COGNITIVELY CONGRUENT COLOR PALETTE FOR EMOTIONAL MAPPING

by

Andrei Kushkin, M.A.

A dissertation submitted to the Graduate Council of
Texas State University in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
with a Major in Geographic Information Science
August 2022

Committee Members:

Alberto Giordano, Chair

Amy Griffin

Eric Sarmiento

Injeong Jo

FAIR USE AND AUTHOR'S PERMISSION STATEMENT

Fair Use

Duplication Permission

DEDICATION

To the great future of humanity.

ACKNOWLEDGEMENTS

This work would not have been possible without the intellectual support of Dr. Amy Griffin, Dr. Injeong Jo, and Dr. Eric Sarmiento. I am grateful to Dr. Alberto Giordano for his guidance, for reviewing my manuscript, and for providing a great number of invaluable comments. I am also thankful to Dr. Alexander Savelyev, who has helped me in developing the idea for this research. I am very grateful to my wife Nika for having my back throughout the entire study program and for the help with proofreading and formatting the dissertation.

TABLE OF CONTENTS

Page

LIST OF TABLES

Table **Page**

LIST OF FIGURES

LIST OF ABBREVIATIONS

Abbreviation	Description
AMT	Amazon Mechanical Turk
CIE	International Commission on Illumination
CSV	Comma Separated Value
EVT	Ecological Valence Theory
GeoJSON	Geographic JavaScript Object Notation
GPS	Global Positioning System
HCI	Human Computer Interaction
HSL	Hue Saturation Lightness
IRB	Institutional Review Board
NASA-TLX	NASA Task Load Index
sRGB	Standard Red Green Blue
UX	User Experience

ABSTRACT

Emotions are touchstones of human experience and fundamental to everyday human life. Maps of emotions and sentiments are used to make our cities safer; to study natural disaster response; to inform marketing, business, and tourism-related research. The most common way to visualize emotions is by using color, such as placing point symbols on maps, with different colors standing for different experienced emotions. Recent findings in psychology suggest that humans have subjective associations between colors and abstract notions, including emotions. There is also evidence that such associations impact objective task performance. Thus, showing emotions on maps using general cartographic color palettes may lead to a mismatch between the emotion associated with a color and the emotion it represents. This mismatch may bias the viewer’s attention, perception, and understanding.

There are guidelines for choosing optimal colors for different mapping contexts, but none helps in picking colors for showing emotional geographic data. This study aims to address this gap by designing and evaluating a cognitively congruent color palette — a set of colors matched to emotions in a way that is aligned with human associations.

The set of candidate colors for this palette was obtained by a user experiment. Participants were given a list of emotions and asked to pick a color for each emotion. A second user experiment was conducted to identify the most optimal color-to-emotion assignments. Participants were asked to match each color from a given set to emotions from a list. The probability of emotion being selected depending on the color served as a

measure of how suitable the color is to represent that emotion. Due to the many-to-many nature of associations between colors and emotions, a dynamic palette generation tool was created. This tool solves the color assignment problem depending on the combination of the selected emotions.

A sample cognitively congruent color palette was evaluated in a third user experiment regarding its influence on the map use experience, performance, and map-based decision making. The participants planned a walking tour using one of two maps showing the main attractions and how people feel in different parts of town: one using the cognitively congruent palette and the other using a general cartographic palette for categorical data. Upon task completion, participants completed a questionnaire to assess subjective task complexity and overall visual preference.

The comparison results show a significant difference with small to medium effect size in task completion time and subjective workload estimate. Both are lower for the map that used a cognitively congruent palette. Comparing the frequency of visits to different sites suggests a significant relationship between the type of color palette and how often people go to the attractions, providing evidence of the influence of color palette type on map-based decision-making.

The outcome of this study is twofold. First, the tool developed for choosing cognitively congruent colors to visualize emotions will help researchers, cartographers, and designers make informed design decisions and create visualizations with reduced cognitive load and are likely to inspire the desired response from the users. Second, the findings provide a basis for further research, like investigating how map-based decisions can be influenced by color or whether the effect of reduced perceived difficulty is the same for different thematic mapping techniques.

I. INTRODUCTION

Emotions are inherent to every human being and play a significant role in our life experience, social interaction, and wellbeing. Psychological research provides evidence that emotions can impact our cognition and behavior and affect attention, memory, action, and decision-making (Coppin and Sander 2016a). Being one of the defining characteristics of a human, emotions have attracted the attention of cartographers relatively recently. However, many applications could benefit from a geographic analysis of the spatial distribution of emotional experiences. Placing emotions on maps can help urban planners to make cities safer and more comfortable by including citizen's experiences of the place in the planning process (Zeile, Höffken, and Papastefanou 2009; Resch et al. 2015; Zeile et al. 2015; Fathullah and Willis 2018; Jiři Pánek 2018). Social scientists use emotional maps for a range of studies, from the investigation of relationships between ethnic communities within a city and perceived levels of comfort and fear (Curtis et al. 2014; Matei, Ball-Rokeach, and Qiu 2001) to tourist experience research (Kim and Fesenmaier 2015) and to understand how local and indigenous people of remote territories perceive ecology and the use of natural resources (Graybill 2013). Cultural geographers build maps of grief to provide insights into relational spaces and therapeutic environments (Maddrell 2016) and maps of happiness to estimate its spatial distribution and learn how happiness levels correlate with demographic characteristics (L. Mitchell et al. 2013). Other applications that could benefit from a geographic analysis of the spatial distribution of emotions include natural disaster studies (Caragea et al. 2014; Lu et al. 2015) and marketing and business-related research (Hao et al. 2013).

Color is a visual variable that is most often used for showing emotions on maps, regardless of the emotion classification model and cartographic visualization method. For example, point symbols are placed over a base map, with different colors standing for a different experienced emotion or sentiment (Caragea et al. 2014; Lu et al. 2015; L. Mitchell et al. 2013). Colors are also used to represent emotions in non-spatial visualizations, like psychological self-report probes (Sacharin, Schlegel, and Scherer 2012) or interactive charts of emotion response taxonomies (A. S. Cowen et al. 2021). Usually, authors use categorical color schemes of random colors or design their own color schemes based on the subjective understanding of what color is more suitable to show each emotion.

It is well known that colors have strong psychological effects. Recent findings in psychology suggest that humans also have subjective associations between colors and abstract notions, including emotions (D'andrade and Egan 1974; Hemphill 1996; Mohammad 2013). These associations can affect the performance of visualization users even when the color itself is not task-relevant (Goodhew and Kidd 2020; Lin et al. 2013). It is also recognized that choosing an appropriate color palette for a particular dataset is not just a matter of choosing a visually attractive representation. When mismanaged, the use of color can impose an impaired reaction to the visual stimuli and thus cause user confusion and hinder visual data analysis (Schloss et al. 2018; Silva, Sousa Santos, and Madeira 2011). At the same time, interpreting color meanings becomes easier when colors assigned to concepts in visualizations match people's expectations.

Despite the large body of literature on color palette design and optimization, there are no existing guidelines for choosing colors for mapping emotions. Using existing cartographic color palettes to show the spatial distribution of emotions on maps may lead to a conflict with the subliminal color to emotions associations. In other words, it can cause an equivalent of the Stroop effect — a conflict between perceptual and semantic processing.

The purpose of the present study was to address the lack of guidelines and knowledge for the informed use of color in data visualization outlined by Silva et al. (2011) in their review. It is impossible to provide solutions for all possible scenarios. Therefore, an attempt was made to help users understand the advantages and disadvantages of using congruent color scales in one specific situation of choosing optimal colors for mapping emotional geographic data. To this end, a cognitively congruent color set for emotional data was developed. The associations were acquired through the empirical investigation of the relationships between colors and emotions. The list of emotions was based on the popular emotion classification models derived from the literature. A software tool was created to solve a practical problem of creating color scales suited for emotional data, where colors are assigned to emotions by maximizing subliminal human associations. A sample color palette generated with this tool was evaluated by comparing it to a conventional cartographic color palette.

This study had two objectives. First – design a color set of cognitively congruent colors for spatial emotional data; second – evaluate a color palette made of the congruent colors. To achieve the first objective, the following research questions were addressed: (1) Which colors are associated with each emotion, and to what extent? (2) Which emotions are associated with each color, and to what extent? To achieve the second objective, the third research question was investigated: (3) Is there any difference in map use performance, experience, and map-based decisions between informationally equivalent maps that use cognitively congruent and general cartographic color palettes to show emotional geographic data?

There are different approaches to color palettes design based on color-concept associations (Lin et al. 2013; Rathore et al. 2020; Schloss et al. 2018; Setlur and Stone 2016), but they generally involve two steps: quantifying color-concept associations and assigning colors to concepts, using the associations from stage one. These steps are well aligned with research questions 1 and 2, matching a corresponding step of color palette design. Thus, two user experiments were conducted to accomplish the study's first objective. The first experiment established the connection between emotions and associated colors. Participants were given a list of emotions and picked a color for each emotion word on a list using a continuous perceptually uniform color space. In the second experiment, the subjects were asked to solve the task backward and match each color to the emotions they thought it represented. The colors used in experiment 2 were congruent color candidates defined during experiment 1. Based on the results of the two experiments, a final set of cognitively congruent colors was defined, where each color-emotion pair had a value that determined how well they matched. To be able to get an optimal assignment of colors to a set of emotions, an interactive tool that generates a cognitively congruent color palette depending on the set of emotions was created.

Another user experiment was conducted to address the second objective and evaluate the resulting color palette. Participants planned a walking tour using a map. Two informationally equivalent maps with spatial emotion data were presented to participants. One map showed emotions with a cognitively congruent palette, and the other used a general cartographic palette for categorical data. This experiment was timed to estimate user performance and included a questionary to assess subjective user experience with the map. The tours created during congruent and incongruent trials were compared to check if there was any difference in decision-making depending on the palette type.

The presented study provides three primary contributions: (1) an empirically derived set of cognitively-congruent colors for 23 emotions, (2) an interactive tool that suggests cognitively congruent color palettes for emotional data that can serve as a guideline for researchers, designers, and cartographers who need to create effective visualizations of emotions. (3) Experimental analyses of map-based task performance under two different color-assignment conditions. The results suggest that using such colors can improve user performance, reduce cognitive load on the viewer, and affect the user inferences. This research provides guidelines for color use that are produced with the support of experimental work, which increases their value in contributing to a greater awareness of practitioners of possible issues in their visualizations.

Documenting color to emotion associations and their effect on map user experience is also important from a theoretical perspective, and this knowledge can provide a basis for further cartographic research. Among possible directions is the evaluation of the effectiveness of different cartographic design methods for showing emotions on maps or investigating the ways of influencing map user decisions with colors. Presented findings may be helpful in psychological research to reveal the cognitive architecture of the human mind through a better understanding of the relationship between colors and emotion.

II. LITERATURE REVIEW

Introduction

There is no well-established definition of emotional mapping in the literature. Usually, it is treated as a branch of thematic cartography that deals with integrating subjective emotional and affective dimensions in maps. The meaning of emotional mapping needs to be unpacked to provide a better context for this research and delimit its scope. Caquard and Cartwright (2014) suggest that there are two major perspectives in emotional cartography: studying emotional responses evoked by the cartographic designs and putting emotions experienced in different places on maps. Caquard and Griffin (2018) extend this with a third perspective of studying emotions elicited by the process of making maps. Current research focuses on the perspective of showing emotions on maps to address the problem of spatial emotional data mapping in a way that reduces the cognitive load on the viewer and facilitates visual analysis.

Thematic cartography has a long history of mapping different geographic, economic, and social phenomena, including both visible and intangible features. Nevertheless, one of the defining characteristics of every human being – emotions, relatively recently gained the attention of cartographers (Griffin and McQuoid 2012). This could be explained by the difficulty of collecting spatial emotional data. Inferring a person's emotional state is not a trivial task, and there is no single gold-standard method for its measurement (Scherer 2005). Psychological literature describes several approaches that can be classified as measuring physiological body indicators (signatures of neural activity, galvanic skin response), capturing and interpreting nonverbal behavior (facial and vocal expression), and collecting a self-report of a person's subjective experience during an emotional episode (Coppin and Sander 2016b; Scherer 2005). The advance in technology made it possible to automate the collection of emotional data by extracting it from sources like social media and adding a spatial component to it. The growing amount of geographic emotional data provides new opportunities to investigate human relationships and experiences with a place. Emotional maps are gaining popularity and have already been employed in various research areas such as tourism (Kim and Fesenmaier 2015; Mody, Willis, and Kerstein 2009), navigation (Gartner 2012; Huang et al. 2014), urban safety and planning (Jiří Pánek, Pászto, and Marek 2017; Jiří Pánek and Benediktsson 2017; Resch et al. 2015; Zeile et al. 2015), and business intelligence (Hao et al. 2013). Different thematic mapping techniques are used depending on the nature of collected emotional data and the purpose of the map. The most common methods are flow maps, proportional symbol maps, dot maps, and choropleth maps.

New map design and distribution technologies, along with data availability, enabled a larger number of people with a wide range of knowledge and training to use and make maps. However, it is hard to convert expert cartographical knowledge into a set of distinct rules that, when followed, can ensure an effective map design. The lack of universal transferable map design guidelines for any mapping context is considered one of the main problems of modern cartography (Griffin et al. 2017). This lack of map design guidelines is particularly topical to emotional cartography. For example, the latest edition of the "Guide to effective map design" — a textbook discussing the map design techniques and best practices — provides suggestions on mapping of various features like elevation, climate, water bodies, geology, and hazards, but has no mention of mapping emotional data (Peterson 2020). This is not surprising, as there is a relatively small amount of empirical research on design factors for emotional mapping, with most work focused on spatially representing emotions or collecting geographic emotional data using maps (Griffin et al. 2017; Griffin and McQuoid 2012).

What is an emotion?

The question of what an emotion is has been discussed in the psychological literature for more than a hundred years, starting with James' (1884) seminal paper. Until today there is still no singular universally accepted definition of emotion (Cabanac 2002). According to Scherer (2005) and Coppin and Sander (2016b), who provide an overview of the current approaches to defining, conceptualizing, and measuring emotions in the domain of affective sciences, a consensual view is that emotion is a multicomponent concept. In alignment with the multicomponent model, Gerrig and Zimbardo (2008) define emotion as "a complex pattern of bodily and mental changes that includes physiological arousal, feelings, cognitive processes, visible expressions (including face and posture), and specific behavior reactions made in response to a situation perceived as personally significant." Psychologists also distinguish emotions from other affective phenomena such as feeling, mood, attitude, passion, and affect (Gerrig and Zimbardo 2008; Scherer 2005). There are several theories and multiple taxonomies of emotions, which can be generally divided into two major branches — discrete and dimensional emotion theories (Barrett 2017; Gerrig and Zimbardo 2008; Hamann 2012; Sander 2013).

Discrete emotional theory suggests that there are distinct emotions that people can experience and identify. An illustration of such an approach is the concept of "basic emotions" – a small set of emotions that share a particular property. Different emotion theorists propose different criteria for identifying basic emotions, including from as few as 2 to as many as 18 in their lists (Ortony and Turner 1990). One of the most well-known examples of basic emotions models is Ekman's version with 7 emotions (sadness, disgust, surprise, anger, fear, happiness, contempt) that produce facial expressions universally recognized worldwide with high agreement across diverse populations (P. Ekman and Friesen 1971; 1986). Other scholars use empirical data to identify how many emotions are necessary to describe the human emotional experience. Cowen et al. (2019; 2021) and Cowen and Keltner (2017; 2020) argue for a richer emotional space, reporting that 16 to 28 emotional categories are necessary to represent the emotional reaction of participants depending on the nature of presented stimuli.

By contrast, the other major theoretical position is represented by dimensional theories of emotion. This approach conceptualizes emotions as combinations of several fundamental factors or dimensions (Sander 2013). Every emotional experience or episode can be mapped to a multidimensional emotional continuum with a set of coordinates. There seems to be little agreement about the number and nature of the dimensions that provide an optimal framework for studying emotions. Many psychologists, as well as social scientists and visualization researchers, resort to two-dimensional models, such as the valence-arousal model (Barrett 1998; Bartram, Patra, and Stone 2017; Hamann 2012; Kragel et al. 2019), where valence depicts pleasantness or unpleasantness, and arousal denotes the level of physiological change the emotion causes in a person. Other researchers advocate that more dimensions are necessary. For example, Fontaine et al. (2007) suggested a four-dimensional model of valence, arousal, dominance, and unpredictability, which was then used by Guthier et al. (2014) in a Twitter-based emotional mapping study.

The question whether emotions are better conceptualized in terms of discrete categories or underlying dimensions has been much debated in the psychological literature with the lack of consensus (Hamann 2012; Harmon-Jones, Harmon-Jones, and Summerell 2017; Barrett 1998). Harmon-Jones et al. (2017) suggest that both dimensional and discrete perspectives have value for understanding of the structure and functions of emotions. The distinction between dimensional and discrete emotional models is also reflected the nature of the emotional data used or collected in emotion-related research. In the first case, it is quantitative and in the second it is categorical.

Spatial emotional data

Different approaches to measuring and collecting emotional data may be divided into three main groups. The first group measures bodily reactions such as electrodermal and cardiovascular responses, facial and vocal expressions, or electromyography and electroencephalography (Coppin and Sander 2016b). Nold (2009) used this approach in his emotional mapping project to collect spatial emotional data with a wearable device that measured galvanic skin response and GPS location information. The resulting data, in this case, takes a form of a GPS track with a physiological arousal value for each participant at each point. Measuring physiological indicators eliminates self-report biases but provides little information about the subjective emotional experience (Coppin and Sander 2016b).

The second group of methods relies on inferring the emotional state of a person based on user-generated content. Social networks are used frequently as sources of such data. Spatial emotional information can be extracted from text, like geo-tagged Twitter messages (Guthier et al. 2014) or georeferenced images from Flickr (Ashkezari-Toussi, Kamel, and Sadoghi-Yazdi 2019). These data are usually represented as points, with associated emotions stored as attributes. The extraction of emotional information from secondary data is usually automated. The abundance of available data sources opens opportunities for exploring the complex relationship between emotions and places. At the same time, one should take into account the limitations of the existing emotion recognition algorithms that demonstrate different reliability depending on the emotion model used, the quality of initial annotations, and even on the different domains and topics (Bostan and Klinger 2018).

The last group of approaches to obtaining emotional data is based on collecting self-reports. It aims to assess the "feeling component" of emotional experience (Shuman, Schlegel, and Scherer 2015). The self-reports can be based on both discrete and dimensional emotion models and may come in the form of a set of emotion labels or a free-response format (Scherer 2005). In emotional mapping, self-reports usually employ everyday language where the terms "emotions" and "feelings" are used interchangeably. Because of this, collected emotional data are often mixed with other affectual phenomena and personal experiences of a locale. For example, Pánek (2018) describes an emotional mapping methodology focused on collecting human experiences with the city, asking whether a place was dangerous, interesting, good for meeting with friends, or giving you a feeling of pride for the city. Bleisch and Hollenstein (2018) visualize place-related emotional data using other categories: aesthetics, comfort, safety, facilities, accessibility, interaction, and memories. Emotional data collected using this group of methods provide maximal accuracy and a fine-grained resolution of the emotional experience description. From the perspective of the spatial component, there is some uncertainty regarding the exact location of such experiences. The data usually come as polygons or points with associated emotional categories stored as attribute data (Curtis et al. 2014). The main disadvantage of self-reported spatial emotional data is that it is hard to analyze it quantitatively and compare the findings from different studies (Scherer 2005). Sometimes a combination of bodily reaction measurement and self-report of emotional experience is used. In such cases, participants wear a special measuring and tracking device while explicitly sharing their feelings (Kim and Fesenmaier 2015; Resch et al. 2015).

