conduct experiments to confirm if these results would apply to the development of guidelines for palette design. Using the results of previous experiment we generated affective palettes for ranking palettes.  These generated palettes were modeled to assign weights such that a higher palette weight represented the cumulative strongest color combinations; we believe that palette weight would be a good predictor of a palette's suitability for a particular affect.  We used the insights from the previous studies to design sets of palettes for each affect and ran a validation study in which people selected the best and worst palette for an affect from a set of 5 choices.

## 6.1. Palette Design

The palettes were designed manually based on frequency of use in each affect obtained from study 2 results. For each affect, we generated every possible combination of 5 colors using the 41 color palette used in study 2 (749,398 combinations of 5 color palettes) and calculated the palette weight of each summing the color frequencies in the corresponding affect from Study 2. The weight of the color was the frequency of its use across each affect in study2. Hence the metric Palette Weight was the sum of the frequency of the colors in the corresponding palette in the list.  We then sorted the list from highest to lowest and manually selected candidate palettes from three relative areas: the top weighted palettes (higher frequency colors), the lowest weighted palettes (lower frequency colors) and the middle area (mix of lower and higher frequency colors). We tried to minimize color replication in the palettes, although this was difficult in the highest weighted palettes because there were a few very heavily weighted colors in these: we ensured that no two palettes shared more than 3 colors.  Figure 6.1 shows examples of two good and 2 bad palettes for each of Calm and Negative. Good palettes have the higher frequency colors while the bad palettes have the lower frequency colors in study 2.

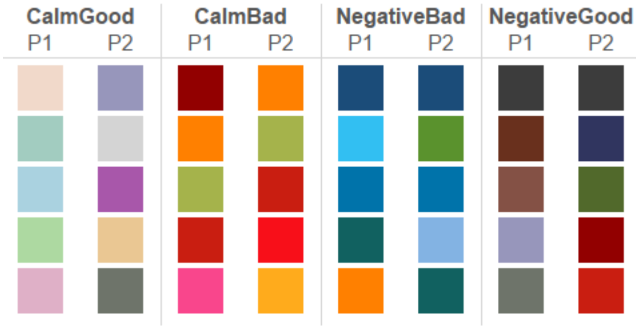


**Figure 6.1** **Examples of good (high weight) and bad (low weight) palette.**

## 6.2. Method

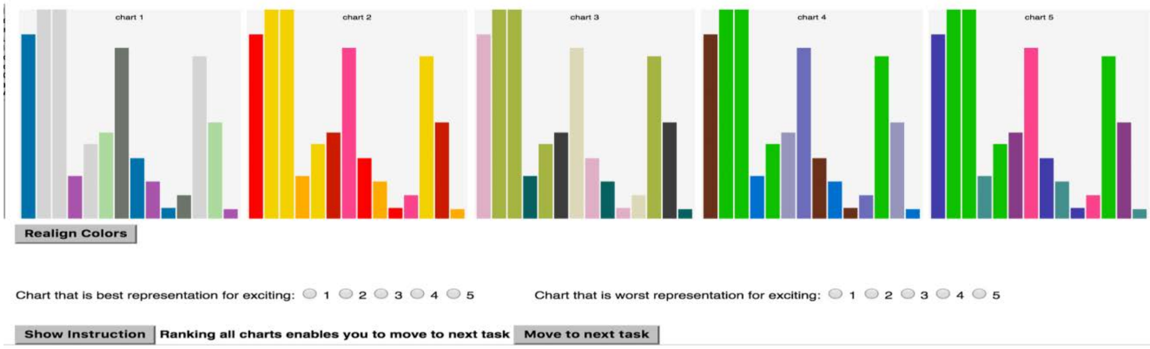


**Figure 6.2** **Study 3 Interface: The figure shows the web interface for study 3. Participants saw 5 identical bar charts, each colored with a different palette. Participants ranked the best and worst of 5.**

In each trial a participant saw 5 identical bar charts, each colored with a different palette. The participant was asked to identify one as Best and one as the Worst. There were 8 affective tasks. For each affective category, there were 15 possible palettes, binned into 5 "good", 5 "medium" and 5 "bad". These were only used for randomization: in each trial, 2 palettes were randomly selected from the "good" bin, 1 from the "medium" bin and 2 from the "bad" bin. Each participant did 2 repetitions of each affective task (2 Best, 2 Worst) and participants saw possible palettes for only one affect in each task.

## 6.3. Metrics

We had 2 independent variables: Affect (8) and palette weight (PW). Our dependent variable was the rating of Best/Worst for each palette. For each palette we thus had rating, the individual colors in that palette, and the frequency weighting for each color and the summed palette with.

## 6.4. Hypothesis

We had the following hypothesis:

**H4**: Higher weighted palettes would be more likely to be rated Best than low weighted palettes;

**H5**: Lower weighted palettes would be more likely to be rated as the Worst.

## 6.5. Participants

38 users (and an additional 2 with incomplete data) participated. They were roughly distributed by gender. All had normal or corrected-to-normal vision. Participants were entered into a draw for potential reimbursement. None had taken part in the previous studies.