Spatial emotional data on maps

Spatial emotional data are shown on maps using linear, point, and aerial symbols. Usually, the choice of symbology depends on the nature of the underlying data. On the maps that are based on GPS tracks or self-reported paths, emotional data are displayed as trajectories with colors showing the intensities of emotional experience. As shown in figure 1a, some authors overlay point symbols representing the hot spots on a trajectory (Bergner and Zeile 2012; Jiři Pánek 2018). Figure 1b illustrates another approach that uses a continuous color scheme for the entire track, turning it into a form of a heatmap (Höffken et al. 2014). A more artistic approach presented in figure 1c displays the emotional tracks both in color and in 3D (Fathullah and Willis 2018; Nold 2009).

Maps of emotions produced based on self-reported data usually employ point symbols (figure 2a) that are colored according to the category of emotional experience at each location (Bleisch and Hollenstein 2018; Pánek 2018). Individual points on such maps may represent an emotional experience of one participant at a given location or an aggregate characteristic that combines the experiences of multiple participants. In studies that focus on one particular emotion, initial point or polygon data are interpolated into heatmaps (figure 2b) covering the entire area of interest (Curtis et al. 2014; Jiří Pánek, Pászto, and Marek 2017) or aggregated by a unit area into a choropleth map (Matei, Ball-Rokeach, and Qiu 2001). On interactive maps, multiple individual points may be aggregated into a single point symbol depending on zoom level (Klettner and Gartner 2012).

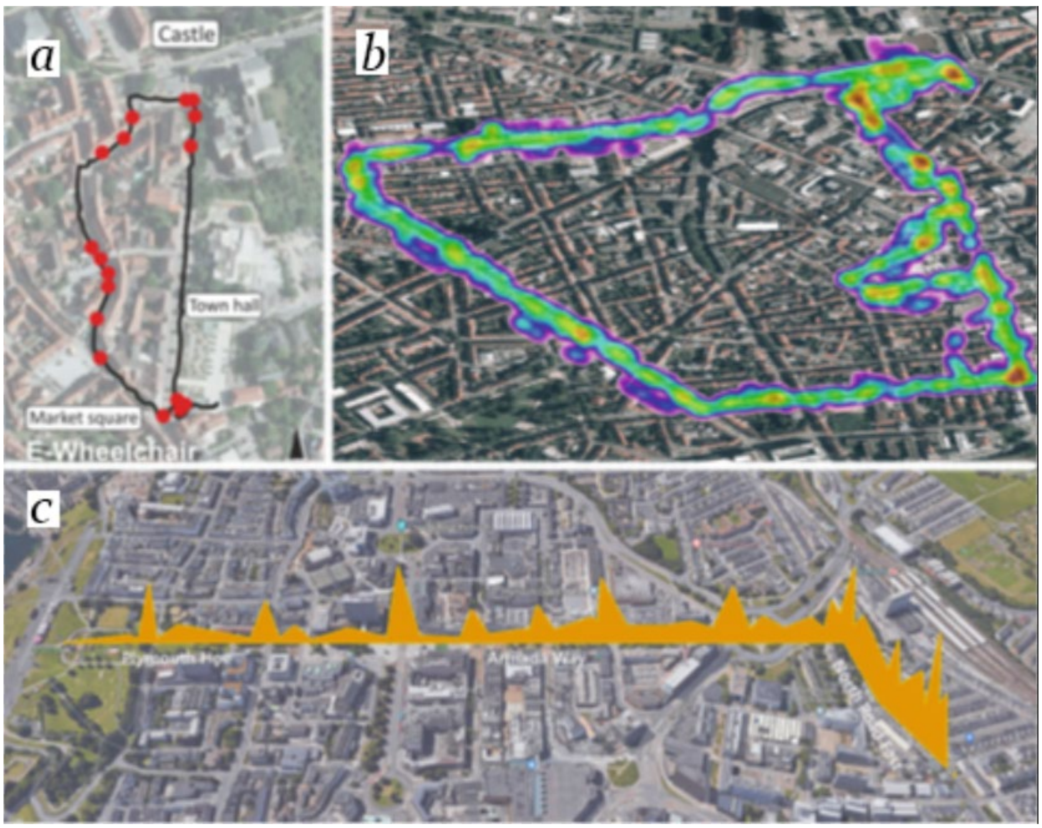


Figure 1. a) Emotional data shown as symbols overlaying the trajectory (Bergner and Zeile 2012), b) Emotional data as heatmap trajectory (Höffken et al. 2014), c) Emotional data track in 3D (Fathullah and Willis 2018).

Maps of emotions, moods, and sentiments based on the data inferred from user-generated content, mainly from social media, are the most abundant and demonstrate higher variability in applied symbology. There are examples of dot maps (Caragea et al. 2014; Kang et al. 2019), choropleth maps (L. Mitchell et al. 2013; Nguyen, Varghese, and Barker 2013), grid-based (Ashkezari-Toussi, Kamel, and Sadoghi-Yazdi 2019) and surface interpolation (Hauthal and Burghardt 2013) heatmaps, point symbol maps (Guthier et al. 2014; Lu et al. 2015), text maps (Hao et al. 2013) and even emotion "weather" maps (Misue and Taguchi 2015).

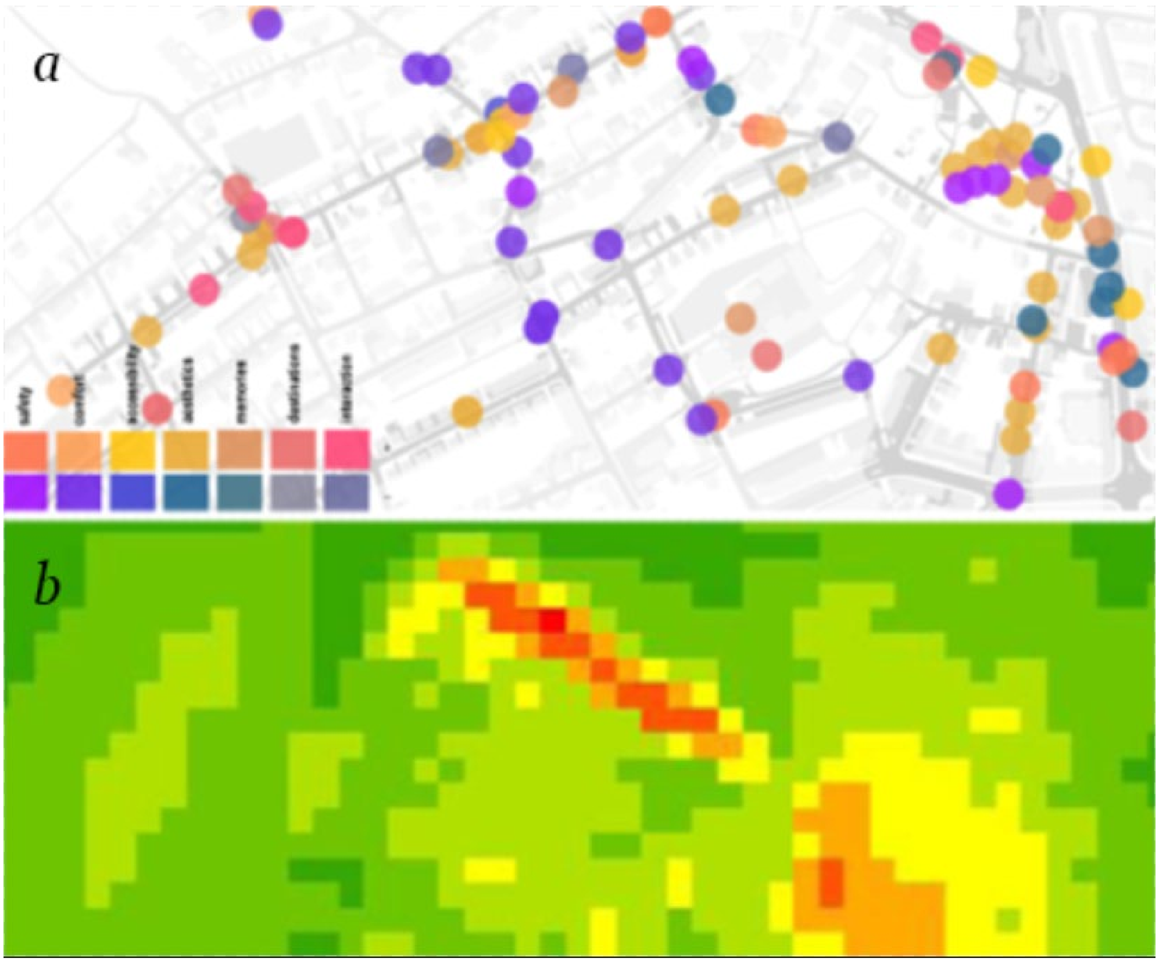


Figure 2. a) Emotional experiences as point symbols (Bleisch and Hollenstein 2018), b) Aggregated heatmap of fear spaces (Curtis et al. 2014)

It seems that it is safe to say that almost every method of thematic cartography is used for making maps of emotions. At the same time, most of the different ways to visualize emotions on maps share the use of color for encoding emotional or sentimental categories. Whether a discrete or dimensional emotion model is used, colors indicate a type of emotional experience. On maps that show only two (happy, sad) or three categories (positive, negative, neutral), diverging color schemes with a corresponding number of colors is usually applied, with red-green and red-blue being the most common color combination. On maps with more kinds of emotions, categorical color palettes are used. In most cases, the reasoning for choosing a particular color to represent an emotion is not provided. This suggests a conclusion that the colors are either randomly assigned or chosen according to the author's subjective understanding of what color fits a particular emotion.

Color on maps

It is unsurprising that color is the most common way to show emotions on maps. According to Bertin (1983), color is one of the seven main visual variables used in cartography to present data of both qualitative and quantitative nature. From the semiotic point of view, each cartographic symbol (a mark on a map, a line, a color fill, etc.), along with the concept it refers to, forms a sign (MacEachern, 1995). Depending on the degree of resemblance between the visual representation (sign-vehicle) of the sign and its referent, all signs can be categorized as iconic, indexal, and symbolic. Iconic signs represent their referents by similarity, indexal signs point to their referents by association with it, and symbolic signs refer to their meaning by a rule and convention (MacEachern, 1995). Also, as outlined by Rod (2001), cartographic symbols are polysemic, which means they have a denoted meaning (directly expressed) and a connoted meaning (mediated or released by another more basic meaning). Thus, colors on maps can be treated as sign-vehicles falling somewhere on the iconic to symbolic continuum and bearing denoted and connoted meaning.

This makes the choice of color scheme for data representation on maps a vital design decision that can affect viewer interpretation, decision making, and emotional response (Anderson and Robinson 2021; Christen, Brugger, and Fabrikant 2021; Muehlenhaus 2012). Choosing proper colors for data representation is also considered very important in the area of data visualization (Christen, Brugger, and Fabrikant 2021; Silva, Sousa Santos, and Madeira 2011).

Existing guidelines and tools for assigning colors in thematic cartography are primarily concerned about the kind of the data being mapped, suggesting sequential, diverging, or qualitative color palettes (Brewer 1994; Brewer, Hatchard, and Harrower 2003; Silva, Sousa Santos, and Madeira 2011; White, Slocum, and McDermott 2017). These recommendations are more concerned about the perceptual aspects of color, like providing good color contrast and being colorblind safe. At the same time, the contextual or symbolic dimension of color well known in the area of visual communication (Bartram, Patra, and Stone 2017; Zhou and Hansen 2016) and recognized in cartography (Dent, Torguson, and Hodler 2008; Lambert and Zanin 2020) is missing from these guidelines.

There is evidence suggesting that contextually-relevant color assignment could help viewers make more efficient judgments of displayed data (Lin et al. 2013; Schloss et al. 2018). Thus, when selecting a color scheme for a thematic map, it is important to match it to the nature of the data and make sure that the connoted meaning of the colors is aligned with the mapped phenomena and the context of the map. This idea is supported by Thyng et al. (2016) and Samsel et al. (2017), who advocate for the use of intuitive color assignments for categorical data on thematic maps. Cartographic research in symbol congruence is relatively scarce. Some of the few examples are Anderson and Robinson (2021), who advocate for the use of affectively congruent colors, and Klettner (2020), who suggests that the contextual congruence principle should be applied when choosing the shape of a point symbol in a thematic map design.

Color in psychology

There is a large body of literature on the psychology of color, covering a wide range of aspects. Two topics are of interest in the context of this study: color-concepts associations and color effects on behavior.

The findings in conceptual color associations suggest that colors have rich symbolic functions and bear meanings. Some of these meanings are universal across all cultures, while the others are more culture-specific (Moller, Elliot, and Maier 2009; Tham et al. 2020). Color associations have two primary sources. The first one is grounded in the physical appearance of objects. A simple example of such associations is yellow being associated with lemons and blue with the sky. A more complicated example is the Ecological Valence Theory (EVT) of color preference proposed by Palmer and Schloss (2010). It states that color preferences result from people's combined liking/disliking of associated colored objects. For example, strongly disliked dark greenish-yellow is associated with strongly disliked entities such as dirty water or rotten food. In contrast, more pleasant blue is associated with more pleasant entities such as the clear sky and clean water.

The second form of color associations is related to abstract conceptual concepts. It is considered to be based on common metaphors, linguistic and cultural conventions, or on some innate unconditioned responses to certain stimuli (D'andrade and Egan 1974). These subjective associations between colors and abstract notions include associations with emotions (D'andrade and Egan 1974; Hemphill 1996; Mohammad 2013). Color-emotion associations have been explored by a vast body of research. Consistent color-emotion associations have been identified along with a good amount of cross-cultural variability (Cyr, Head, and Larios 2010; Jacobs et al. 1991; Or and Wang 2014). Jonauskaite et al. (2020) tested associations of 20 emotion concepts to 12 color terms in 4,598 participants from 30 nations speaking 22 native languages. Their study demonstrates robust universal color-emotion associations that are modulated by linguistic and geographic factors.

Elliot and Maier (2012; 2014) state that color meanings are also context-specific. The same color carries different meanings depending on the context, leading to variability in interpretation. Moreover, Kaya and Epps (2004) provide evidence that color-emotion relationships are highly dependent on personal preference and experience with a particular color. There are many attempts to establish color-to-emotion correspondence and create color-emotion models that match a color space to the emotional space (A. S. Cowen and Keltner 2021; Gobron et al. 2010; Hanada 2018; Nijdam 2009; Ou et al. 2018). Usually, different emotional models are used, which makes it difficult to compare color representations suggested by different research, and as shown by Fugate and Franco (2019), there is no one-to-one correspondence between emotions and colors. The same color may represent different emotions, and different colors may represent one emotion. Demir (2020) attempted to summarize color to emotions associations identified by multiple studies (table 1). Despite the fairly large body of literature included in the summary, it only provides a broad color-to-emotion correspondence with overlapping and controversial color associations. This is probably caused by the differences in data collection approaches in the reviewed literature. Some studies use varying color samples, while others collect responses to color words instead of using actual color stimuli. Furthermore, the number of colors and emotions used in color-emotion matching tasks also vary, which makes the comparison of results even harder.

Table 1. Research on emotional perception of the colors (Demir 2020)

Color	Color-emotion associations
Red	Love, anger, passion, courageous, excitement, angry, and aggressiveness. Speed, danger, and aggression.
Blue	Pleasure, comfort, calm (relaxing), sad/sadness (depression), trust (reliability), security and coldness. Warmth, cheerful, hope, optimism, pleasantness, and happiness.
Yellow	Warmth, cheerful, hope, optimism, pleasantness, and happiness. Orange Enthusiasm, courage, disturbing, distressing, pleasantness, and happiness.
Orange	Enthusiasm, courage, disturbing, distressing, pleasantness, and happiness.
Green	Peacefulness, safety, balance, hope, relaxation, coldness, calmness, and happiness with the image of nature (especially forest) and refreshing.
Purple	Relaxation and calmness, followed by happiness, sadness, tiredness, power, fear, boredom, excitement, and comfort with the image of dignified and stately. Nostalgic, romantic, frustration, and sadness
White	Youthful, pleasant, innocence, peace, and hope with the image of purity, being simple and clean.
Black	Sadness, despondency, depression, fear, serious, and anger with the image of death, mourning, and tragic events.
Gray	Sadness, despondency, depression, boredom, confusion, tiredness, loneliness, anger, and fear with the image of bad weather.

Another topic of color research in psychology is dedicated to the impact of color on psychological functioning in humans. It has been demonstrated that color affects cognition and behavior (Elliot and Maier 2014; Tham et al. 2020). For example, color can affect performance in IQ tests (Elliot et al. 2007), creativity and cognitive tasks (Mehta and Zhu 2009; Yamazaki 2010), and in sports (Hill and Barton 2005). Color can also impact judgment and decision-making (Amhorst and Reed 1986; Kliger and Gilad 2012). Elliot and Maier's (2012) "color-in-context" theory suggests that colors trigger different types of motivation, which can inhibit or enhance performance, depending on the context.

Aside from the mentioned effects that occur just due to the presence of some color (e.g., it is a part of the background), there are cases when color affects task performance by interfering with the meaning. The most well-known phenomenon demonstrating a conflict between perceptual and semantic processing caused by color is the Stroop effect (MacLeod 1991; Stroop 1935). In his study, Stroop demonstrated that readers are slower and more prone to mistakes when naming the color of words printed in a color that conflicts with their meaning. The same effect is observed when color-associated words (Goodhew and Kidd 2020; Kinoshita, Mills, and Norris 2018) or images of the objects are used instead of direct color words (Naor-Raz, Tarr, and Kersten 2003). This impaired reaction to incongruent stimuli is very important for applications when colors are used to encode different categories. Congruent color assignments that match people's expectations and associations make it easier for viewers to read and interpret color-coding systems in visualizations (Lin et al. 2013; Schloss et al. 2018; 2019). Aside from semantic congruence, researchers also paid attention to the affective congruence of colors and data context on thematic maps. Anderson and Robinson (2021) suggest that affectively congruent color schemes amplify the perception of the affective qualities of maps with emotive topics, while incongruent may cause confusion.

The reviewed empirical work indicates that colors carry meanings and have an influence on cognition. Thus, showing emotions on maps using general cartographic color palettes may lead to a mismatch between an emotion denoted by a color on the map and the one connoted by that color. When ignored, this mismatch can lead to a conceptual Stroop effect, hindering the visual data analysis. Showing emotions on a map using matching congruent colors has the potential to improve semantic coherence and reduce the perceived cognitive load. Despite considerable interest and work in the field of color-emotion associations, more research is needed to provide recommendations for applying semantic color congruence when designing cartographic color palettes for categorical emotional data.

Design of color palettes

Color plays a central role in data visualization and thematic cartography. Empirical research has shown that people prefer colorful maps over achromatic ones and that properly colored maps increase map-reading accuracy and therefore allow more insights into the data. (Brewer et al. 1997). The question of designing appropriate color palettes (also called color mapping) that facilitate visual data analysis received a lot of attention in the literature. Silva et al. (2011), followed by Munzner (2014) and Zhou and Hansen (2016), provide a comprehensive review of the topic of color mapping in visualization. The principles of color mapping outlined in the mentioned reviews are also applied in the design of cartographic color palettes. Two major design guidelines can be recognized in the literature: perceptual fitness and fitness to data.

Human vision is not equally sensitive to different wavelengths of the visible spectrum (Zhou and Hansen 2016). When not considered during color palette design, this may lead to imposing structures or patterns that are not present in the data, simultaneously obscuring existing features and details (Borland and Taylor Ii 2007; Bernice E. Rogowitz, Treinish, and Bryson 1996; B.E. Rogowitz and Treinish 1998). Perceptually uniform color spaces like Munsell, CIELab, and CIELuv were developed to address this issue. Such color spaces allow designing colormaps in which perceived color differences match actual differences in data they represent and do not produce false boundaries perceived in data. In computer graphics, perceptually organized color spaces usually represent colors in three dimensions using coordinates of hue, saturation, and lightness (Brewer 1994). Even with the help of perceptually uniform color spaces color map design remains challenging because people see colors differently and the same color looks different with different surroundings. Other perceptual aspects that need to be considered are simultaneous contrast, color vision deficiencies, the dependence of perceived lightness on hue and saturation, and color nameability (Brewer 1996; 1994).

The second major color palette design guideline follows the idea of highlighting the most important features of the data with the most salient features of the visualization. It is crucial to consider the type of data being represented. White et al. (2017) argue that three data properties have the most influence on color map design and selection: level of measurement, data polarity, and data classification. Thus, it is not surprising that color palette taxonomy mirrors the taxonomy of data types (figure 4).

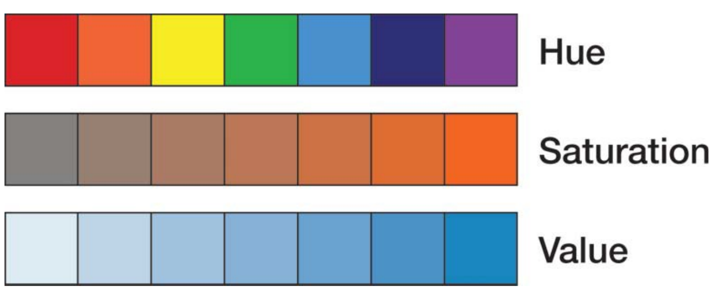


Figure 3. Main dimensions of color

Colormaps can be categorical or ordered. Ordered colormaps can be sequential or diverging. There are also some special colormaps like binary, which is a kind of categorical palette, and bivariate colormaps that encode two attributes simultaneously.

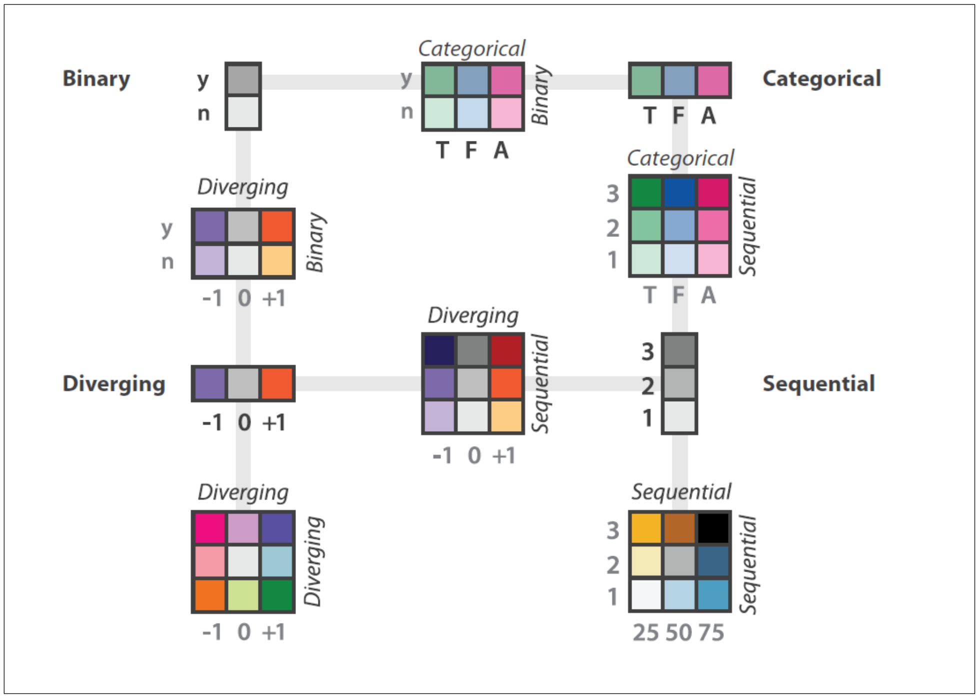


Figure 4. Colormap categorization (Brewer 1994)

Sequential colormaps for ordered data should use visual variables of lightness and saturation because they introduce implicit perceptual ordering. Depending on the data classification approach, colormaps can be continuous or segmented. It is suggested that continuous colormaps are more appropriate for providing a general data overview, while segmented are better for obtaining specific information (White, Slocum, and McDermott 2017). In case there is a natural or meaningful dividing point in the data, or it is important to emphasize both extremes in distribution, a diverging color palette is a good choice (Brewer et al. 1997).

For categorical data, both nominal and ordinal, segmented colormaps are more suitable because they emphasize the discrete nature of the data. It is better to use lightness and saturation for ordinal data to imply the ordering. Categorical colormaps, also known as qualitative, are designed for showing nominal data. Hue is considered the most suitable visual variable to encode categories and groupings because it does not have an implicit order (Harrower and Brewer 2003). The design of qualitative color palettes is based on two constraints – the ability of viewers to distinguish between colors and to remember the meaning of each color (Silva, Sousa Santos, and Madeira 2011). The number of discriminable colors is limited to between six and twelve, with fewer being the better.

In addition to general color mapping guidelines, the literature outlines more specific factors of colormap design: task needed to be accomplished with the visualization, spatial frequency of the data, intended audience, and semantic color connotations (Silva, Sousa Santos, and Madeira 2011; Zhou and Hansen 2016). Existing cartographic color scheme-building tools, created to aid the color palette design and selection for thematic mapping, only address the perceptual and data-dependent considerations. For example, ColorBrewer (Harrower and Brewer 2003), probably the most well-known web-based tool, offers the automatic generation of sequential, diverging, and qualitative color palettes. Only segmented color schemes are available, but there is an option to get a color-blind safe, print, or computer screen-friendly palette. Colormaps produced by such tools incorporate many perceptual guidelines and provide safe suggestions. At the same time, they can still be finetuned and adjusted to a particular map or visualization. Lee et al. (2013) use ColorBrewer palettes as input to demonstrate a perceptually driven color optimization algorithm for qualitative color palettes that maximizes class visibility, allowing for more effective data visualization.

The question of semantic color connotations also received attention in the literature. It is recognized that matching the denoted meaning of colors and color semantics allows viewers to gain insights from visualization more efficiently (Silva, Sousa Santos, and Madeira 2011; Zhou and Hansen 2016). The idea of the connotation-based color assignment is not new in cartography. Physical phenomena are traditionally represented on maps in colors consistent with their nature: water is shown in the shades of blue, vegetation in shades of green, etc. (Peterson 2020). The same principle applies to the design of colormaps for thematic maps too. Harrower and Brewer (2003) state that in qualitative color schemes, classes should be visually related if the represented phenomena are related. Thyng et al. (2016) discuss colormap design guidelines for effective oceanographic data display and suggest the use of intuitive colors, such as displaying sea ice concentration by a colormap that increases from dark ocean blue to white. Samsel et al. (2017) emphasize the importance of intuitive representations of environmental data for effective visualization and introduce sets of intuitive environmental colormaps. Research in data visualization has also investigated the optimization of color palette design to produce color-concept assignments that are easy to interpret (Lin et al. 2013; Schloss et al. 2018; Setlur and Stone 2015). The results suggest that semantically-resonant color palettes provide significant performance benefits in data reading tasks.

Designing semantically interpretable color palettes requires estimates of human color-concepts association. Different approaches to obtaining these data exist, including user studies (Jonauskaite et al. 2020), automatic extraction from images (Rathore et al. 2020), and texts (Setlur and Stone 2015). Schloss et al. (2018) suggest that there is no one-to-one correspondence between colors and meanings and that people interpret color-coding systems based on the simultaneous association strengths between all presented objects and colors.

As discussed in the “Color in psychology” section, colors have strong emotional connotations. The importance of such connotations is recognized in cartography, and the topic of the relationship between maps and emotions has become more popular (Griffin et al. 2017; Griffin and McQuoid 2012). Three main directions in emotional mapping research can be delineated: (1) maps of emotions, (2) emotional impacts of maps on users, and (3) the impact of emotions on the mapping process (Caquard and Griffin 2018; Griffin and McQuoid 2012). However, research focused on semantic or affective connotations of color in map design is scarce. These connotations have been studied in cartography mostly from the affectual perspective, focusing on the emotional response of viewers to different color palettes. The results of empirical color research provide evidence that all three dimensions of color (hue, saturation, and lightness) influence the emotional responses (Suk and Irtel 2010). Bartram et al. (2017) demonstrated that categorical color palettes might convey different affective connotations. Relations between perceptual color dimensions, palette composition (hue clusters, color frequency), and certain affect types are presented.

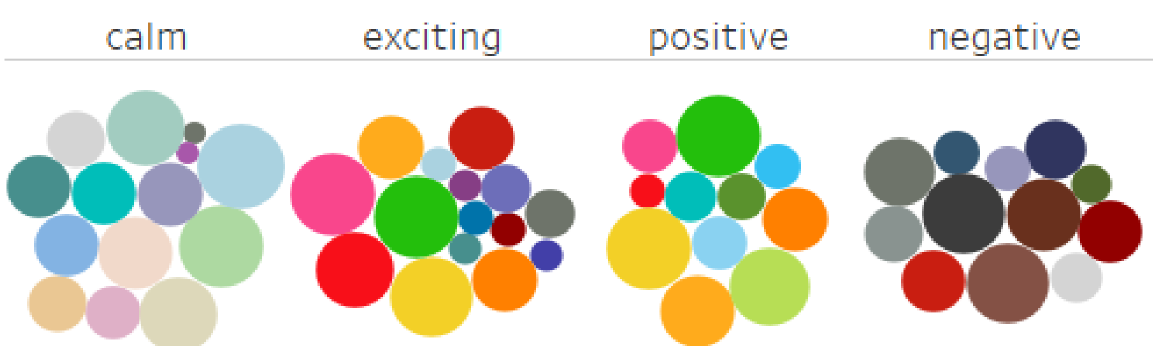


Figure 5. Affective color palettes (Bartram, Patra, and Stone 2017)

In their recent work, Anderson and Robinson (2021) evaluate the relationships between the affective congruence of the categorical color palette and the context of the map topic. Their results suggest that affective congruence influences subjective map response and that the perception of emotive content in maps can be amplified or diminished by manipulating the congruency of categorical color assignment. At the same time, no evidence was found that affective congruence impacts data reading speed in a way that semantic congruence presented by Lin et al. (2013) does.

Conclusion

Based on the provided overview of relevant work regarding the use of color in data visualization, the psychological effects of color, and the current state of the emotional mapping, the following conclusions can be made. Color is one of the most prevalent visual variables used in data visualization. Color palettes used to symbolize the data have an impact on the effectiveness of the visualization. There is no universal colormap that works best for all scenarios and datasets. At the same time, color has psychological effects, demonstrates consistent associations with concepts, and bears substantial connoted meaning.

Spatial emotional data can take 2 forms, depending on whether the dimensional or discrete model of emotions is used. Data of the dimensional model as well as the intensities of a single discrete emotion are continuous, and thus displayed using sequential color schemes, varying on lightness or saturation. Discrete emotional data are essentially discrete and are shown on maps using categorical color palettes varying on hue. Research on color to emotion associations typically employ the model of discrete emotions, and their findings more directly relate to mapping of individual emotions with categorical color palettes.

Existing guidelines for categorical colormap design suggest that perceptual aspects should be balanced with the context of the visualization and color-concept associations. In other words, metaphoric color associations should be considered in the design of categorical color palettes. Using general cartographic color palettes for mapping emotions may lead to interference between denoted and connoted meanings of color on a map. This mismatch can impose an impaired reaction to the visual stimuli (a conceptual equivalent of the Stroop effect) and thus hinder the visual data analysis. At the same time, a color assignment that matches human intuition and expectations can make the interpretation of visualizations easier.

Despite a significant amount of research on the color-concept and color to emotion associations, there are no recommended color palettes for mapping emotional geographic data. Potential effects of cognitively congruent colors for emotional mapping on objective map use performance, subjective viewer experience and map-based decisions have not been investigated. Given the growing popularity of emotional mapping, empirically tested color assignment recommendations are of high importance for the informed use of color in emotion visualization.

The goal of this research is to address the lack of guidelines for choosing optimal colors for emotional mapping by designing and evaluating a cognitively congruent color set in which colors are matched to emotions in a way that is aligned with subjective human associations. Specifically, it was evaluated how cognitive color congruence (vs. incongruence) influences map-based task performance, map-based decision making, perceived task complexity, and overall visual preference. To this end, the following research questions were addressed. (1) Which colors and to what extent are associated with each emotion? (2) Which emotions are associated with each color, and to what extent? (3) Is there any difference in map use performance, experience, and map-based decisions between informationally equivalent maps that use the cognitively congruent and general cartographic color palette to show emotional geographic data?

This research aims to estimate color-emotion associations and to provide the first in-depth analysis of the interaction of the semantic connotations of the color palette used for mapping spatial emotional data with the map user experience and performance. This way, it contributes to the literature on categorical colormap design (Lee, Sips, and Seidel 2013; Lin et al. 2013; Schloss et al. 2018), to studies of color-emotion associations (Demir 2020; Hanada 2018; Jonauskaite et al. 2020; Fugate and Franco 2019), and the general body of emotional mapping research (Griffin and McQuoid 2012). Specifically, the presented study extends upon the work of Lin et al. (2013) by assessing its relevance to the mapping of spatial emotional data and follows Anderson and Robinson (2021) in the evaluation of the effects of color palette congruency to the mapped data on user experience with categorical thematic maps. The developed color choice suggestions apply to mapping emotional data, collecting spatial emotional data, and designing non-spatial emotional data visualizations.

III. RESEARCH METHODS

Two primary research efforts were combined to develop answers to the outlined research questions. First, two user experiments were conducted to elicit knowledge about what colors can be considered cognitively congruent for a set of 23 discrete emotions. The resulting quantified color to emotion associations were used to develop an interactive tool that generates a congruent color palette based on the selected emotions. Second, another user experiment was completed to evaluate a sample congruent color palette, produced with the tool mentioned above, regarding its effect on map use performance, experience, and decision making.

The human ability for assignment inference suggests that it is possible to create multiple cognitively congruent color palettes for the same set of concepts. This requires balancing design objectives of color discriminability, nameability, and connotation. There are different approaches for semantically interpretable color palette design. Typically they involve two steps: quantifying associations between each color and concept and then assigning colors to represent concepts in a way that maximizes the interpretability of the palette (Bartram, Patra, and Stone 2017; Rathore et al. 2020; Schloss et al. 2018; Setlur and Stone 2015). A direct and most reliable way of estimating human color-concept associations is by human judgments. Such user studies usually involve rating the strength of association between colors and concepts (Schloss et al. 2018), selecting colors that fit concepts best (D'andrade and Egan 1974; Ou et al. 2004) or naming concepts associated with colors (Demir 2020; Hanada 2018). There is an alternative approach of automatically deriving human color-concept associations from large user-generated datasets like tagged images (Hauthal and Burghardt 2013; Rathore et al. 2020) or textual data (Bostan and Klinger 2018; Mohammad 2016). Despite the advantages of automation and the use of publicly available data, this approach is computationally intense and requires a sufficient amount of manually annotated data for training the algorithm.

The present research follows the first approach and relies on human judgments for acquiring data about color-emotion associations. It combines the selection of the colors that fit concepts best and naming concepts associated with the selected colors.

Evaluation of colormaps in data visualization (Borkin et al. 2011), cartographic color palettes (Anderson and Robinson 2021; Gramazio, Laidlaw, and Schloss 2017), and other map symbols (Klettner 2020) is usually based on user studies. These studies are usually built around a task that participants are asked to do using a map or a visualization. The task completion time is often used to measure objective task performance. The post-task feedback is collected to assess the subjective user experience. Present research follows a similar approach and combines a map-based task with a questionnaire to assess objective performance measures and the subjective user experience. This study, consisting of three user experiments and uses a quantitative methodological approach. Experiments 1 and 2 follow a within-subject design, while experiment 3 was a between-subject user study. Studying the actions of people in response to stimuli makes this behavioral research.

Each of the three experiments conducted within this research was a separate online-based user study. Experiments were conducted consecutively, with each subsequent experiment building on the results of the previous one. Participants for each user study were recruited separately using an online crowdsourcing platform Prolific. The use of crowdsourcing platforms for behavioral data collection is common in the literature and has been successfully implemented in color and emotion-related research (Christen, Brugger, and Fabrikant 2021; A. S. Cowen et al. 2019; Mohammad 2013). Heer and Bostock (2010) replicated existing laboratory experiments on Amazon Mechanical Turk (AMT) to demonstrate the validity of crowdsourcing for graphical perception experiments. Their crowdsourced results show higher variance but are consistent with laboratory findings. Other research outline that crowdsourcing often lacks sufficient data quality control and should be used with caution to acquire meaningful data for behavioral research (Peer et al. 2021b). Crowdsource approach to visual perception experiments leads to the lack of control over conditions like display type, lighting, viewing angle, and distance. At the same time, crowdsource conditions more closely mimic real-world data visualization scenarios (Heer and Bostock 2010). Based on the comparison of different crowdsourcing platforms, it appears that Prolific outperforms other competitors, including AMT, in terms of data quality and cost per observation (Gupta, Rigotti, and Wilson 2021; Hulland and Miller 2018; Peer et al. 2021a; Sheehan 2018). Thus, Prolific was used for all three user experiments of this research.

All three human subject studies of this research were reviewed and approved by the Texas State University Institutional Review Board (project 8076). Data collection was implemented using Qualtrics online survey software. Only participants located in the United States, with English being their first language, were recruited to participate in each study to reduce the possible impact of cultural differences in associations of colors to emotions. All participants were 18 years of age or older. Each participant participated only in one experiment of this study. Participants from previous experiments were excluded from recruitment for the next ones. To ensure that collected data are not affected by color vision discrepancies, participants were required to pass an online version of the Ishihara color vision test (Marey, Semary, and Mandour 2015) and to complete the survey on a laptop or desktop computer to provide ample screen size. Stimuli of all three user experiments were presented to viewers on a neutral grey background (Munsell neutral value gray scale N7) to minimize the influence of simultaneous color contrast on the perceived colors.

At the beginning of each user experiment, after providing informed consent, participants took a 12-plate version of the Ishihara color vision test. If they entered the correct number in at least 10 of the 12 plates, the color vision was regarded as normal, and participants proceeded to the next step of the survey. The plates used for the test are presented in Appendix A. The age and gender of the participants were acquired for each experiment to assess the basic demographic characteristics of the sample for a better understanding of study limitations and applicability. Where applicable, experiments included training tasks and questions with known answers for additional data quality control. After the main trial, at the last step of each user experiment, there was an optional free text question asking to provide general feedback about the study. Finally, after data submission, the participants were automatically redirected back to Prolific with a survey completion code.