## 6.6. Results

As the palette sets were very different in the **range of weights,** we normalized the weight metric to **relative weight position:** that is, the percentage of the overall range that the weight represented. So, for example, the Calm range was 135 from the lowest weight to the highest weight: a Calm palette with a weight of 109 had a relative weighted position of 80.7. Figure 6.3 developed by Dr. Lyn Bartram using the results of the study shows the results of palette ratings by weight and affect. The circles represent individual palette weights used. We then used a logistic regression analysis to determine if this would be a significant predictor of Best/Worst choice. The result was extremely significant: [$X^2$ (1,1218) =1093.32, $p$ <.0001]. These results confirm that palettes are more likely to be ranked higher as their weight increases. Conversely, palettes with low weight were more likely to be selected as the Worst.

These results confirm our hypotheses **H4** and **H5** that palette weight calculated from our previous studies proved a strong predictor of how people ranked it for affect expressivity. More generally, they validate our essential conjectures that even simple palettes of 5 colors can convey different affective impressions, though it can be seen in Figures 6.2 and 6.3 that is a stronger finding for some affects than others. The relative difference between Best and Worst in Trustworthy was smaller, and there were more outliers. This might be due to the case that the ranges of weights in these palettes were smaller: instead of a few highly weighted colors, the preferred colors were more evenly used, and thus the weight ranges were smaller.

We calculated the preferred colors for each affect by counting how many times the hues occur in the palettes rated best for that affect. We then simply selected the colors with the highest count for each affect. Figure 6.4 shows the preferred colors for each of the affects in Study 3. These strongly reflect the results from Study 2, as we might expect.

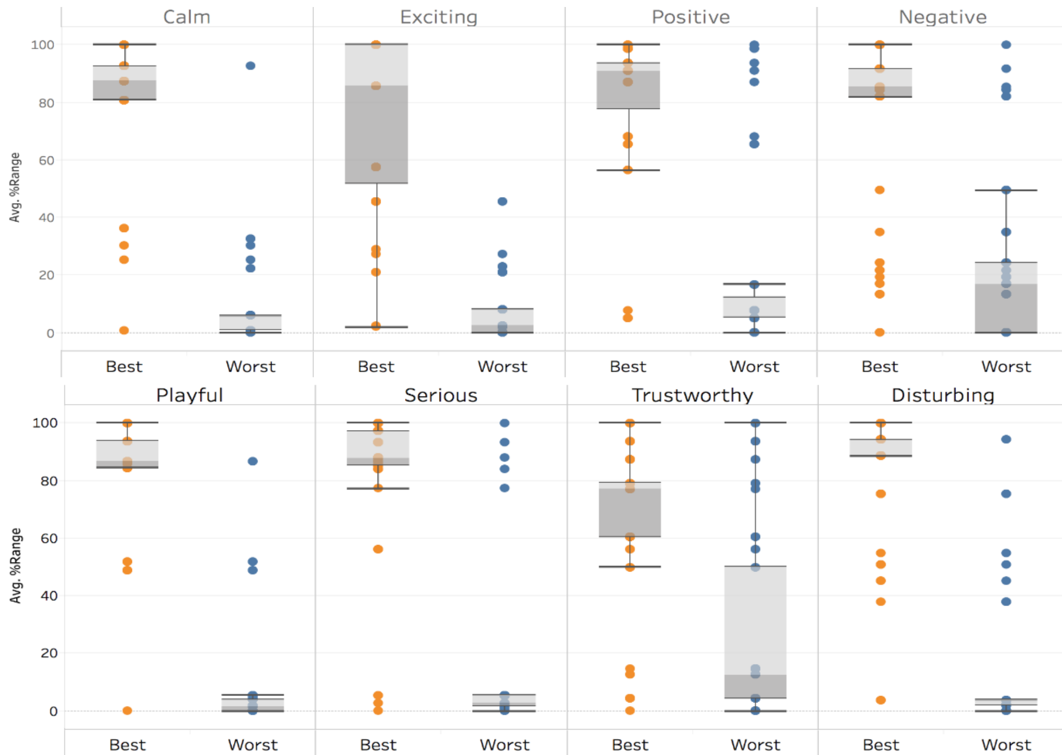


**Figure 6.3** The boxplot shows the distribution of the palette weights for the best and worst rankings across each affect. These are normalized weights.

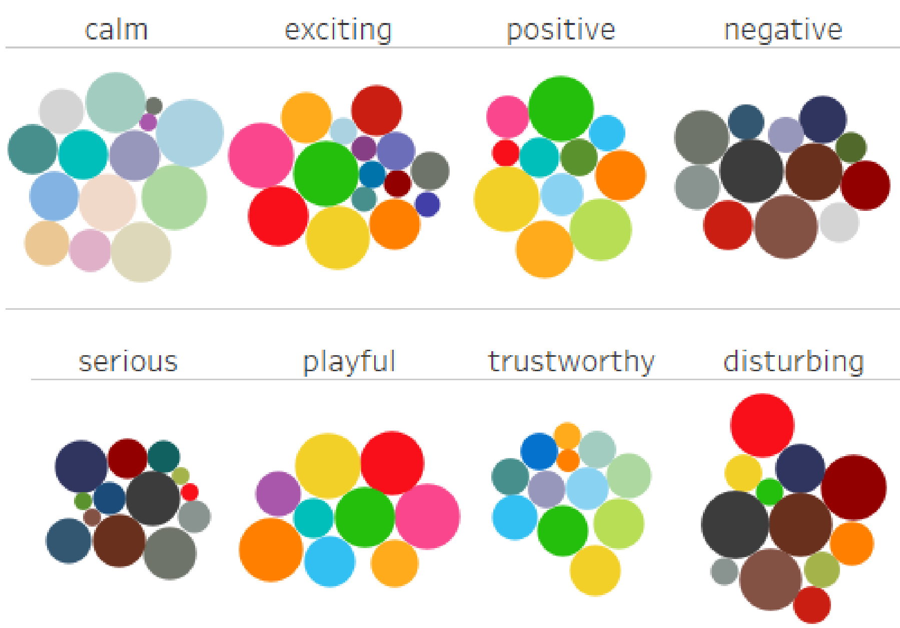


**Figure 6.4** This figure shows the preffered colors for each affect in study 3.

# Chapter 7.

# Discussion

Operating the affect and color space model in information visualization is challenging with little previous work. Our results help us to describe affect with measurable color properties. We can reliably associate color properties with affective response even in the limited scope of color selection in simple information visualization representations, extending previous work in individual color-affect relations.