Sample size plays an important role in testing for statistical significance. A fairly large difference between the sample means will not be statistically significant with a small sample size, and even a small difference between sample means with a very large sample size can produce a statistically significant result (Urdan 2016). Effect size and confidence interval also depend on the sample size. Statistical power analysis can be used to determine the sample size that is necessary to detect the statistical significance at a specified level α with a hypothesized effect size (Cohen 1992; Dean, Voss, and Draguljic 2017). The power of a statistical test is the probability of obtaining a statistically significant result. It is a function of the sample size, the significance level α, and the effect size. When solving this for the sample size, significance level α is usually chosen by the experimenter. The value of the effect size can be estimated based on data from similar research, from a pilot study, or set at a particular level depending on the size of the difference a researcher is looking to identify (Cohen 1992; Dean, Voss, and Draguljic 2017). In this research required sample size for each experiment was estimated by a priori power analysis solved for the medium effect size using G*Power software (Faul et al. 2007).

Experiment 1. Identify candidates for congruent colors

Human judgments were collected to estimate the color-emotion associations and obtain candidate colors for a cognitively congruent color set. Experiment 1 aimed to identify the colors associated with each emotion from a list of 23 discrete emotions. Participants saw each emotion one at a time and selected the color that represents this emotion in their opinion using an interactive color picker. The color picker allowed to choose any color from a continuous color space.

Emotions used in the present study include the Ekman's 7 basic emotions (anger, contempt, disgust, fear, happiness, sadness, surprise) and 16 additional emotions (amusement, annoyance, awe, boredom, confusion, contentment, disappointment, grief, elation, embarrassment, interest, joy, pride, relief, serenity, shame) synthesized based on affect categories used the literature (table 2). Basic emotions were included as they are widely used and can make the results of the current study more comparable to the other research. The other emotions were added to address the limited ability of the basic emotions to describe the spectrum of human emotional experience (A. Cowen et al. 2019). The selection was based on the frequency of mentions and the semantic discriminability of emotion concepts. Different models suggest different total number of discrete emotions. Some of the attempts to provide an exhaustive catalog of all human emotions and experiences include Brown (2021) who mentioned 150 and described 87 emotions and Smith (2015), who listed 154 different worldwide emotions and feelings. Given this, the list of 23 emotions explored in the present research is not comprehensive and presents only a limited perspective on all possible emotional experiences.

Table 2. Discrete emotions used in the literature

Author	Emotions
(Plutchik 2001)	serenity, joy, ecstasy, admiration, trust, acceptance, terror, fear, apprehension, amazement, surprise, distraction, grief, sadness, pensiveness, loathing, disgust, boredom, rage, anger, annoyance, vigilance, anticipation, interest, optimism, love, submission, awe, disapproval, remorse, contempt, aggressiveness
(Scherer 2005)	anger, pride, elation, happiness, satisfaction, relief, hope, interest, surprise, anxiety, sadness, boredom, shame/guilt, disgust, contempt, hostility
(Scherer et al. 2013)	interest, amusement, pride, joy, pleasure, contentment, admiration, love, relief, compassion, sadness, guilt, regret, shame, disappointment, fear, disgust, contempt, hate, anger
(Kim and Fesenmaier 2015)	anger, contempt, disgust, distress, fear, guilt, sadness, interest, shame, surprise, enjoyment
(Keltner et al. 2016)	amusement, anger, awe, boredom, confusion,

	contempt, content, coy, desire, disgust, embarrassment, expression, fear, gratitude, happiness, interest, love, pain, pride, relief, sadness, shame, surprise, sympathy, triumph
(A. S. Cowen and Keltner 2017)	adoration, admiration, amusement, anger, aesthetic appreciation, anxiety, awe, awkwardness, boredom, calmness, confusion, contempt, craving, disappointment, disgust, empathic pain, entrancement, envy, excitement, fear, guilt, horror, interest, joy, nostalgia, pride, relief, romance, sadness, satisfaction, sex desire, surprise, sympathy, triumph
(A. S. Cowen et al. 2019)	adoration, amusement, anger, awe, confusion, contempt, contentment, desire, disappointment, disgust, distress, ecstasy, elation, embarrassment, fear, interest, pain, realization, relief, sadness, surprise, sympathy, triumph
(A. Cowen et al. 2019)	adoration, amusement, anger, awe, confusion, contempt, contentment, desire, disappointment, disgust, distress, ecstasy, elation, embarrassment, fear, guilt, interest, love, neutral, pain, pride, realization, relief, sadness, serenity, shame, surprise, sympathy, triumph
(Demszky et al. 2020)	admiration, amusement, anger, annoyance, approval, caring, confusion, curiosity, desire, disappointment, disapproval, disgust, embarrassment, excitement, fear, gratitude, grief, joy, love, nervousness, neutral, optimism, pride, realization, relief, remorse, sadness, surprise
(A. S. Cowen and Keltner 2020)	amusement, anger, awe, concentration, confusion, contemplation, contempt, contentment, desire, disappointment, disgust, distress, doubt, ecstasy, elation, embarrassment, fear, interest, love, pain, pride, realization, relief, sadness, shame, surprise, sympathy, triumph

In experiment 1 opened with a training task (figure 6), which was included before the main trial to ensure that participants understood how to use the color picker and were able to select a specific color. In this task, participants were asked to set the color of at least 3 out of 4 white rectangles to be as close as possible to the color of the sample rectangle on their left.

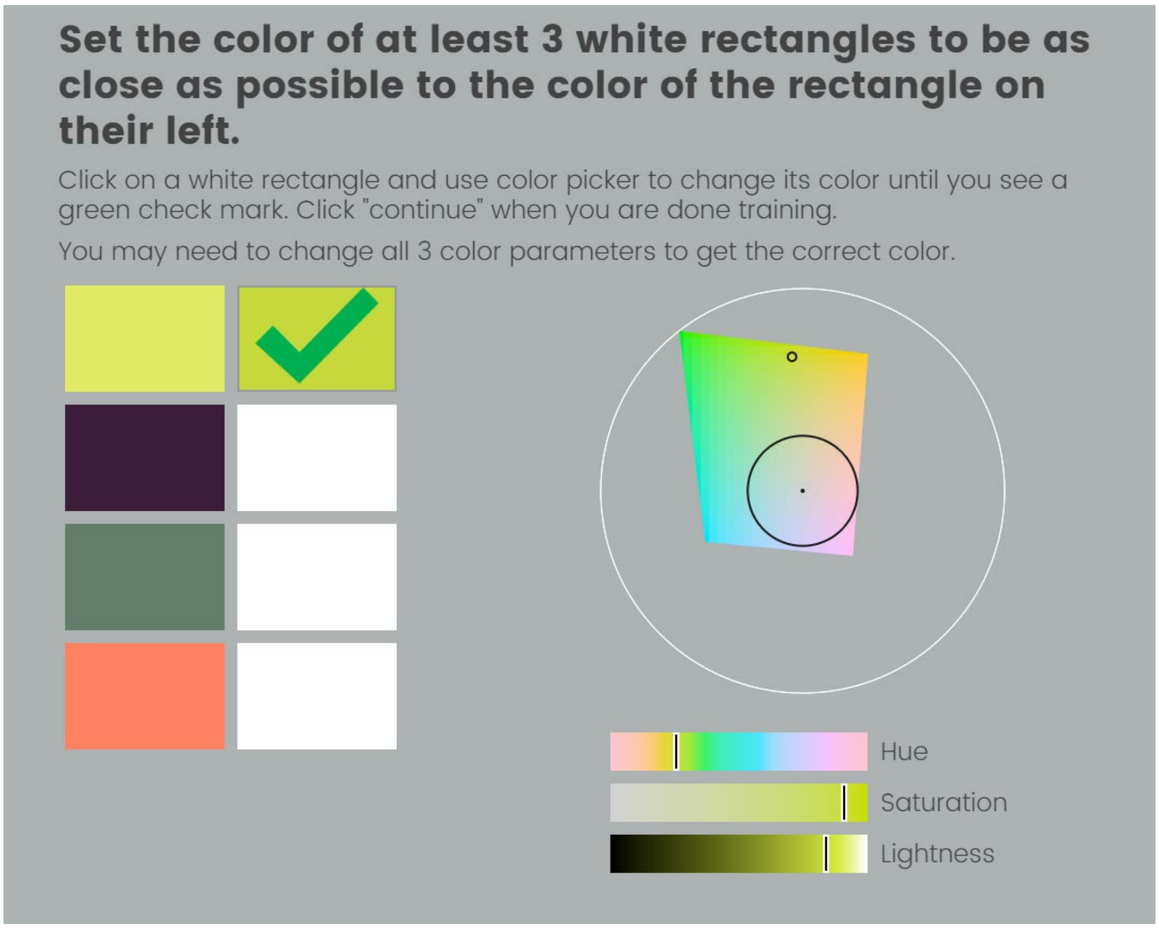


Figure 6. Training task in experiment 1

The colors were automatically compared using the CIEDE2000 version of the CIELab ΔE color distance formula. The ΔE or DE is a measure of distance (dissimilarity) between colors in the CIELab color space. Shorter distances indicate greater similarity between colors (Luo, Cui, and Rigg 2001). The original definition of ΔE was simply

Euclidian distance, and Brainard (2003) states that, on average, the human eye cannot perceive differences between colors with $\Delta E < 2.2$. However, the formula has been updated to measure distances between colors with similar lightness but different hues more accurately (Sharma, Wu, and Dalal 2005). Mokrzycki and Tatol (2011) suggest different values of ΔE that correspond to noticeable differences between colors. They stated that colors are perceived as different when $\Delta E > 5$. Several values of ΔE were manually tested to select a suitable threshold value for comparing user selections with the sample colors in the training task of experiment 1 of this study. It appeared that the color distance of 5.5 provides a sensible level of difficulty in matching a color to a sample swatch. The color distance between the sample color and the user-selected color was calculated in real time, as the user was modifying their selected color. When it dropped below 5.5, a green checkmark indicated a successful matching of the colors. This value also matches the findings of Stone et al. (2014), who suggest that minimum step in CIELab needed to make two colors visibly different is between 5 and 6. When 3 colors were matched, a "next" button appeared, allowing to proceed to the main trial.

In the main trial of experiment 1 (figure 7), participants used a custom interactive color picker to select a color for each emotion. Emotions were displayed one by one in a randomized order. A randomly selected emotion was presented twice to assess the consistency of the color choices within the same participant. The color picker allowed choosing colors using a continuous perceptually uniform CIELuv color space. This is one of the two color spaces introduced by the International Commission on Illumination that approximate human vision and are designed to be perceptual uniform (Schanda 2007). CIELuv is considered more suitable for applications that deal with colored lights, such as computer displays. This color space uses lightness (L) and two chromatic coordinates (u and v) that are not very user-friendly, especially for non-expert users.

The color picker was implemented using an "HSLuv" project (Boronine 2022) to resolve this issue and make it more intuitive to use for the participants. HSLuv relies on a special color space that allows using the CIELuv in the dimensions of the HSL color model by manipulating dimensions of hue, saturation, and lightness. For experiment 1 the JavaScript implementation of HSLuv was combined with the "d3-color" and "d3-color-difference" JavaScript modules for seamless conversion of the user-selected colors from one color space to another, obtaining different color representations and calculating color distances.

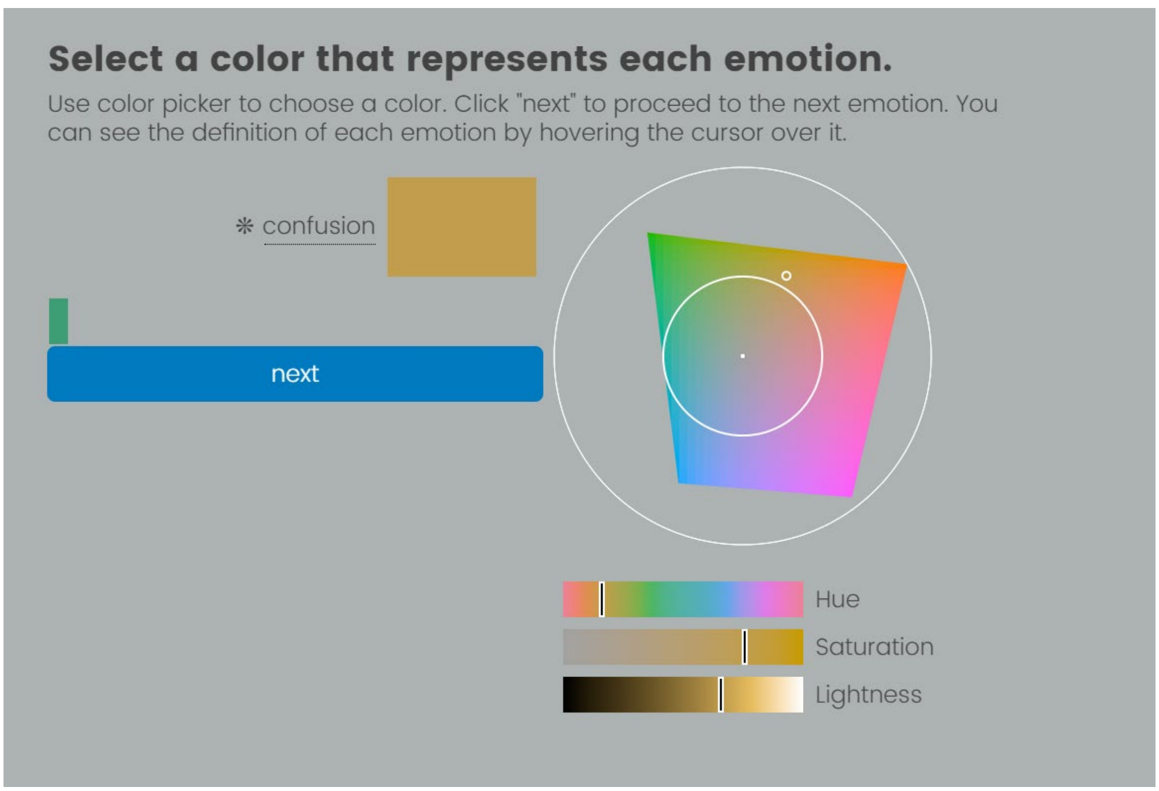


Figure 7. Experiment 1, main trial

During the color picking trial participants had access to the definition of each emotion, which appeared when participant was hovering a cursor over the word. The definitions for emotion terms (table 3) were obtained from the online version of the Cambridge English Dictionary ("Cambridge English Dictionary: Meanings & Definitions" n.d.). The time required to select a color for each emotion and the total time for the whole task was recorded for data quality assessment.

Table 3. Definitions of emotions used in experiment 1

amusement	the feeling of being entertained or made to laugh
anger	a strong feeling that makes you want to hurt someone or be unpleasant because of something unfair or unkind that has happened
annoyance	the feeling or state of being annoyed
awe	a feeling of great respect sometimes mixed with fear or surprise
boredom	the state of being weary and restless through a lack of interest
confusion	a situation in which people do not understand what is happening, what they should do, or who someone or something is
contempt	a strong feeling of disliking and having no respect for someone or something
contentment	happiness and satisfaction, often because you have everything you need
disappointment	feeling unhappy because someone or something was not as good as you hoped or expected, or because something did not happen
disgust	a strong feeling of disapproval and dislike of a situation, person's behavior, etc.
grief	very great sadness, especially at the death of someone
elation	a state of extreme happiness or excitement
embarrassment	feeling ashamed or shy, a state of self-conscious distress
fear	an unpleasant emotion or thought that you have when you are frightened or worried by something dangerous, painful, or bad that is happening or might happen
happiness	the feeling of being happy
interest	the feeling of wanting to give your attention to something or of wanting to be involved with and to discover more about something
joy	the emotion evoked by well-being, success, or good fortune or by the

	prospect of possessing what one desires
pride	a feeling of pleasure and satisfaction that you get because you or people connected with you have done or gotten something good
relief	a feeling of happiness that something unpleasant has not happened or has ended
sadness	the feeling of being unhappy, especially because something bad has happened
serenity	the quality of being peaceful and calm
shame	an uncomfortable feeling of guilt or of being ashamed because of your own or someone else's bad behavior
surprise	the feeling caused by something unexpected happening

Initially, the color picker was configured to reset all controls to the middle value at the beginning of each trial. A 3D scatterplot of all colors selected by participants, obtained from a pilot study, indicated that this approach leads to a bias in color selection. Many participants manipulated only 2 color parameters, keeping the lightness at the initial level. On the 3D plot it showed as a plane in the middle of the color space (figure 8). Another pilot study was conducted with the color picker reset to a white color with minimum saturation at the beginning of each trial to address this issue. The results of a second pilot showed that this approach leads to another bias in color selection. This time many colors were centered around zero saturation, forming a vertical line in the center of the color space. Given this, the color picker was reset to a random color at the beginning of each trial to avoid both kinds of bias. Testing this approach with another pilot study proved that resetting to a random color helped, and no visible bias was introduced to the color selections by the data collection instrument. The starting color of each trial was recorded along with the final user choice to check that participants did not submit the random preset color as their selections. Submissions, where these two colors were systematically similar, had been disqualified.

A total of 95 participants were recruited for experiment 1 through the crowdsourcing web service Prolific. The general demographic characteristics of the sample were as follows: 51 females and 44 males with a mean age of 36, ranging from 19 to 76 years old. Participants were compensated with 1.10$, which, when pro-rated for the average duration of the task, is equivalent to a 7$ per hour rate.

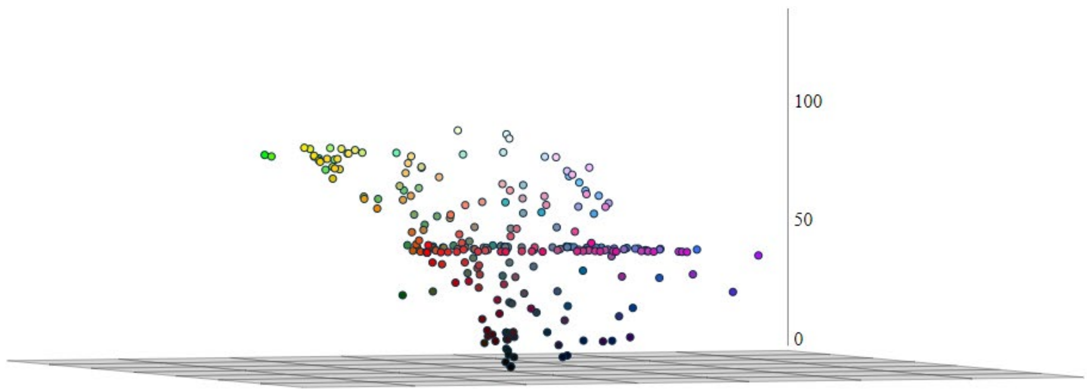


Figure 8. Scatterplot of color submissions in CIELab color space with bias

Experiment 2. Quantify the interpretability of candidate congruent colors

The purpose of the second experiment was to identify which colors obtained in experiment 1 are more reliably interpreted as representing a particular emotion. Quantification of the color interpretability based on the frequency of each emotion being selected as matching to a corresponding color allowed to create a color set that could be used to produce cognitively congruent color assignments to emotions.

There were 32 colors produced as a result of experiment 1 (table 6). In experiment 2 participants matched these colors to the emotions that each color may represent. The task of matching the colors to emotions could be formulated in two ways: the best fit for an individual color and the best fit for a set of colors. Since color-concept associations usually demonstrate many-to-many relationships (Schloss et al. 2018; Fugate and Franco

2019), different combinations of emotions would likely result in different sets of assigned colors. Some colors would be interchangeably used for different emotions. Given this, testing a single set of emotions for the best set of colors would be only representative of that particular assignment case. Testing all possible combinations that could be made from 23 emotions is not feasible. Thus, experiment 2 was designed to estimate the best fit for each individual color.

During the main trial of experiment 2 the participants saw all the colors one by one in a randomized order and selected all emotions they thought each color might represent (figure 9). Emotions and their definitions were the same as in experiment 1. Emotion choices were presented in individual containers with emotion term and a checkbox to indicate it was selected or not. These containers were rendered in the alphabetical order for each trial to make it easier for participants to find the answer they wanted to select. Definition of each emotion was available to participants by hovering a cursor over the corresponding container. An additional answer option, "none" was included in each trial to avoid forced replies when participants did not feel an association of the current color with any emotion. The time spent to select emotions for each color and the total time for the whole task were recorded.

A total of 99 participants were recruited for experiment 2 through the crowdsourcing platform Prolific. The general demographic characteristics of the sample were as follows: 50 females and 49 males with a mean age of 38, ranging from 18 to 78 years old. Participants were compensated with 1.10$, which, when pro-rated for the average duration of the task, is equivalent to a 9$ per hour rate.

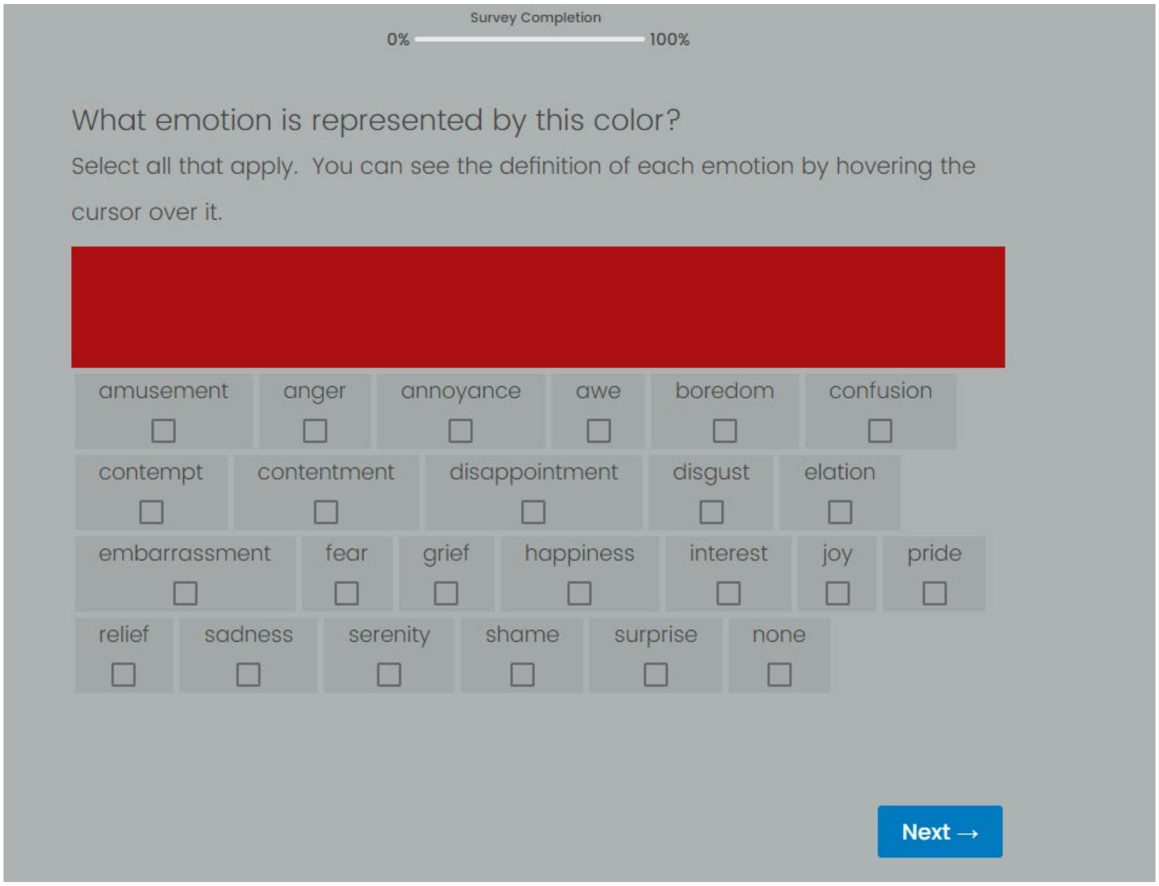


Figure 9. The color interpretability assessment instrument

Experiment 3. Assess the effect of a congruent color palette

The second objective of this study was the evaluation of the resulting cognitively congruent color palette in terms of its effect on the map user experience, task performance, and map-based decision making. To this end, another user experiment was conducted. The logic of this experiment was to compare two groups of participants who solved a map-based task and answered a short post task questionnaire.

The task was to plan and draw a one-day walking sightseeing tour using one of two tourist maps of a small historic town. Each map showed attractions and how people feel in different parts of town. Emotional data were shown with a cognitively congruent palette on one map, and with a conventional color palette on the other map. The tour planning task was chosen because it represents a common task a map could be used for and involves reading and processing the information displayed on the map.

The task included several conditions to keep the results comparable. First, the tour should avoid places with negative emotional reviews; second, the tour should start and end at the hotel; third, the tour should be continuous and follow the street network. First requirement was necessary to make sure that participants do not ignore the information about emotions and follow the same logic when planning a tour. The other 2 requirements were aimed at making sure that participants did not just “connected the dots” with straight lines but engaged with the map and used the road network to plan a sensible tour.

To avoid a possible influence of recognition or other knowledge about the place, no real town was used for experiment 3. The base map of the town was created with a procedural city map generator (“Medieval Fantasy City Generator by Watabou” 2022). It was then exported in GeoJSON format and edited in QGIS. The base map was styled in a minimalist way to avoid possible contrast issues with the thematic content. A uniform light grey background was applied to the land, and a light blue fill was assigned to the water. The initial building footprints were replaced with the road network to make more room for the attraction and emotion symbols and make the map less cluttered. The roads were divided into 2 classes – major roads and minor roads. Both classes were displayed in grey, with major roads being wider. Some of the main roads were labeled in black font on a white background. The parks were shown with thin green outlines, no background fill. The symbols for the attractions were designed in the same size, using black lines and white fill. A total of 9 attraction symbols were added to the map: a hotel and 8 “official” tourist sites. The hotel was placed in the center of the map to balance the distance to the places of interest. Attractions were evenly distributed across the town, following the street layout. The 4 “unofficial” attractions did not have a dedicated symbol and were only represented on the map by the clusters of emotional data.

Since the map used in this experiment depicted a fictitious town, the emotional data were also artificial, manually constructed as if obtained based on social media postings, a common source of spatial emotional data. Such data are usually visualized using dot density mapping, where each dot represents a geocoded social media post classified by a dominant emotion. The same cartographic method was applied to show emotional data on the map for experiment 3. Each dot on the map was supposed to represent a single emotional experience derived from a social media post.

The maximum recommended number for categorical data classes on a map is 7 (MacDonald 1999; Silva, Sousa Santos, and Madeira 2011). To provide as much variation of emotional reviews and still have a usable number of classes on the map, a total of 8 emotions were selected: 4 positive (joy, surprise, serenity, interest) and 4 negative (fear, disgust, boredom, disappointment). The reasoning behind this selection was to pick emotions that are generally relevant to a tourist map, include some of the Ekman’s basic emotions, and vary the intensity of emotions.

Symbols representing emotions were created in several steps. First, polygons of arbitrary shape were added around each attraction. Four more polygons were added to represent the “unofficial” places of interest. Next, 2 or 3 sets of random points with varying densities were generated inside of the polygons that represented each place. Each set of points represented one emotion. “Good” and “bad” places were assigned with combinations of positive and negative emotions, respectively. Then a few emotional outliers were added to each place. Finally, the positions of emotional dots were manually adjusted to avoid overlapping with the attraction symbols and with each other.

Maps for the experiment 3 were designed to be informationally equivalent. The only difference was in the palette used to show emotional data. One map (figure 10) used the ColorBrewer qualitative set 1 palette for categorical data. The colors were randomly assigned to emotional categories. The other map (figure 11) used cognitively congruent color palette obtained using a color palette generation tool, which was designed based on the results of experiment 2. All the colors used to show selected emotions on maps are presented in table 4.

Table 4. Colors used to show emotions on maps

emotion	cognitively congruent colors		conventional cartographic colors	
boredom		6e6c68		e41a1c
disappointment		a0a1a5		984ea3
disgust		ac1011		377eb8
fear		070808		4daf4a
interest		3fad41		999999
joy		ebe049		f781bf
serenity		91a3cf		a65628
surprise		f080f1		ffff33

Due to the concerns regarding the sex balancing on Prolific, particularly participant pool leaning more towards young females, and some participants registering both as male and female to participate in more studies, experiment 3 was split into 2 separate surveys. Each survey was aimed at collecting data only from male or female participants respectively. These separate surveys relied on the prescreening option provided by Prolific and included an additional question about the participant's sex. In cases when the answer to this question mismatched with the expected, the participant was disqualified from taking the survey.

The male and female surveys in experiment 3 were identical and followed the procedure similar to the surveys in experiments 1 and 2. First, the participants read the description of the study and gave the informed consent to participate. Next, they took the Ishihara color vision test, and those who had passed continued to the main trial. Each participant was randomly assigned one of the two maps to perform the route planning task. The maps were assigned in a balanced way to get the same total number of congruent and incongruent trials. Task completion time was recorded and served as a measure of user performance. Drawn route was saved as separate image for subsequent decision-making analysis. Upon the map task completion, participants filled out a questionnaire to share their experience with the map.

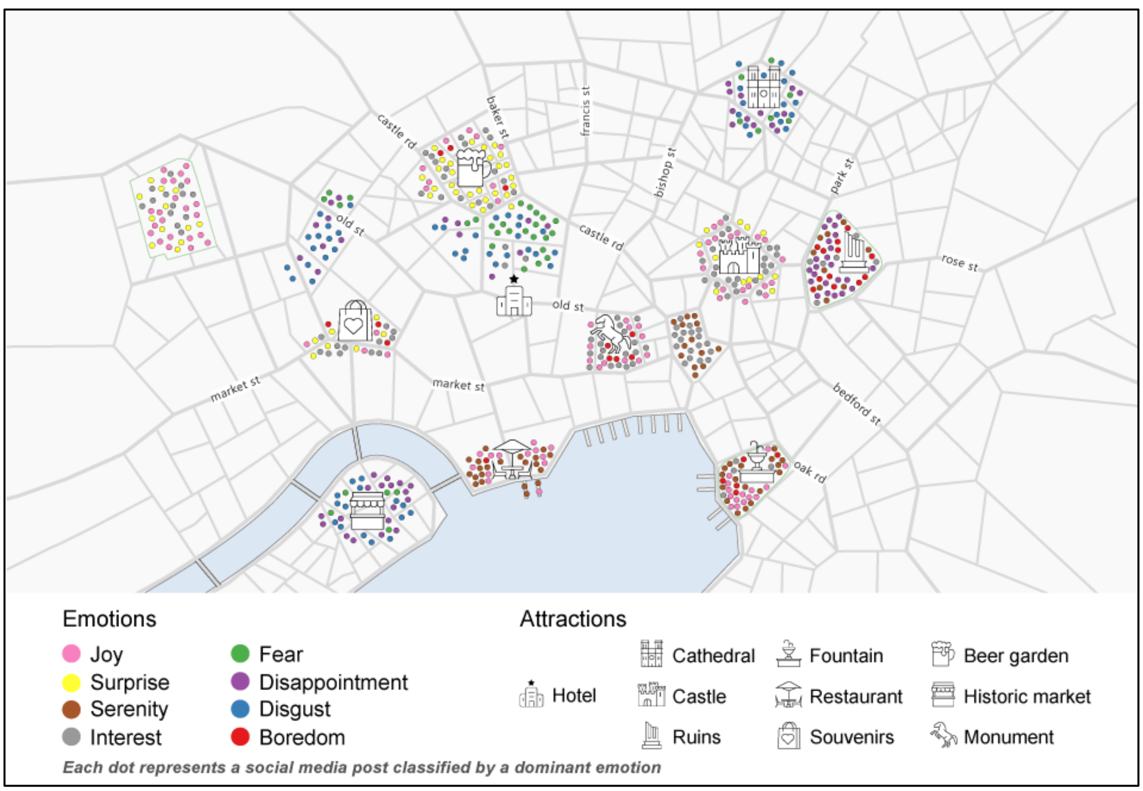


Figure 10. Map with ColorBrewer colors

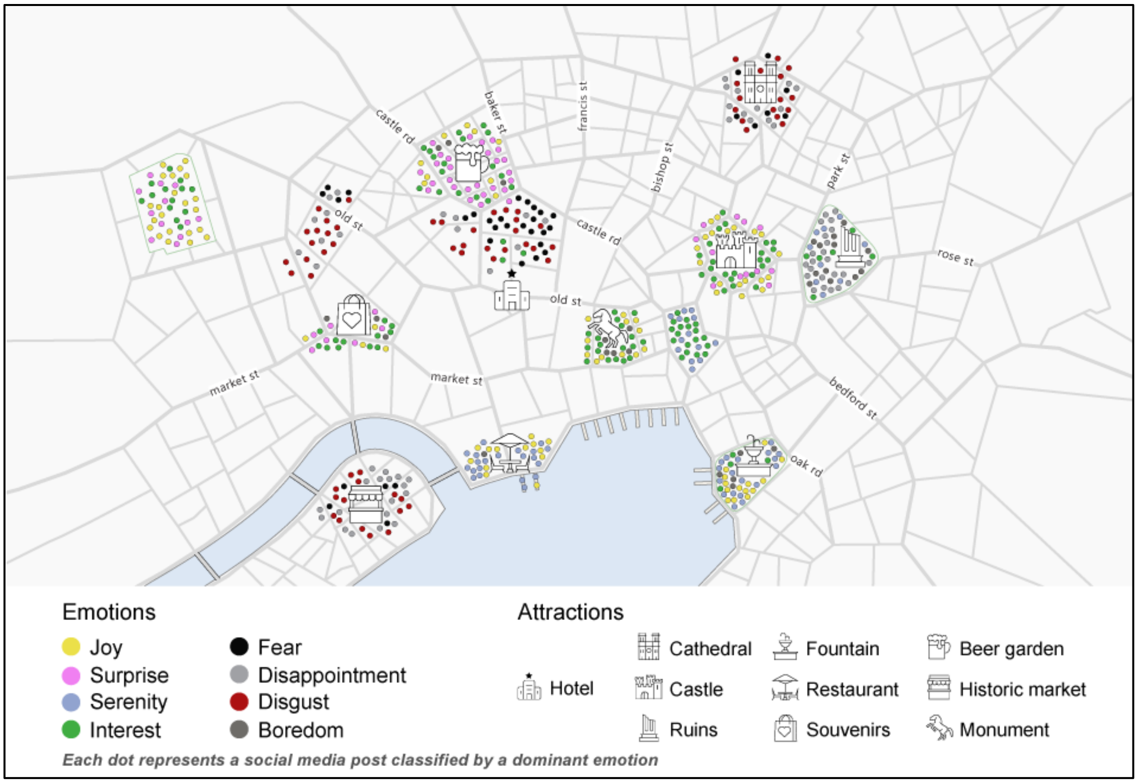


Figure 11. Map with congruent colors

To assess subjective user experience with the map and answer one of the stated research questions, the perceived difficulty of the task was measured. To this end, NASA Task Load Index (TLX) was used (Hart and Staveland 1988). It is a subjective workload assessment tool designed to collect feedback from operators working with various human-machine interface systems. The workload is a complex notion but essentially represents the amount of effort people have to exert mentally and physically to use the interface (Hart and Wickens 1990; Miller 2001). Hart and colleagues operationalized workload using six dimensions: mental, physical, and temporal demands, frustration, effort, and performance. NASA TLX has been cited hundreds of times and used in various applications, from aircraft certification and nuclear power plant control rooms to website design (Hart and Field 2006). While most applications of the TLX are for physical interfaces, any interface experience requires some level of workload and thus can make use of the TLX. Like other user experience (UX) metrics, it helps in comparing interfaces and understanding whether the workload is higher or lower depending on the differences in the interfaces.

The standard version of the NASA TLX includes a weighting procedure that estimates which TLX dimensions are more relevant to the participants' personal definition of workload as related to the task. This procedure requires 15 comparisons, one for each pair of dimensions. In practice, many researchers skip the weighting step, reducing the time needed to administer the TLX. When the weighting step is skipped, the instrument is referred to as Raw TLX. When compared to the original version, it was found to be either more sensitive, less sensitive, or equally sensitive (Hart and Field 2006). A non-weighted version of NASA TLX was used in present study to keep the survey shorter and reduce the cognitive load on the participants.

The questionnaire, that participants were asked to fill out upon completion of the map task consisted of 9 questions: 6 for the Raw TLX and 3 additional questions. The TLX questions were designed in the form of a slider, scaling from 0 to 100, following the design of the official NASA TLX app by NASA's Ames Research Center. One of the additional questions was a free text question "What was your logic for designing the tour?" Its goal was to check whether participants did what was expected and followed the task properly. The other question addressed the user's overall visual experience with the map, asking to rate the map in terms of how pleasant it was to look at. The last was an attention check question, asking participants to select a particular value on a slider. Both visual experience and attention check questions were designed as sliders same to the TLX question. The entire questionnaire was presented to participants on the same page, with the free text question always coming first and the rest in a random order. The layout of the questionnaire presented in Appendix A.

A total of 239 participants were recruited for experiment 3 through the crowdsourcing web service Prolific. The general demographic characteristics of the sample were as follows: 120 females and 119 males with a mean age of 35, ranging from 18 to 91 years old. Participants were compensated with 1.10$, which, when pro-rated for the average duration of the task, is equivalent to a 10$ per hour rate.

IV. RESULTS

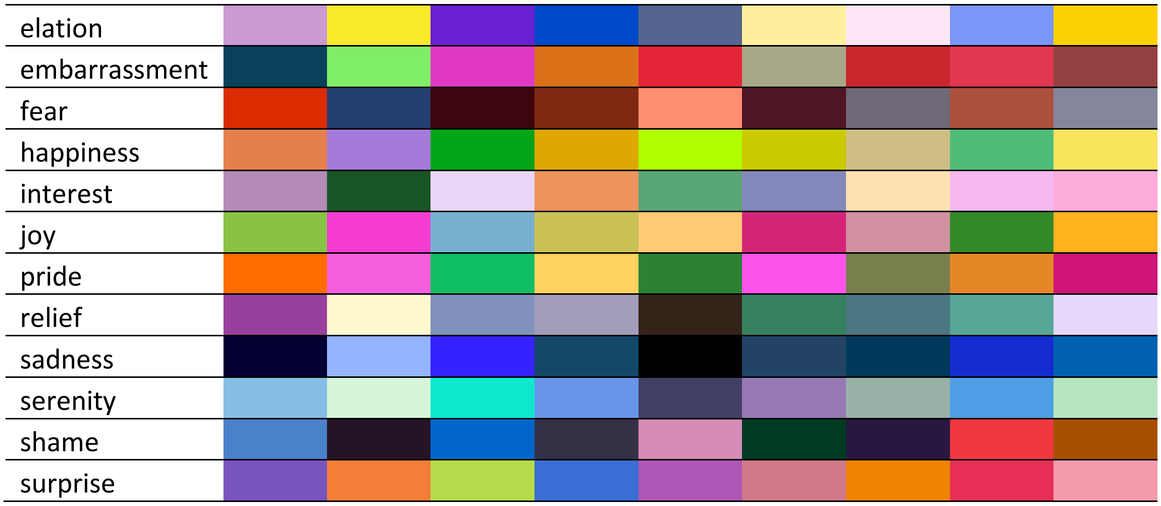
Survey data for each experiment were downloaded from Qualtrics in comma-separated values (CSV) format. Incomplete, nonsensical, or unrealistically quick submissions, as well as submissions from participants who failed to answer control questions or did not follow the task directions, were rejected on Prolific. New participants were recruited to replace the rejected ones. Data from the valid submissions were analyzed using Python and the statistical software package R.