Our results show consistent patterns in lightness and chromaticity of color and the composition patterns of how hues are used together in palettes are affectively distinct. From our studies in user-designed palettes, we could define a metric of color frequency use in Affect. This metric proved a reliable predictor of good affective palettes offering the suggestion on which colors to choose to convey the desired affect.

One of our primary goals in this is to create guidelines for designers that would recommend starting palettes in a particular affect, similar to work by Bartram et al. (Lockyer and Bartram 2012). While these will never replace the skill of an experienced designer, they can reduce the time spent exploring and providing guidelines to start will be precious.

Maureen Stones points out that recent work at the Brown University has created a palette generator called Colorgorical (Gramazio, Laidlaw, and Schloss 2016) that balances different properties such as perceptual distinctness, color name uniqueness, and an aesthetic component called pair-preference to create color palettes for categorical data. She suggested that the affect study results show that for some of the affects we studied we can have filters for lightness, hue and chroma applied to palette generators like Colorogorical that would allow us to achieve palettes for designers interested in a specific affect.

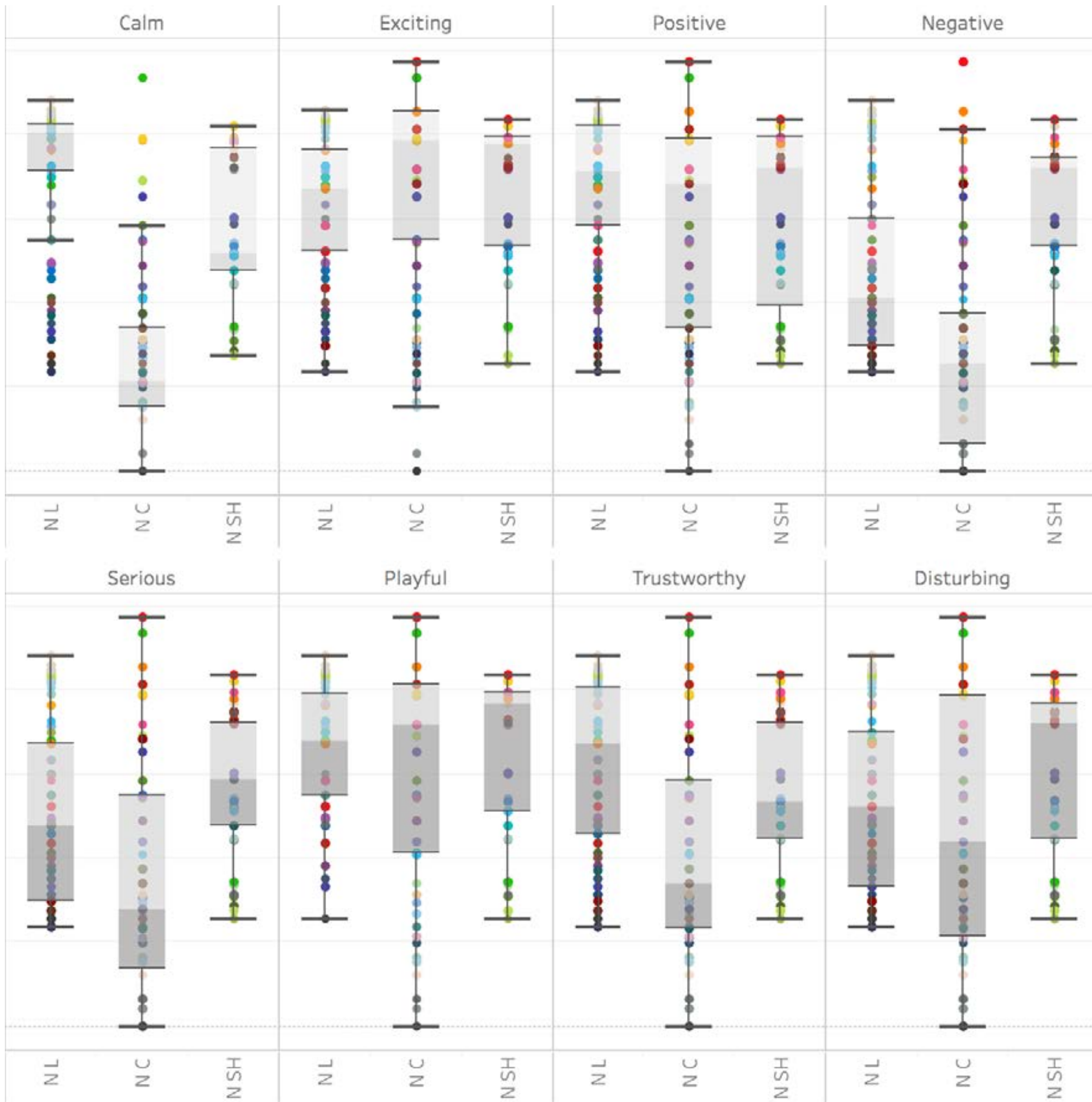


**Figure 7.1 This figure shows the L, C, H distributions for each affect in study 2 with non designers. Hue is rotated by 60°.**

Figure 7.1 by developed by Maureen Stone using the results of the non designer study summarize the mapping between affect and LCH ranges for each affect. Here, each of L, C and H has been mapped to a common range, then plotted. Also, hue angle has been rotated so that all the warm colors are together (normally they straddle zero). The box plots show the distributions.