Experiment 1

Data collected in experiment 1 were sets of colors defined in a perceptually uniform color space that were selected as associated with each emotion (table 5). The distribution of selected colors is well aligned with the many-to-many associations between colors and emotions, as the literature suggests. Participants selected different colors to represent the same emotion, and similar colors were associated with different emotions. Some emotions demonstrate more uniform color associations than others. Bright and saturated colors were generally assigned to positive emotions, while negative emotions were more often associated with darker colors.

Table 5. Sample of colors associated with emotions. Each column represents a participant

amusement									
anger									
annoyance									
awe									
boredom									
confusion									
contempt									
contentment									
disappointment									
disgust									
grief									



The analysis of the data from experiment 1 consisted of several steps. First, color selections were visually inspected using interactive 3D scatterplots in CIELab color space for all responses grouped by emotion (figure 12). Individual 3D scatterplots for each emotion are available on GitHub with the link provided in Appendix B. Visual inspection of these interactive charts suggested that the distributions of color choices in CIELab color space were different for different emotions, with some being more similar to each other.

Next, a repeated measures ANOVA test was conducted for each color dimension (L, a, b) to demonstrate that colors were not selected randomly and there is a statistically significant difference between colors selected for different emotions. It was then followed by multiple pairwise paired t-tests to identify which emotions are significantly different in terms of the corresponding color parameters. Next, to identify the candidates for the most representative and thus congruent colors for each emotion, a clustering analysis was applied. As a result, one representative color was extracted from each cluster. Last, the strength of association with the corresponding emotion was quantified for each cognitively congruent color candidate. Based on this value, a final selection of the 32 cognitively congruent colors was made (table 6).

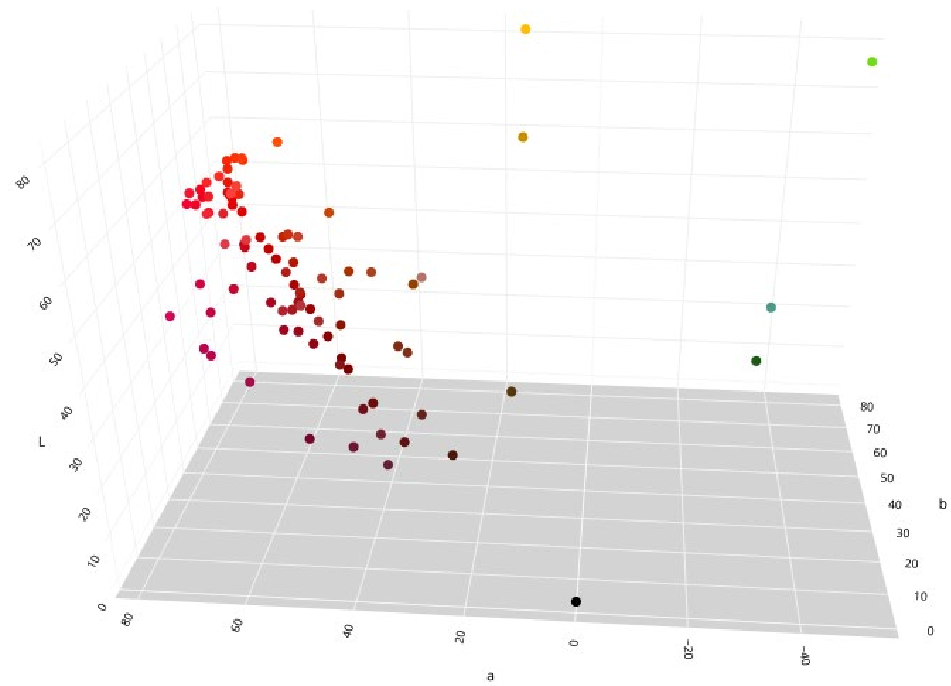


Figure 12. 3D scatter plot of colors selected for anger

Repeated measures ANOVA was conducted to determine whether or not there was any effect of emotion (independent variable) on the "L" color dimension (dependent variable). The assumption of normality was checked using QQ plots that draw the correlation between the given data and the normal distribution. Outliers were identified using the box plot method and then removed. The assumption of sphericity was automatically checked using Mauchly's test during the computation of the ANOVA. The Greenhouse-Geisser sphericity correction was automatically applied to factors violating the sphericity assumption. The mean values of the "L" color dimension were statistically significantly different between at least two emotions, $F(12, 411) = 33$, $p < 0.000$, $\eta_g^2 = 0.45$. Given that ANOVA results showed a significant difference, post hoc pairwise comparisons using paired t-tests were applied, with p-values adjusted using the Bonferroni multiple testing correction method. The results for a total of 253 t-test comparisons (presented in Appendix B) demonstrate that the mean “L” values are significantly different for 164 pairs of emotions.

Repeated measures ANOVA to determine whether or not there was any effect of emotion (independent variable) on the “a” color dimension (dependent variable) followed the same procedure as ANOVA for the “L” color dimension. The mean values of the “a” color dimension were statistically significantly different between at least two emotions, $F(11, 387) = 8$, $p < 0.000$, $\eta_g^2 = 0.19$. Post hoc pairwise t-test comparisons (presented in Appendix B) demonstrate that the mean “a” values are significantly different for 87 out of 253 pairs of emotions.

Repeated measures ANOVA for the “b” color dimension as the dependent variable was conducted the same way as previously described ANOVA tests. The mean values of the “b” color dimension were statistically significantly different between at least two emotions, $F(11, 389) = 9$, $p < 0.000$, $\eta_g^2 = 0.19$. Post hoc pairwise t-test comparisons (presented in Appendix B) demonstrate that the mean “b” values are significantly different for 91 out of 253 pairs of emotions.

Next, cluster analysis was applied to organize color choices for each emotion into sensible groupings. This approach follows the method of Setlur and Stone (2015), who applied k-means clustering to quantize input colors into visually discriminable clusters using CIELuv Euclidean distance. Since there are thousands of clustering algorithms and none of them has been shown to dominate the other (Jain 2010), different algorithms with different parameters were tested to see which one produced more meaningful results. A simple k-means clustering and two density-based spatial clustering algorithms — DBSCAN and OPTICS, were used (Ester et al. 1996; Ankerst et al. 1999). Density-based algorithms proved to be more suitable for this study because such algorithms perform better with irregularly shaped clusters of varying density (Duan et al. 2007; Liu et al. 2012). Both density-based clustering algorithms required manual finetuning of their parameters for the best performance.

The clustering analysis was implemented using “Scikit-Learn” — a free software machine learning library for the Python programming language (Kramer 2016; “Scikit-Learn: Machine Learning in Python” 2022). The interactive 3D scatterplots produced by each algorithm, where each point has been assigned to a color-coded cluster (figure 13), were visually inspected, and the one that suggested more meaningful clusters was selected for further analysis. Individual 3D scatterplots with classified points for each emotion can be found on GitHub using a link provided in Appendix B.

After finishing the clustering analysis of colors for each emotion, a geometric median algorithm described by Vardi and Zhang (2000) was applied to extract the candidates for the congruent colors from each identified cluster. The position of each extracted color candidate was inspected using another series of interactive 3D scatterplots to ensure its correctness (figure 14). Individual 3D scatterplots with color candidates extracted from each cluster for all emotions are published on GitHub, and the link to it is provided in Appendix B.

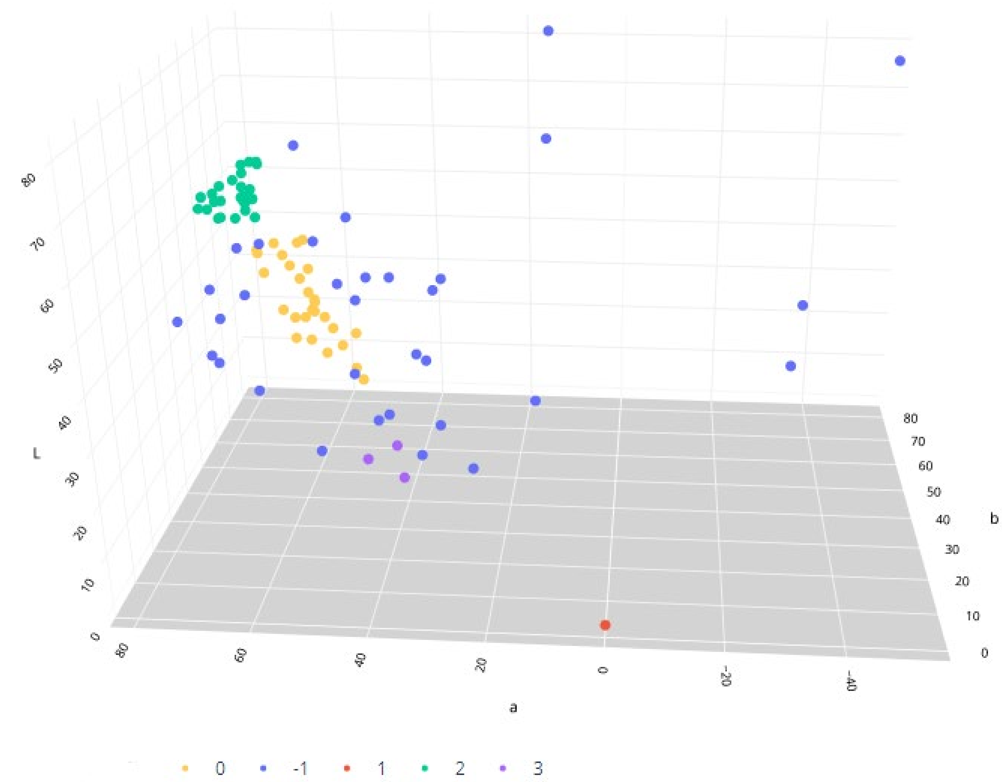


Figure 13. 3D scatter plot of classified dots for anger. "-1" indicates noise

Since clusters varied by the number of color points, the size, and the shape, it was necessary to quantify the degree of association between an extracted candidate color and a corresponding emotion. This congruency rating (r) was calculated as the ratio of the number of points in the cluster (n) to the median distance ($\tilde{d}$) from each point to the geometric median of that cluster ($r = \frac{n}{\tilde{d}}$). Candidate color coming from a cluster with more dots situated closer to each other got a higher rating than a color from a cluster with fewer points or with the points being farther away from each other.

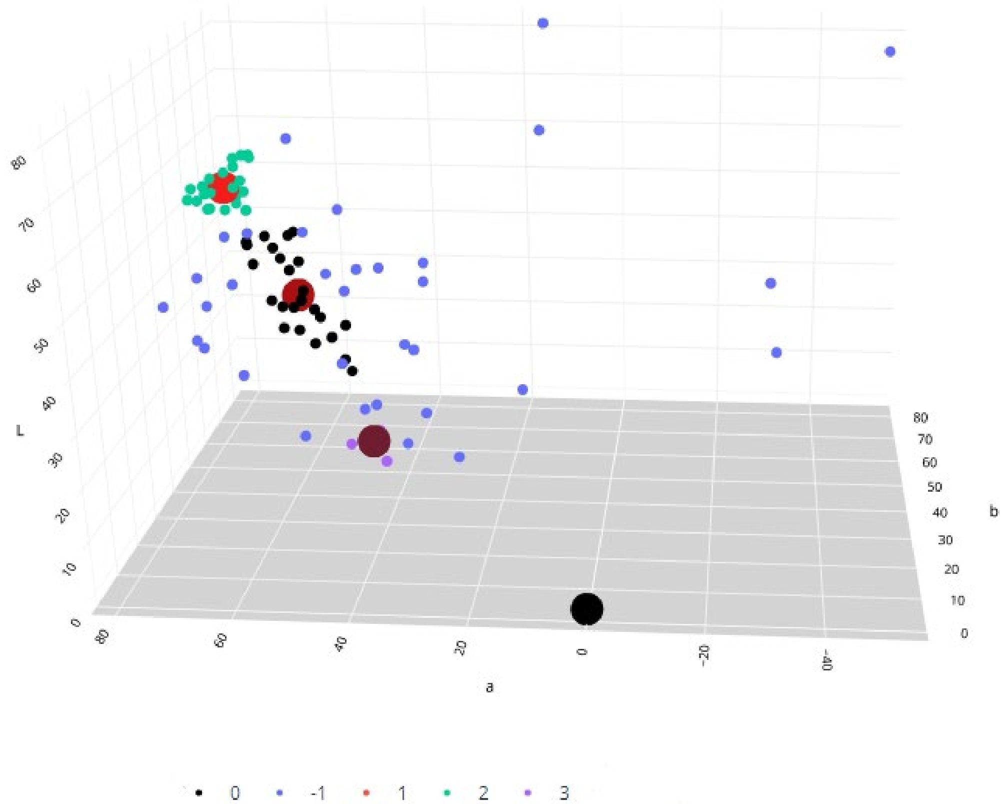


Figure 14. 3D scatterplot with classified dots and candidate colors for anger. "-1" indicates noise

The total number of cognitively congruent color candidates was about 100. Some colors identified as congruent for different emotions turned out to be very similar to each other. Similar colors less than 5 ΔE apart were aggregated to a single color using the geometric median to improve discriminability and minimize the variability in brightness and saturation among the candidate colors. The remaining set of colors was further reduced by selecting colors with the highest congruency ratings while preserving as much difference in color hue as possible. The resulting set of 32 congruent color candidates (table 6), was then tested in experiment 2 to estimate interpretability of each color.

Table 6. Candidate congruent colors

#e23dc2	#f080f1	#eda4b3	#eeb8e0	#62202b	#9b1c45	#ac1011	#dc2265	#ef2119
#c94949	#f07723	#e5914e	#f9b308	#ebe049	#4290ac	#34b0f4	#8ce7f7	#c9f1ec
#91a3cf	#ada8ff	#424326	#465838	#767928	#3fad41	#6e6c68	#838586	#a0a1a5
#eee3e8	#204c6e	#40718f	#282a36	#070808				

Experiment 2

Data collected in experiment 2 were arranged in the form of a two-way contingency table of counts for each color emotion pair (presented in Appendix B). A Chi-square test of independence was used to examine whether there is a relationship between an emotion and a selected color (Hanada 2018; Lutabingwa and Auriacombe 2007; Olsen and St George 2004). It has been argued that the standard chi-square test is unsuitable for the data collected with multiple-choice questions where participants select all answers that apply (Mahieu et al. 2021; Loughin and Scherer 1998). Since this was the case in experiment 2, a multiple-response Chi-square test version implemented as R statistical software package "MultiResponseR" by Mahieu et al. (2021) was applied in this study. It was followed by a multinomial logistic regression analysis to estimate how suitable each color is for representing an emotion. Obtained probabilities of each color being selected depending on the emotion served as the metric of interpretability.

The results of Chi-square test with $\chi^2 = 6981$, $p = 0.0005$, and effect size Cramer's V = 0.22 suggest that variables of color and emotion are not independent. In addition to the Chi-square test, the “MultiResponseR” package allows determining the significance of associations between each pair of the tested variables by conducting multiple-response hypergeometric tests per cell. In particular, it showed for a given emotion and a given color if this emotion was cited for this color in a proportion that significantly differs from the overall average citation proportion of this emotion in all colors combined (Mahieu et al. 2021). The resulting table from this test is presented in Appendix B.

Probabilities of each color being selected for a particular emotion as calculated by multinomial logistic regression are presented in Appendix B. These values, combined with the results of hypergeometric tests per cell, were used as a basis for solving a color to emotion assignment problem. Only the probabilities for color-emotion pairs that demonstrated statistically significant relationships were included in the calculation of the optimal assignment. Color assignment algorithms for categorical data suggested by Schloss et al. (2018) were implemented with a Python script to create a cognitively congruent palette for any possible combination of 23 emotions. This script was then turned into a web app (figure 15) that generates a cognitively congruent palette for the selected choice of emotions. The app is available at https://colors4emotions.tk/.

Following the approach of Schloss et al. (2018), the tool generates suggested colors for each set of emotions by solving an encoding assignment problem as a linear program. Linear programming, also called linear optimization, is a method to achieve the best outcome (such as maximizing profit or minimizing cost) in a mathematical model with requirements represented by linear relationships (Williams 2013; Schrijver 1998).

Figure 15. Cognitively congruent color palette generation tool

The tool implements both isolated and balanced assignment algorithms from the original article by Schloss et al. (2018). The isolated algorithm for color-object assignment is straightforward and maximizes the color-emotion associations among all chosen color-emotion pairs. The balanced algorithm mitigates conflicts due to many-to-many relationships by simultaneously maximizing the association between all paired items while minimizing the association between unpaired items. An additional constraint of the minimum allowed color distance in CIEDE2000 ΔE units was added to the algorithm to improve the discriminability of colors assigned to different emotions.

Experiment 3

User experiment 3 was aimed at evaluating the cognitively congruent color palette suggested by the tool built as a result of experiment 2 and providing evidence that such a palette has advantages over the conventional categorical color palette when applied to the emotional data. The metrics of task performance (completion time), subjective workload (NASA TLX), and visual experience (aesthetics rating) for congruent and incongruent trials were compared using a t-test or a non-parametric Mann–Whitney U test depending on whether the assumptions for a t-test were met.

Checking if there was any difference in map-based decision-making depending on the type of color palette used was another goal of experiment 3. To this end, the average number of good and bad places visits per user were compared using t-tests, and the frequencies of visits to each place were compared with a Chi-square test. All figures and tables illustrating results in this chapter refer to participants who did congruent trials as group "E" and those who did incongruent trials as group "R."

The completion time of the map task was recorded in seconds for each participant, with the mean values of 219 for congruent trials and 249 for incongruent. As the t-test has an assumption that there are no outliers in both groups, outliers were identified using the box plot method and then removed. Then the data were checked for normality with a Shapiro test, which showed that the distribution could not be considered normal. Given this, the non-parametric test, with the alternative hypothesis that completion time is less for the group who used the map with congruent colors, was implemented with "Wilcox.test" function in R. The results (figure 16) with $W = 4942$, $p = 0.02$, effect size $d = 0.2$, and an estimated difference in location of 24 seconds suggest the rejection of the null hypothesis that completion time for congruent and incongruent trials come from the same population.