Palettes that are composed of colors, selected from near the median of the LCH plots for a specific affect will be more likely to be judged as matching that affect. Some affects have strong LCH spread than others. About the Core affects, Calm is the strongest, requiring high L, low C and cool colors. Negative similar to Calm has low C, but dark colors predominate. Lightness is strongly related to these affects which suggest that palettes with predefined hues can vary this property to tune affect. Both Exciting and Positive are high Chroma and have a larger concentration of warmer hues. Positive is distinctly different than Calm and Negative, shares elemets from the pragmatic affect Playful. We see consistent use of higher chroma colors for Exciting, Playful and Positive. We see trends in what hues are choices, how similarly dispersed colors were in the resulting palettes and overlap of hues with the Pragmatic affects for Exciting, Playful and Positive. The other pragmatic affects show similar overlaps, as we might expect. The differences between palettes compositions and understanding about which colors go with others can be further explored using network diagrams designed by Lyn Bartram (Lyn, Abhisekh, and Maureen 2017).

While we cannot reliably profile each affect, even being able to say what colors to avoid for specific affects can be useful. For example, we can say the following with some authority

1. Both Lightness and Chromaticity are related to valence and arousal. Higher chroma colors are more intense and while lighter are soothing. This difference in saturation in Core affects between the Exciting and Positive and less aroused Calm and Negative indicates that chroma relates to these impressions.
2. Highly saturated light color will NOT be appropriate for Serious or Trustworthy, or Calm; Calm palettes are tightly clustered around the blues, greens, crème and lighter pinks. Pragmatic affects Trustworthy (similar to Calm and Positive) unlike Calm is less tightly clustered and the palettes show blue-yellow and green-yellow themes.
3. Exciting palettes use light and saturated warm colors, concentrated on reds and yellows. The Exciting Cluster highlights strong major hues.
4. Positive is both higher chroma and lighter hues which are clustered around greens, oranges and yellows. Greens form an important cluster in Positive.
5. Playful is similar to Exciting but lighter with major hues yellows, greens, pinks, oranges. Dark red and browns are not Playful; the palettes compose of hues distributed in CIELAB hue space.
6. Disturbing and Negative palettes use dark brown and black and blues. Disturbing palettes have a concentration of dark saturated warm

colors similar to Exciting along with fewer bright colors we presume for contrast.

7. Serious similar to Negative and shares its dark pale browns, blacks and grays and also the blues of calm.
8. Given a set of predetermined hues, both saturation and lightness can be varied to influence the degrees of affect related to arousal dimensions.

These results statistically confirm our hypothesis H2 that lightness relates to valence and H3 that arousal influences colorfulness choice. These results show similarity when compared to our image analysis results. Calm, Playful and Exciting images are much lighter compared to Disturbing, Negative and Serious. Negative and Calm is less colorful (chromatic) than Playful and Exciting. Our preliminary results showed initial understanding for mapping color groups in the limited affect space we explored and what makes affective impression comparatively stronger or weaker. In future work, we hope to better understand what these patterns mean and how they might be applied. This includes exploring how the color patterns we see in the core affects transfer to the more applied, pragmatic affects. We sought to see if there were general color associations with the more abstract dimensions of valence (Positive-Negative) and arousal (Calm-Exciting) that would translate (lend color elements) to the specific expressions of Playful, Serious, Trustworthy and Disturbing.  We certainly saw evidence of these crossovers in our limited set of results. Establishing such reliable associations leads to the provocative question as to whether we can algorithmically determine color selection based on the desired affect's "location" in the PAD affect space. In other words, given a desire to enhance visualization as more reassuring, for example, can we look at where reassuring plots between Calm-Exciting and Positive-Negative and determine the relative hues, chroma and lightness values as a weighted contribution of each? Another future work, how can we balance affect, color and semantic space with perceptual constraints? Further experiments might explore the trade-offs between rich semantic associations and affective color assignment. Given a color combination what can be the preference of designers to combine hues in categorical palettes?

## 7.1. Conclusion

We present a study-driven approach to demonstrate whether color can express affect, even when used as a categorical coloring for simple data visualizations. This study demonstrates clearly that affect is a dimension of categorical color palette design, and motivates extending work in automated palette design to include affective concepts. We believe our results are an encouraging step in the process of linking affective concepts with automated palette suggestion. Because our palette properties are derived from the human level of agreement in matching colors to affect, it has the potential to be a useful component in improving expressivity in Information Visualization.

Our results show a validated relationship between affect, perceptual color properties (hue, chroma and lightness), and palette composition for the eight categories we measured. This confirms and extends the findings in color psychology and design practice in the context of simple information visualization forms and data contexts. In our discussion, we offered one simple application of these results, using LCH filters to apply affect. While this is not enough to clearly distinguish all affects, it helps limit the design space, which can be of significant practical value.