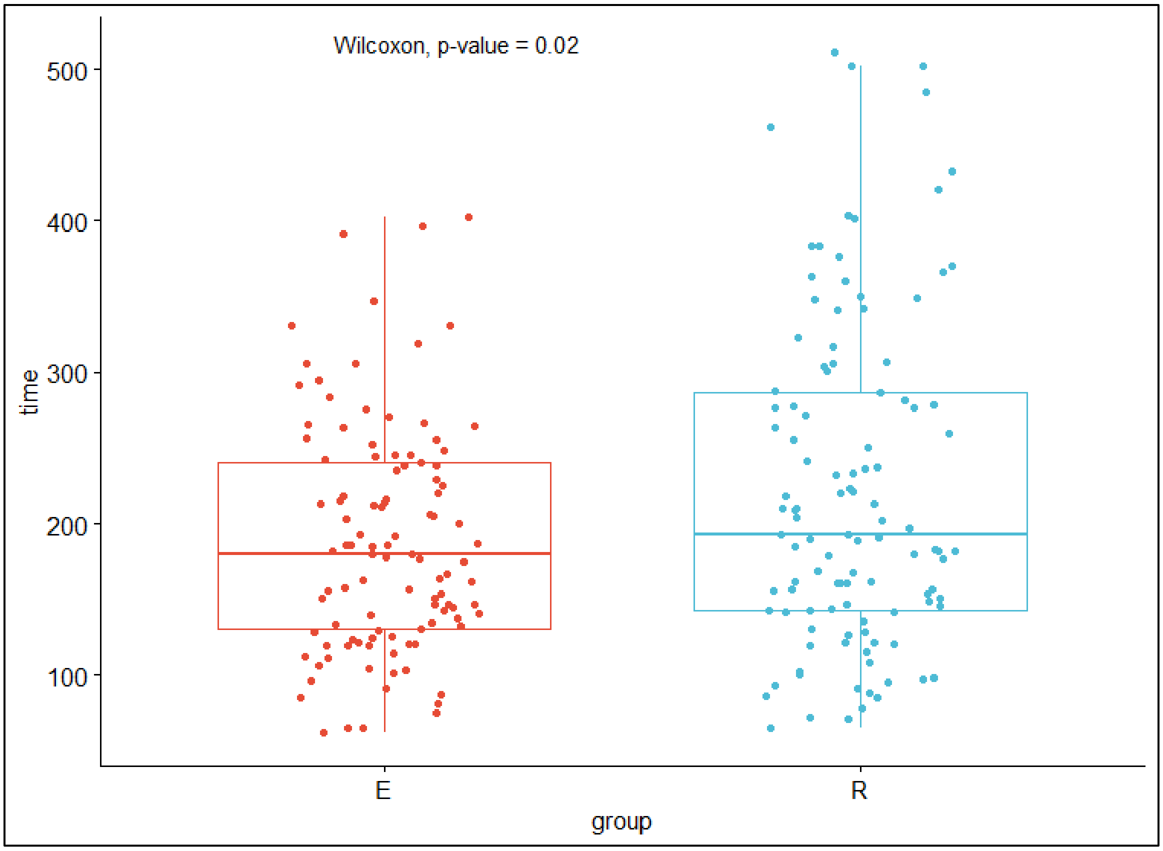


Figure 16. Task completion time comparison

NASA TLX was calculated for each participant using the raw TLX approach, with the mean values of 26 for congruent trials and 31 for incongruent. With the outliers identified using the box plot method and then removed, the data met the assumptions of the t-test. Welch Two Sample t-test, with the alternative hypothesis, that TLX is lower for the group who used the map with congruent colors, was implemented with the "t.test" function in R. The t-test showed (figure 17) that the difference in mean TLX was statistically significant, $t(217) = -2.8$, $p = 0.003$, effect size $d = 0.38$.

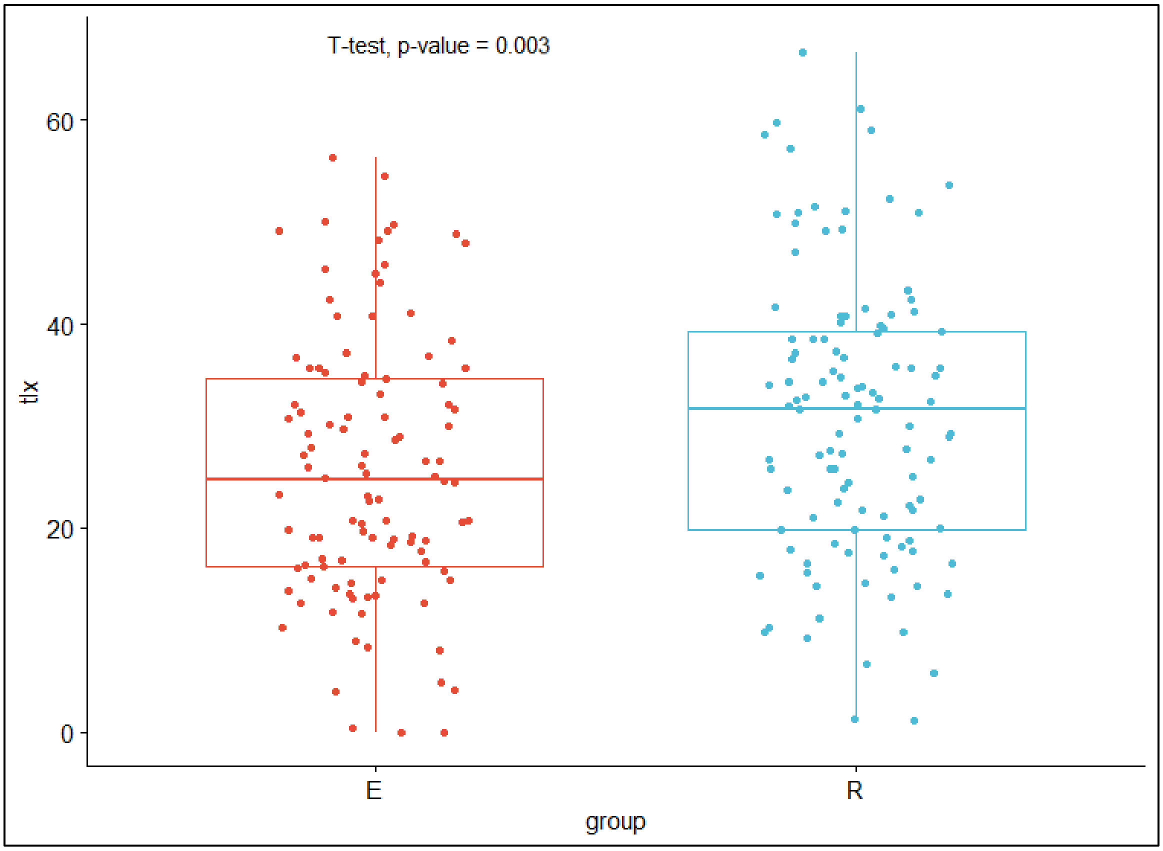


Figure 17. NASA TLX comparison

Ratings of aesthetics measured on a scale from 0 to 100 demonstrated similar average values of 56.4 for congruent and 56.8 for incongruent trials. The assumption of normality was violated, and the Mann-Whitney U test with the alternative hypothesis that aesthetics ratings are not the same for congruent and incongruent trials was applied to compare the data. The results (figure 18) indicate that the null hypothesis should not be rejected with W = 6245, p = 0.96, and effect size d = 0.02.

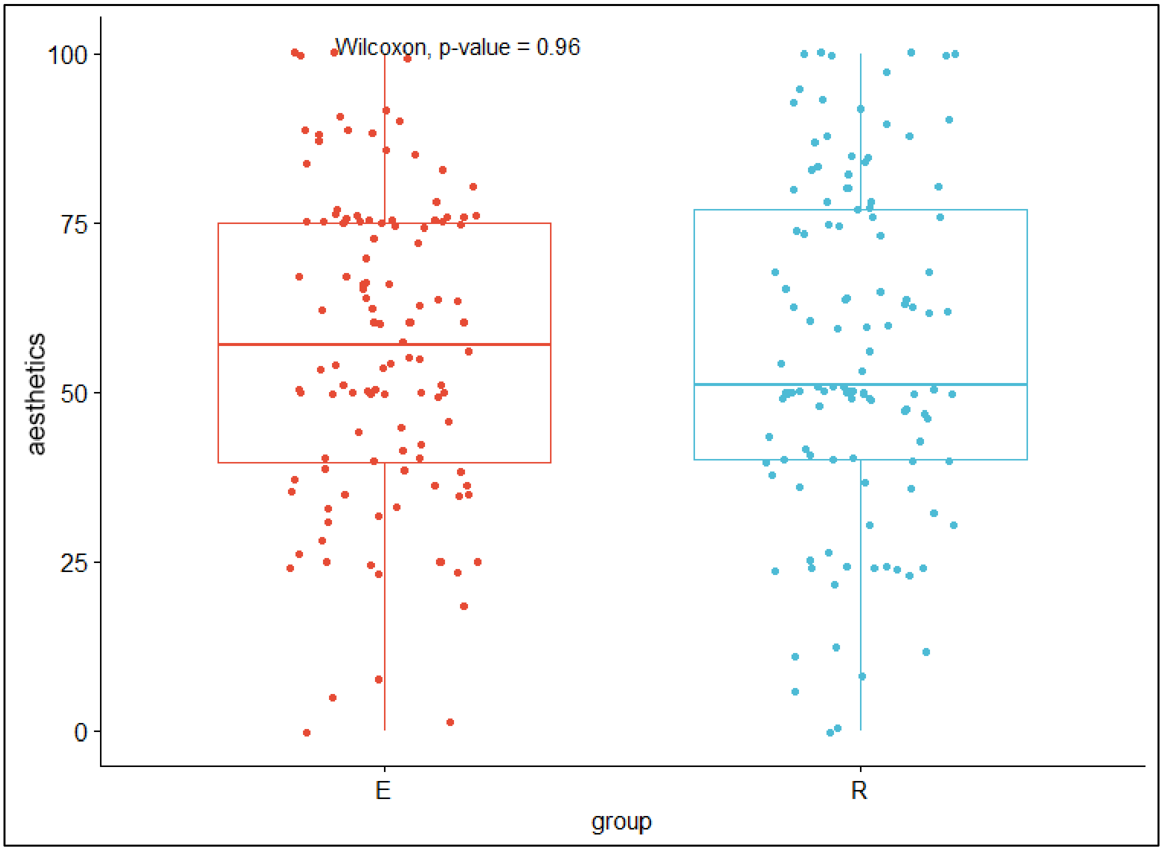


Figure 18. Aesthetics rating comparison

Next, the total number of “good” and “bad” places per user visited by each group was compared to check if there was any difference in decision making. On average, participants who worked with the map using cognitively congruent colors visited 6.9 good places, while those who worked with the incongruent map went to 6.2 good places. The data for both groups were not normally distributed. Thus, the Mann-Whitney U test was used, with the alternative hypothesis that the number of visited good places is not the same for congruent and incongruent trials. The results (figure 19) suggest that there is a significant difference between the two tested groups, with W = 8374, p = 0.0009, and effect size d = 0.46. The estimated difference between the samples is 1.

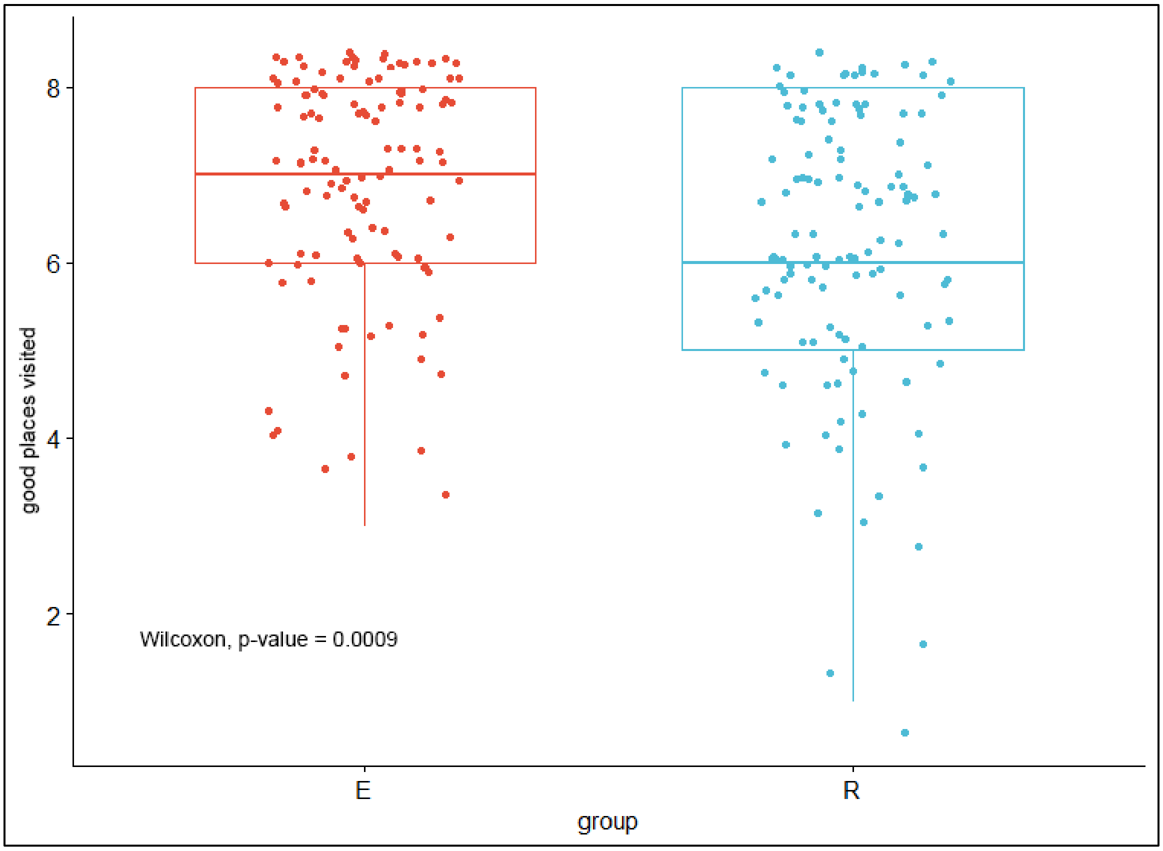


Figure 19. The number of good places visits per user comparison

The average number of bad places visited by each user was 0.6 for congruent and 0.7 for incongruent trials. The data for both groups were not normally distributed, and the Mann-Whitney U test was used, with the alternative hypothesis that the number of visited bad places is not the same for congruent and incongruent trials. The results (figure 20) indicate that the null hypothesis should not be rejected, and there is no significant difference in the number of visited bad places, with $W = 6666$, $p = 0.89$, and effect side $d = 0.1$.

The frequencies of visits to each place were compared with the Chi-square test of independence to provide an additional perspective on the differences in decision-making. Since each participant visited more than one place, the multiple response version of the Chi-square test was applied, similar to experiment 2. The results of $\chi^2 = 26$, $p = 0.0005$, and effect size Cramer's V = 0.12 suggest that the null hypothesis should be rejected, meaning that there is a significant relationship between the color palette used on the map and the frequency of place visits. The results of the multiple-response hypergeometric test per cell (table 4) demonstrate that good places are visited more often at congruent trials, and bad places are visited more often at incongruent trials, except for the place called "ruins." However, only 2 highlighted cells demonstrate values that are significantly different from the expected.

Table 7. Hypergeometric test per cell for frequencies of visits per place

	E	R
"good" places		
castle	98.3	93.2
beer garden	89.6	85.5
fountain	69.6	65.0
monument	99.1	91.5
park	79.1	70.1
restaurant	77.4	72.7
souvenirs	92.2	85.5
square	85.2	62.4
"bad" places		
large bad area	5.2	13.7
cathedral	7.0	10.3
market	7.8	20.5
ruins	33.9	16.2
small bad area	4.4	6.8

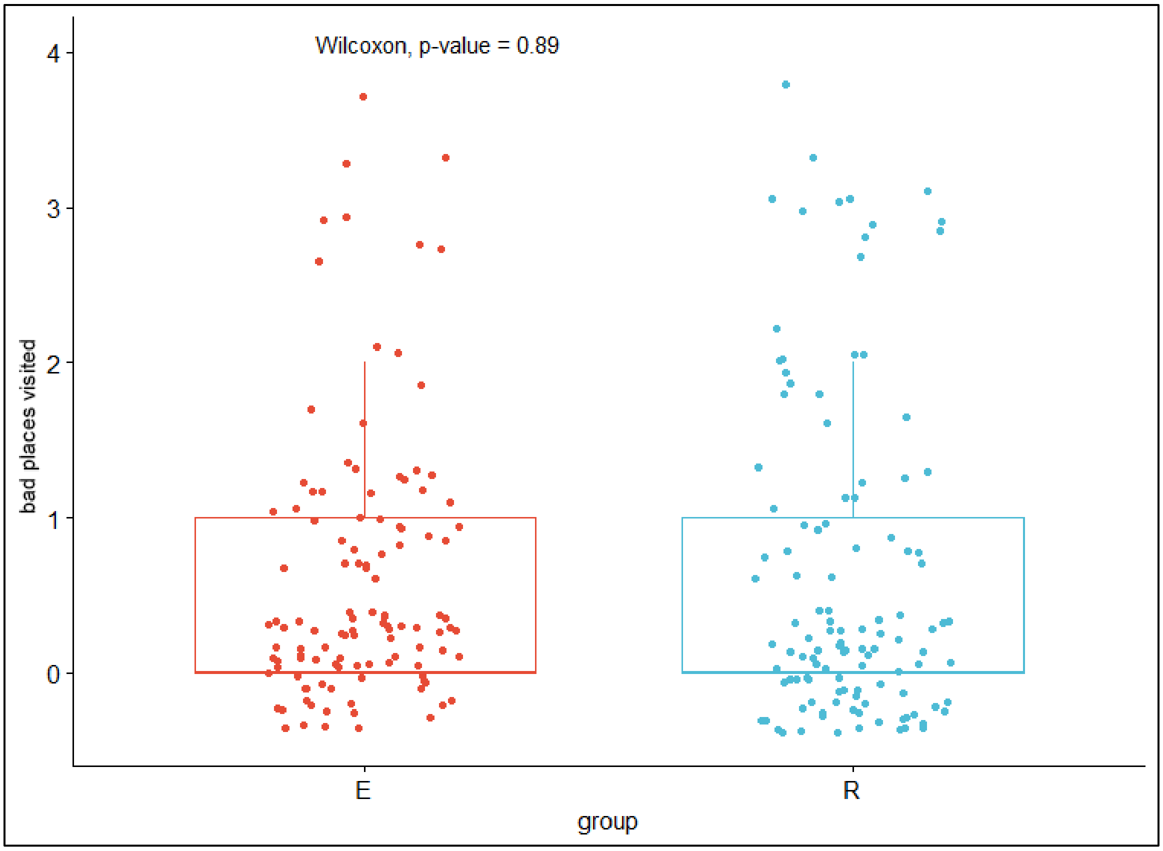


Figure 20. The number of bad places visits comparison

V. DISCUSSION

The first of two main goals of the presented research was to design a color set for emotional data in a way that colors assigned to each emotion match the subliminal human color-emotion associations. To achieve this goal, two research questions were stated. Answering the question “Which colors are associated with each emotion, and to what extent?” helped identify the candidate colors for the suggested color set. Answering the question “Which emotions are associated with each color, and to what extent?” helped in better understanding the relationship between the colors and emotions and in quantifying the strength of association between the candidate colors and emotions (the interpretability of the colors). Based on the answers to these two questions, it appeared that the optimal color assignment depends on the combination of the emotions due to the complex many-to-many associations. An interactive congruent color palette generation tool was designed to automate the process of color assignment optimization. This tool solves the color assignment problem depending on the selected set of emotions, maximizing the associations between the colors and emotions.

The second goal of this research was the evaluation of the resulting cognitively congruent palette. To this end, a third research question was asked: “Is there any difference in map use performance, experience, and map-based decisions between informationally equivalent maps that use a cognitively congruent and a general cartographic color palette to show emotional geographic data?” The answer to this question provided evidence that using a cognitively congruent palette when mapping emotions can influence task performance, user experience, and decision making.

Which colors are associated with emotions?

As described in chapter 2, the presence of associations between colors and emotions has been extensively demonstrated by previous research. Following the findings presented in the literature, the hypotheses for the experiment 1 were that some emotions would get more consistent and specific color selections than others; emotions that are more alike would be associated with more similar colors than those that are different; that there would be a certain amount of variability of color choices, but the colors would not be selected entirely at random.