A more challenging application as suggested by Maureen Stone would be to include affect on the design of palettes where some colors are already defined, especially if they fall outside of the simple LCH model of affect. A simple example would be creating a Trustworthy palette for T-Mobile that included its signature bright purple. Here, we would ideally be able to model how to combine that playful color with others to create an overall Trustworthy affect.

The visualization scenario where a user might want to interact with data in some nonstandard ways may be achievable by manipulating the display to alter the underlying affective context in the data. In this way, users can be stimulated to ask questions and receive feedback about the data they are visualizing. Designers used one of the visual features (Cairo 2013), Color effectively to transform the visualization into a powerful visual metaphor. Also, another interesting implementation can be in visualizing for correlation between data mapped to the affective dimensions using stimulus separated by perceptual properties. Can changing representation using affective stimulus make use of the human visual system for effective cognition reducing the burden on computers? The evocative nature of color can be used in systems to represent affective structures of themes in textual content in documents where there is a need for visually distinct colors and codify a large number of categories. Recently systems like Synemania (Krcadinac et al. 2013; Krcadinac et al. 2016) used both color and abstract animations to evoke emotions for representing thematic structures in text. Future empirical studies that map the features of visualization systems using emotional animations and find effective ways to combine motions, shapes and colors will be important for storytelling in information visualization systems.

## 7.2. Limitations

Our goal was to build a relationship between affect and measurable properties of color palettes. Our results provide initial suggestions on which colors to choose for conveying the desired affect and also colors from core affects overlay with pragmatic affect. Our work provides recommendations for what colors should a designer choose for expressing a given affect in the limited affect space we considered. Being able to link colors and affect absolutely for all cases was not the goal of this work.

In our research, we were interested in the relative locations of color groups in affect space. Based on fundamental work on affect we paired endpoints of the core and pragmatic affect in order to understand what makes desired affect impressions comparatively stronger or weaker. This does not provide us with absolute quantification of a palette concerning an affect.

Because we were interested in the relative locations of color groups in affect space, we paired endpoint tasks of the affect model: (Calm-Exciting, Positive-Negative) to establish (if any) differences. Where there was not a clear opposite (Trustworthy-Disturbing) we did not pair the tasks. If we were concerned with absolute mappings, we concur this would have introduced bias, but we are not expecting to be able to absolutely quantify all possible palettes with respect to affect, but rather to understand what might make a desired affective impression comparatively stronger or weaker. We drew the pairing from the core theoretical work in mapping affect. Similarly, we considered these differences in one of the pragmatic affects (Serious-Playful) that is a clear semantic opposite.

We tested only simple visualization forms (bar charts and maps) where the size of the colored areas was large. It is not clear how well such color schemes would apply to more fine-grained visualizations such as scatter plots or line charts. Our studies also assumed no other constraints on color assignment, such as existing color identities, or additional color in brushing or user interface elements. We did not include any special relationship with respect to the relative size of the colored areas in the charts and the relative contrast of each color with respect to the background (high contrast draws attention). Participants could reassign the 5 colors as they desired and were not constrained to mapping a color to a particular location or weight. Hence, participants design choices were simply aggregated into the palette specification. Similarly, we did not analyze relative contrast across the chosen palettes or look at where the high contrast colors were positioned. We only capture the alpha values and not the actual colors produced after altering the alpha value. Creating the actual colors would have simply added small bubbles but we were only interested to see if alpha was significant. Hence we show the distribution of the actual colors viewed in the palette. We don't feel this invalidates what we did find, given our goals. Finally, we only used light grey backgrounds, which clearly influence lightness and chroma choices.

## 7.3. Future Work

Our work suggests ways to address the development of features for the visual language for affective visualizations that would be interesting to explore further. For example, the psychological dimensions of affect (arousal and valence) are shown to be strongly influenced by lightness and chroma. This indicates that these properties can be used to "tone" palettes of predefined hues to these affects, either by modulating the color itself or by optimizing these values over the palette as a whole. In the future works, we plan to examine different animation, shape, speed, motion, texture and other visualization features and how they affect human affective systems. This will provide us with information to propose generalized principles for evoking affect in data visualization.

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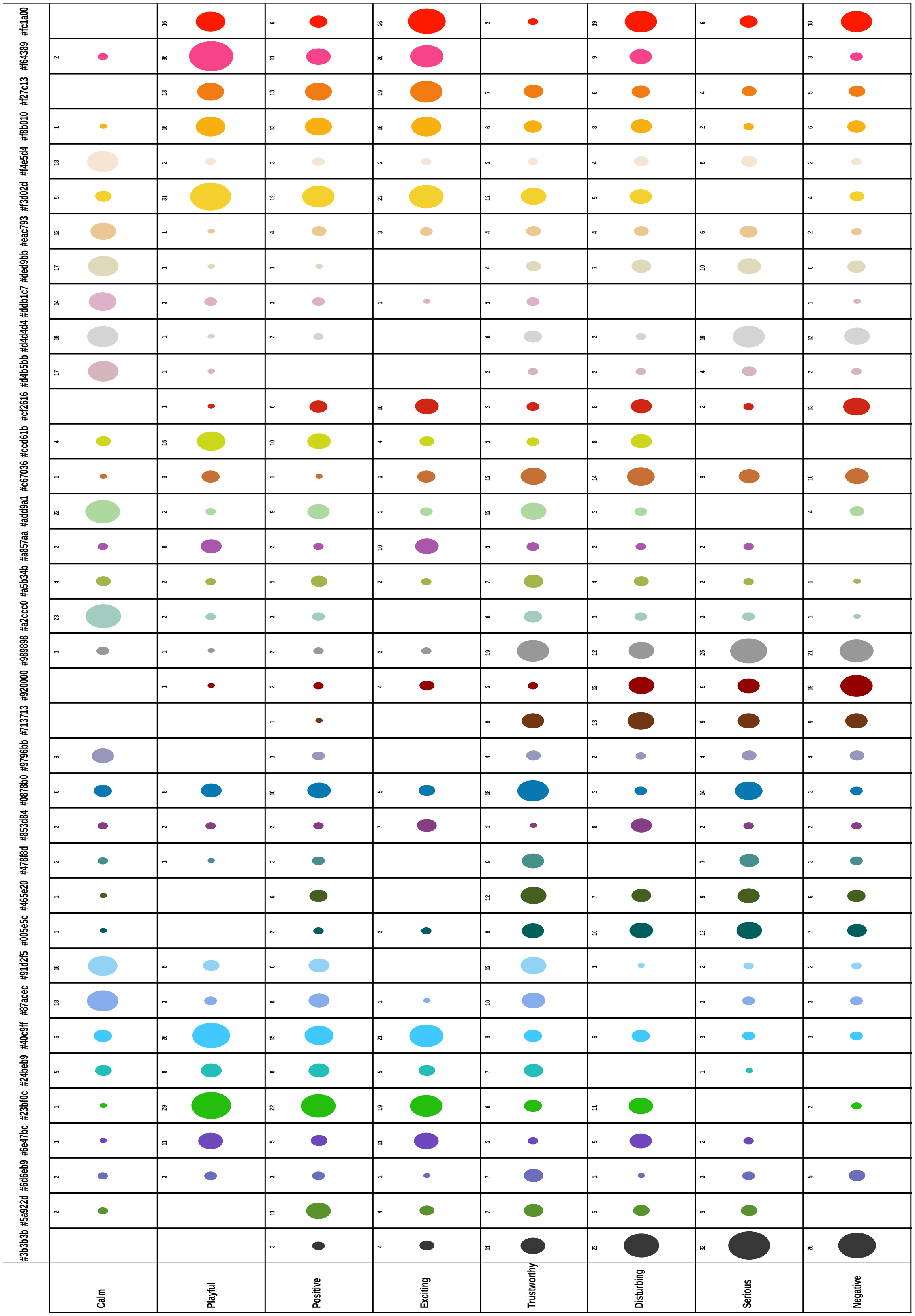
# Appendix A.

## User Design Study 1 Palette Details

The image in the next page shows the details of the colors used in our master palette in each column. Each row  shows the frequency of the color by affect and the bubble size corresponds to the affect in design study 1. The affects are sorted by Lightness. Calm is the lightest and Negative is the darkest.


#fc1a00
#f64389
#f27c13
#f8b010
#f4e5d4
#f3d02d
#eac793
#ded9bb
#ddb1c7
#d4d4d4
#d4b5bb
#cf2616
#ccd61b
#c67036
#add9a1
#a857aa
#a5b34b
#a2ccc0
#989898
#920000
#713713
#9796bb
#0878b0
#853d84
#47878d
#465e20
#005e5c
#91d2f5
#87acec
#40c9ff
#24beb9
#23bf0c
#6e47bc
#6d6eb9
#5a922d
#3b3b3b
Calm
Playful
Positive
Exciting
Trustworthy
Disturbing
Serious
Negative

# Appendix B.

## User Design Study 2 Palette Details

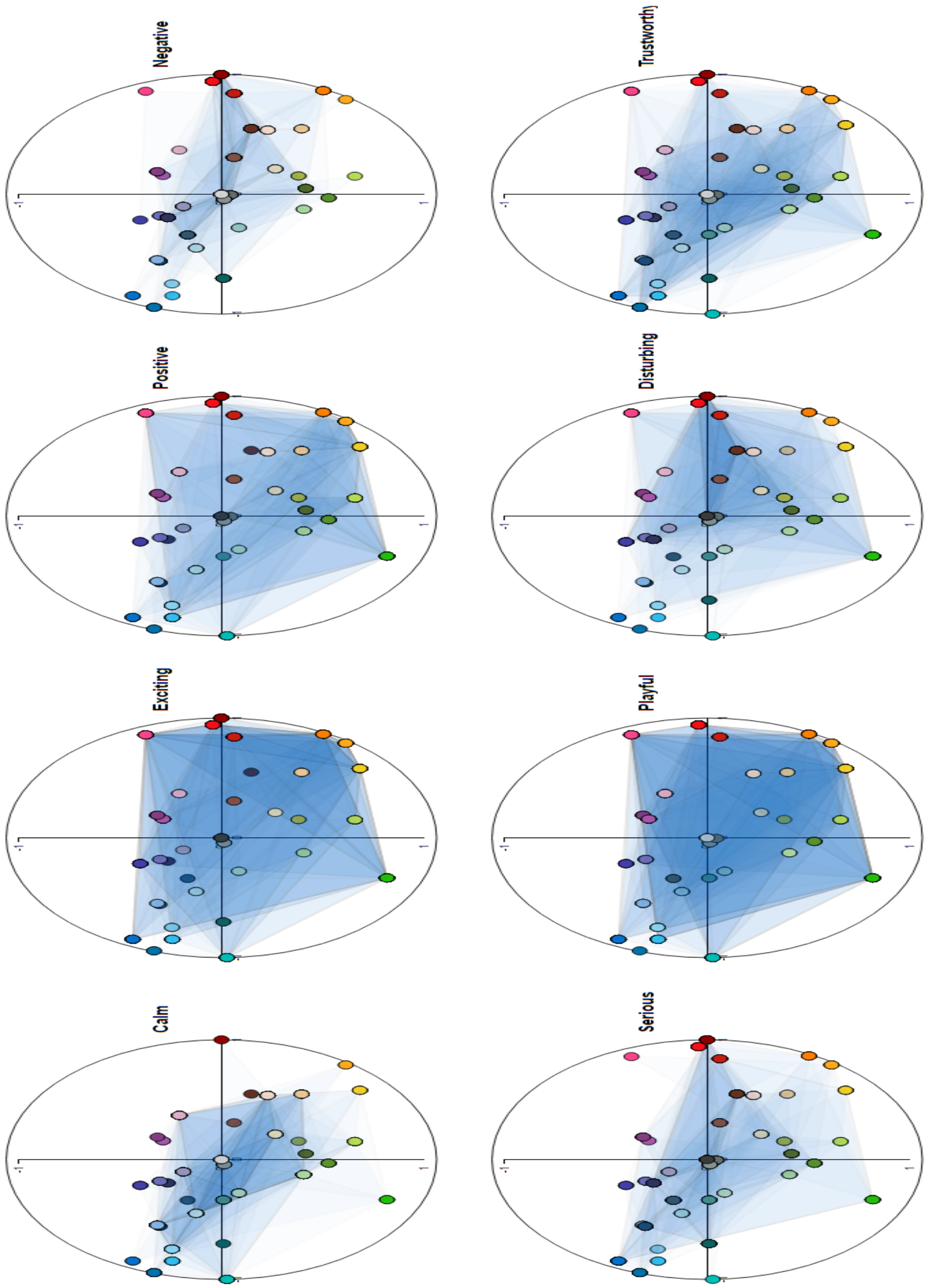
The image in the next page shows the details of the colors used in our master palette in each column. Each row  shows the frequency of the color by affect and the bubble size corresponds to the affect in design study 2. The affects are sorted by Lightness. Calm is the lightest and Negative is the darkest.

| | #1b4c79 | #3c3c3c | #5a922d | #6d6eb9 | #6e746a | #8ad2f1 | #00beb9 | #23bf0c | #32bff2 | #83b3e3 | #423fa8 | #478f8d | #863e85 | #0073aa | #0572cd | #9796bb | #30355f | #51692b | #69301d | #116160 | #335671 | #845145 | #899390 | #920000 | #a2ccc0 | #a5b34b | #a857aa | #aad2e0 | #add9a1 | #b7de55 | #c91e11 | #d4d4d4 | #ddd8ba | #dfb0c7 | #eac793 | #f1d9ca | #f3d027 | #f80f19 | #f9468c | #ff8000 | #ffab1c |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Calm | 2 | 2 | 3 | 6 | | 18 | 10 | 3 | 5 | 20 | 2 | 8 | 1 | 5 | 2 | 16 | 2 | 2 | 1 | 1 | 1 | 1 | 2 | | 27 | | 2 | 40 | 26 | 6 | | 14 | 19 | 18 | 16 | 20 | 3 | | | | 1 |
| Disturbing | 2 | 18 | 7 | 4 | 9 | 3 | 2 | 15 | 1 | | 9 | 3 | 4 | 1 | 3 | 4 | 11 | 7 | 19 | 2 | 1 | 13 | 9 | 18 | 5 | 12 | 3 | 3 | 5 | 7 | 15 | 6 | 10 | 3 | 2 | 8 | 12 | 22 | 9 | 10 | 3 |
| Exciting | 1 | 1 | | 2 | | 2 | 13 | 29 | 11 | 2 | 11 | | 5 | 2 | 12 | 1 | 1 | | | 2 | 1 | 1 | 1 | 11 | 2 | 2 | 6 | 3 | 2 | 11 | 19 | 1 | 1 | 2 | 5 | | 33 | 30 | 35 | 39 | 25 |
| Negative | 6 | 31 | 3 | 3 | 15 | 1 | | | 1 | 4 | 1 | | 5 | 4 | 2 | 8 | 16 | 12 | 21 | 6 | 13 | 18 | 16 | 18 | 2 | 2 | 1 | 6 | 2 | 1 | 14 | 18 | 6 | 1 | 3 | 6 | | 11 | 1 | 6 | 1 |
| Playful | | 1 | 5 | 6 | 1 | 6 | 15 | 33 | 16 | 4 | 5 | 2 | 7 | | 13 | | | | | | 2 | | 1 | | 3 | 1 | 17 | 6 | 3 | 10 | 9 | 5 | 2 | 8 | 7 | 7 | 40 | 24 | 36 | 26 | 24 |
| Positive | 3 | 1 | 11 | 2 | 1 | 9 | 10 | 22 | 15 | 3 | 3 | 1 | 4 | 2 | 6 | 3 | 1 | 8 | 1 | | | 3 | 1 | 3 | 2 | 5 | 5 | 7 | 6 | 21 | 5 | 3 | 4 | 9 | 9 | 9 | 28 | 12 | 17 | 16 | 24 |
| Serious | 12 | 25 | 8 | 4 | 19 | 1 | | 6 | 1 | 4 | 3 | 7 | 6 | 6 | 10 | 4 | 18 | 8 | 16 | 9 | 11 | 6 | 16 | 16 | 4 | 3 | 1 | 9 | 6 | 3 | 8 | 10 | 9 | | 1 | 4 | 5 | 6 | 1 | 5 | 4 |
| Trustworthy | 12 | 5 | 9 | 8 | 5 | 11 | 1 | 11 | 11 | 8 | 4 | 7 | 8 | 13 | 11 | 9 | 6 | 5 | 7 | 4 | 6 | 5 | 9 | 4 | 10 | 6 | 6 | 11 | 14 | 16 | 5 | 8 | 3 | 6 | 9 | 4 | 13 | 4 | 5 | 7 | 9 |

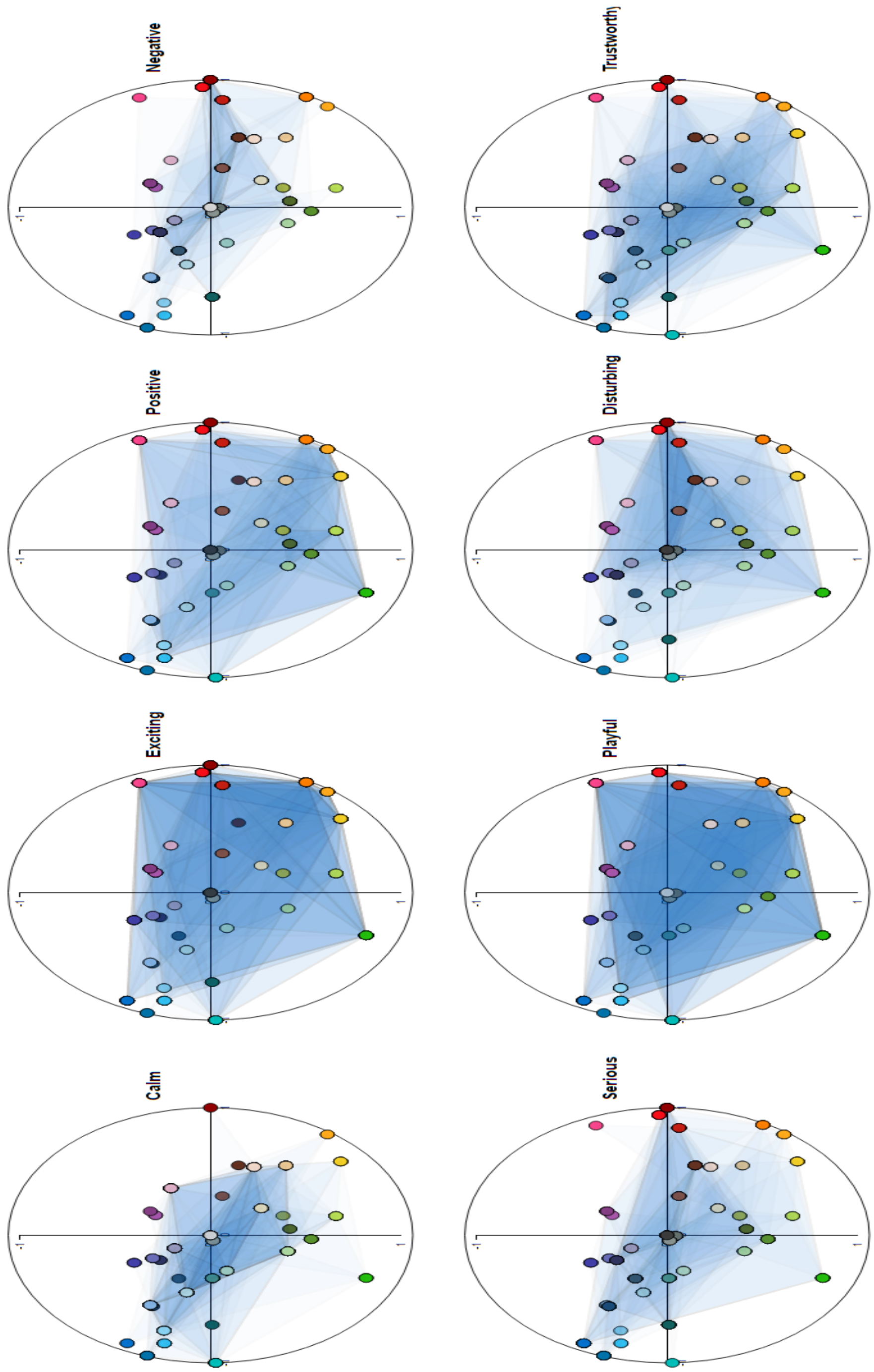
# Appendix C.

# Circular Hue Distribution

### Study 1



## Study 2


Negative
Trustworthy
Positive
Disturbing
Exciting
Playful
Calm
Serious

# Appendix D.

## Palettes For Ranking Study

These are the sets of palettes developed for the ranking study. Each affect has 15 palettes, grouped as Good, Medium and Bad. The colors in the good palette have the higher frequency colors obtained from study 2. Palette Weight is sum of the 5 weights in each Palette.


Trustworthy
Disturbing
Playful
Serious
Negative
Positive
Exciting
Calm
P1
P2
P3
P4
P5
quality
Good
Medium
Bad

# Appendix E.

## Online Color Palette Generation Tool

I used this tool to generate 40 sets of hue for each affect. I used the ranges obtained from the image analysis to set the chroma and lightness values and generate 40 sets of hue per affect. The generated sets were weighed against the images, and the results are discussed in chapter 4.