The results of experiment 1 follow the initial hypotheses. Some emotions, like anger, happiness, and disgust, demonstrate fairly consistent color selections, while others, like awe, confusion, and surprise characterized by higher variability in chosen colors. Colors selected for positive emotions could be described as brighter and more saturated than colors picked for negative emotions, which were darker and less saturated. Despite the variability in color selections and similar colors being chosen to represent different emotions, the overall distribution of color choices does not look random. This conclusion is supported by the results of ANOVA comparisons conducted for each color dimension of the CIELab color model. The results showed that at least two emotions were significantly different from each other on each color dimension between the 23 tested emotions ($p < 0.000$). According to Cohen (1988) the reported generalized eta squared of 0.19 for "a" and "b," and 0.45 for "L" indicate a large effect size. According to the follow-up t-tests of all possible 253 pairs of emotions, only 39 of them were not significantly different at least on one color dimension. Emotion pairs that did not show significant difference mainly consisted of similar emotion like sadness-grief and joy-surprise. However, a few pairs included not similar emotions. For example, pair embarrassment-pride did not demonstrate a significant difference in either of the color dimensions. This could happen because the distribution of color choices for these emotions in CIELab space produced similar average values of color dimensions, even though the shapes of the distributions were different. Alternatively, these might be the cases of type 2 errors happening due to a large number of multiple comparisons.

Overall, the results of the statistical tests for the data collected in experiment 1 could be considered as evidence that there is a relationship between colors and emotions, and it is possible to characterize different emotions by different colors, assigning each emotion with a color that is different from the colors assigned to the other emotions.

Color selections obtained in experiment 1 are well aligned with the literature. In particular, they are very similar to the color-emotion associations presented by Fugate and Franco (2019) and Gilbert et al. 2016 (2016). Such as different shades of red being a popular choice for anger, gray for boredom, dark blue, and black for sadness. Color selections from experiment 1 also match with the general color-emotion associations summarized by Demir (2020). Collected data demonstrate fairly low specificity (one color being exclusively selected for a particular emotion) and consistency (only similar-looking colors being selected for an emotion), supporting the findings of Fugate and Franco (2019).

In the most of previous investigations, participants indicated color-emotion associations using color swatches or color words. Because of this, identified color-emotion associations are sometimes attributed to as imposed by the limited range of answer choices. It is also mentioned in the literature that the use of categorical representations of color limits the ability to identify exact color-to-emotion associations (Tham et al. 2020). For instance, many English speakers might agree that anger is associated with red, but is this association with a range of colors categorized as red or with more specific exemplars of red?

Following the methodology of Gilbert et al. (2016), the present study addressed the limitation of constrained color-matching method by using an interactive color picker that allowed choosing any color from a perceptually uniform continuous color space. The color picker used in current study provided controls of 3 color parameters, while dynamically displaying the range of available colors at current levels of lightness. This provided a more accurate control of the selected color than the color wheel with a single light/dark slider used by Gilbert et al. (2016).

Even when not restricted by a limited number of available choices, obtained color to emotion associations are well aligned with the results of the previous studies. This suggests that identified color-emotion associations are not entirely task-specific or imposed by the data collection instrument. Selecting colors from a continuous color space also helped in understanding which exact color is considered more suitable for a corresponding emotion, such as which "red" is associated with anger and which "red" is associated with surprise. Aggregating the collected data with clustering algorithms allowed identification of the colors that demonstrate more reliable associations with the corresponding emotions.

Experiment 1 of the current study had several limitations that can be divided into the following groups: technical, sample, and methodological. The first group refers to the limitations of the screens used to take the survey and the variability of the lighting conditions. This should be considered a confounding factor, introducing additional variability to the responses since different monitors can show the same colors differently, and the same color on identical screens can look different depending on the surrounding lighting. In addition to that, the entire range of available colors is limited to the sRGB gamut. It is worth noticing that Fugate and Franco (2019) claim that participants' judgments are not influenced by perceiving the colors differently based on the device on which they take the survey. They report that the top-indicated color was the same across the majority of emotions between the laboratory control study and the results reported from the online crowdsourcing platform.

The second group, sample limitations, originates in the nature of online studies. Researchers have to rely on the honesty of the self-reported demographic data, and there is no reliable way to entirely exclude low-effort or completely random submissions.

The third group is methodological limitations. The total number of emotions studied in experiment 1 is 23. This is only a fraction of all existing emotional concepts, and thus, results of experiment 1 provide only a limited view of the color-emotion associations. The use of only English language is another methodological limitation. In other languages there may be emotional concepts that are not present in English and vice versa. Finally, the candidates for the cognitively congruent colors, were determined using the specific clustering algorithms with manual parameter tuning. The use of different algorithms or different parameters may have produced other colors that could be more or less congruent than those that were identified.

The main practical application of the outcomes of experiment 1 is to serve as an intermediate step in the identification of the cognitively congruent colors. The resulting color set needs to be evaluated in terms of its ability to represent corresponding emotions. However, the methodology of experiment 1, designed to collect and process the data, can be applied to future research. More data can be collected for the same set of emotions to see if it is possible to refine the most congruent color choices. Same methodology can be applied to a population from a different country or using a different language to see how the color selections compare to each other. The same instrument can be applied to collect data on other discrete emotions, expanding the knowledge about color to emotion associations in a systematic and more comparable way.

Which emotions are associated with each color?

As proposed by Schloss et al. (2018), people interpret color-coding systems by solving a decoding assignment problem. They make inferences about how colors are mapped onto concepts. Given this, experiment 2 was aimed at testing the suggested cognitively congruent colors in terms of their interpretability as corresponding to a particular emotion. A statistically significant relationship between the color and emotions selected as represented by that color was expected. Hypothetically each color-emotion pair would demonstrate a different probability depending on the strength of association between that pair. These probabilities were calculated and served as interpretability ratings, with higher values meaning that this color is more reliably identified as showing that particular emotion.

A Chi-square test of independence was conducted to determine whether two categorical variables of color and emotion are likely to be related in the context of interpreting a color. The results indicate that the null hypothesis should be rejected ($p = 0.0005$), and the variables are not independent of one another. Estimated effect size

Cramer's V= 0.22 indicates a large effect size or strong association between colors and emotions (Volker 2006; Cohen 1988). This suggests that the color candidates used in experiment 2 are likely to be the right colors for creating cognitively congruent color palettes.

The probabilities of each emotion being selected depending on the color were estimated with a multinomial logistic regression. The resulting values are generally quite low. This could be explained by the total number of emotions, as the probability of 1 is divided between 23 possible outcomes. However, a pattern can still be identified in the distribution of probabilities. All emotions can be divided into three groups. First are the emotions (like anger, boredom, disgust) that have a few colors with high probabilities and very low probabilities for the rest of the colors. The second group includes emotions that demonstrate medium probabilities of similar values for multiple colors (like happiness, joy, serenity). In the third group, emotions (like confusion, shame, embarrassment) have low probabilities for a few colors and almost zero probabilities for the rest of the colors. This might happen due to the nature of the color to emotion associations, meaning that some emotions are strongly connected to one or two specific colors, while the others are more "colorful" and demonstrate higher variability in associated colors. The presence of the third group may indicate that some emotions do not have any solid or stable color associations.

Observed probabilities of emotion being selected depending on the color still follow the many-to-many kind of relationship of color to emotion associations outlined in the literature. Pairs with the highest probabilities match the top-scoring color assignments from experiment 1 and the color choices presented by Fugate and Franco (2019) for corresponding emotions.

As different colors demonstrate a similar degree of association with multiple emotions, it is possible to create multiple combinations of congruent color assignments. Quantification of these associations allows applying mathematical methods to solving this assignment problem. Assignment problems, also known as maximum-weight matching problems, are mathematical models describing how to pair items from two categories (Kuhn 1955). For example, such models can optimally assign employees to jobs in a company, machines to tasks in a factory, and trucks to routes in a shipping network (Williams 2013). The probabilities obtained for each color-emotion pair obtained in experiment 2 can be used to address the issue of ambiguity of color assignments by applying a color palette optimization method. This was implemented in the form of an interactive tool that solves the assignment problem depending on the selected combination of emotions. The tool was written in Python, using a linear programming toolkit “PuLP” (S. Mitchell, OSullivan, and Dunning 2011). It chooses one color per emotion, suggesting a cognitively congruent color palette. The mathematical approach used to solve the assignment problem in this research allows for optimization of the solution for a particular factor while being restricted by certain conditions. Given this, an additional optional constraint of minimum color distance was added to the tool. Users can specify the distance in ΔE (CIEDE2000). If possible, the algorithm assigns the colors to emotions keeping the minimum distance between the colors in the suggested palette no less than the specified value. This option may help in producing more sensible palettes with more discriminable colors. The tool creates two versions of a suggested palette (using slightly different optimization algorithms). It also displays an extended set of colors with top-scoring options for each emotion to give the users more flexibility in terms of available color choices. These colors are presented with the corresponding probability scores that can help users manually adjust the suggested palette without reducing the overall suitability of the palette too much. The final color palette for emotional data is expected to be a color-coding system that is easier for viewers to use and understand.

Experiment 2 shares the technical and sample limitations described earlier for experiment 1 and has some limitations of its own. First, when selecting emotions represented by a given color, participants did not have a way to specify the rank of suitability for each choice. Thus, each selected emotion had the same contribution to the overall probability, which might not be the case with actual color to emotion associations. Including the additional weighting procedure could help to calculate more precise probabilities for each color-emotion pair and, by doing this, achieve a more optimal final color assignment. Another limitation of experiment 2 is the total number of colors tested. Having 32 colors tested is comparable to the number of colors used in the other studies with some authors having fewer (Fugate and Franco 2019; Jonauskaite et al. 2020) and some having more (Schloss et al. 2018; Tham et al. 2020). At the same time, including the other possible candidate colors may provide additional information about the color to emotion associations and possibly reveal some other patterns that remained unnoticed on a current set of tested colors.

The practical application of the cognitive color palette tool made based on the results of experiment 2 is diverse. It may be helpful to cartographers who need a symbology for mapping emotions, designers, who need to color-code emotions in their visualizations, or scientists who develop stimuli or measurement instruments that may benefit by using cognitively congruent colors. A possible way to expand on the conducted research would be addressing its limitations and testing more colors or collecting the association weights for each color-emotion pair. Another direction that future research may take is testing how people would solve the simultaneous assignment problem. Instead of showing individual colors, show them all at once and ask participants to match them to the list of emotions.

Testing the palette

Depending on a color palette type, there was expected to be a difference in one or several aspects of map use experience. The first hypothesis was that task completion time and the perceived task complexity would be lower, and the aesthetics rating would be higher for the maps using a cognitively congruent color palette for showing spatial emotion data. The second hypothesis was based on the expectation that the congruent colors would amplify the perception of emotions. The routes produced by participants were expected to go more often through the places characterized by positive emotions, and less often through places dominated by negative emotions.

A small but significant effect of a congruent color palette on task completion time was identified (the Cohen's d measure of effect size $d = 0.2$). On average, participants took 219 seconds per task using a map with cognitively congruent colors and 249 seconds using a map with conventional colors, making an average improvement of 30 seconds or 12%. Though small, this effect can have important practical benefits. Time savings were identified for a simple task on a relatively small map, while viewers often use bigger and more complicated maps in real life. In such cases, the time difference may become more substantial. Moreover, even a small gain in recurring map-based tasks may reduce the total map use time and improve the overall user experience.

Comparing the subjective task load ratings also demonstrated a significant difference between the two palettes. The subjective task difficulty was lower for the cognitively congruent trials with Cohen's d = 0.38. According to Cohen (1988), this value can be interpreted as a small to medium effect. This supports the hypothesis that showing the data with congruent colors reduces the cognitive load, making the task feel easier. Notably, congruent trials were quicker and required less effort from the participants. Each of these effects alone is beneficial for practical applications, but when combined, their effects may complement each other, leading to an even smoother user experience.

The third parameter of the user experience examined in this research was aesthetics. The participants answered a question, "How aesthetically pleasing did you find the map?" using a range slider with values from 0 as "unpleasing to see" to 100 as "pleasing to see." No significant difference was found between how the participants perceived congruent and incongruent maps. On the one hand, this is a departure from the initial hypothesis that a cognitively congruent palette would make the map more pleasing to look at. On the other hand, the finding that the aesthetic ratings for both maps can be considered the same means that the suggested congruent palette looks as good to the viewers as a well-recognized professional cartographic color palette. This can be treated as an additional strength of the congruent palette along with the advantages in the perceived difficulty and task performance. At the same time, the differences in perceived aesthetics could have been too small to detect due to the chosen cartographic method (dot density map). It is possible that using the same two palettes on a different kind of map, for example, a choropleth, may produce a more noticeable difference in how pleasant the users find each map to look at.

The two parameters were compared to test the hypothesis that a cognitively congruent color palette influences the user decision-making process. The first parameter was the number of “good” and “bad” places visited by each user for congruent and incongruent trials. The results demonstrate a significant difference in the number of “good” places visited per user, which was higher for the congruent trials. The effect size Cohen’s d = 0.46 indicates a medium effect. The difference in the number of visited places with negative reviews was lower for congruent trials but did not show statistical significance. This may be explained by the nature of the task, in which participants were explicitly asked to avoid “bad” places but were not required to visit all “good” places on the map. Thus, when planning a tour, the participants did not go to negatively reviewed locations following the task regardless of the colors that showed negative emotions. When they decided which places to visit, cognitively congruent colors might have amplified the perception of positive reviews, motivating people to visit more positive places.

The second parameter used to investigate the decision-making process was the frequency of visits to each place. Basically, it was the total count of users whose tours included that place. The results of the multiple response version of the Chi-square test suggest that there is a significant relationship between the type of the palette and the frequency of visits to different places. Effect size estimated with the Cramer’s V = 0.12 indicates a small effect, according to Cohen’s (1988) general standards. A multiple-response hypergeometric test per cell was conducted to better understand how the congruent palette affects the frequency of visits per place. The results show that there are only two places where the frequencies of visits are significantly different from the expected values for congruent and incongruent trials. However, comparing each place by the percentage of people who went there, one can notice a trend that a higher percentage is typical for the "good" places on congruent trials and the "bad" places on incongruent trials (figure 21). The only exception from this trend is the "ruins," a place considered as bad but designed to be not as unambiguous as other places. It was mainly characterized by the emotions of boredom and disappointment but with a noticeable amount of serenity and interest. The "ruins" received much fewer visits than the "good" places, which means that, in general, it was identified as a "bad" place. However, as it was described with the negative emotions of lower valence and some positive emotions, it was likely to be considered a neutral or good place by some participants.

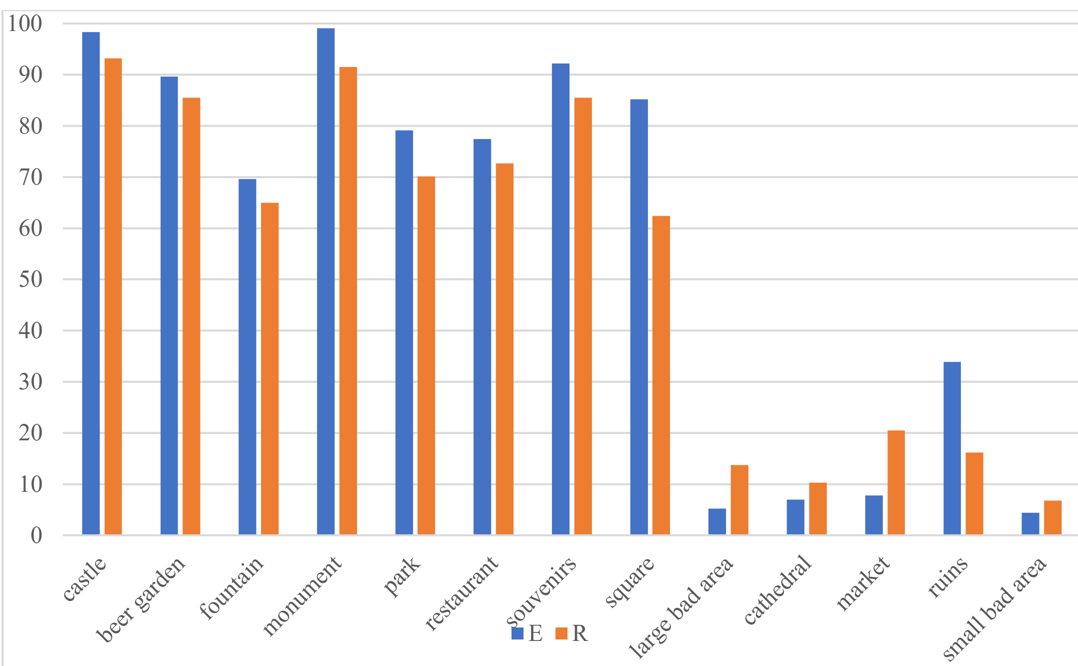


Figure 21. Percentage of people who visited each place

The fact that it was not avoided as often on a map with congruent colors may indicate that users of that map were able to read the color-coding system more accurately and notice the presence of positive emotions. An alternative explanation could be that the places were perceived as blobs of color rather than collections of individual dots. Due to the overall combination of colors, the ruins on the congruent map did not look as similar to the other negative places as on the map with incongruent colors.

Significant differences in task completion time found between congruent and incongruent maps are well aligned with the results demonstrated by Lin et al. (2013), who report that semantically-resonant colors improve speed on chart reading tasks compared to a standard palette. A similar effect of the congruent colors on the task completion time is presented by Goodhew and Kidd (2020). Altogether, these findings invite a conclusion that humans systematically associate emotional concepts with colors in a way that can influence their behavior. This could be explained by the Stroop effect, facilitating the congruent trials and interfering with the task during incongruent trials (MacLeod 1991). The relationship between the type of the palette and the number of "good" places visited by participants and the frequencies of visits per place indicates the influence of the palette on the decision-making. The effect of visualizations on decision-making is recognized and receives attention in the literature (Padilla et al. 2018). For example, Fuest et al. (2021) demonstrate how using different cartographic design variants leads to a different route choice behavior.

This study extends previous investigations of the effects of congruent colors on task performance by adding the measure of perceived task complexity (NASA TLX) and aesthetics rating. These measures provide additional information about the influence of congruent colors on user experience. The differences in decision-making have not been previously investigated in the context of congruent and incongruent colors for emotional mapping. The effect of the congruent colors on decision-making is another contribution of the present study. Presented evidence of the influence of the color palette on map user experience and task performance suggests that a cognitively congruent color palette improves user experience and facilitates visual analysis. The influence of the color palette on map-based decisions suggests that designers and cartographers may unintentionally alter their user's behavior by using a standard categorical color-coding system for emotional data.

Technical and sample limitations outlined for experiments 1 and 2 also apply to experiment 3. It also has some limitations that are specific to this user experiment. First, only one out of many possible cognitively congruent color palettes with just 8 out of 23 available emotions was tested. The findings presented in this research may not hold for different congruent color palettes generated for other combinations of emotions. The second limitation is that color palettes were compared using only one static map with one cartographic method. Comparing user experience and task performance may show different results for other cartographic techniques, such as interactive maps, maps that use other cartographic techniques, or printed maps.

The main practical application of the outcomes of experiment 3 is that it supports the use of the palette generation tool described above by providing evidence of such a cognitively congruent palette being more efficient in emotional mapping than a traditional color palette. When visually comparing colors in congruent and traditional palettes (table 4), one can notice that half of them look almost the same, and some other colors are different, but still have some similarity in hue. This invites the conclusion that the benefits of the cognitive congruency can be combined with the robustness of perceptual color schemes designed to make every color on the map easily distinguishable. One can use the congruent palette as a guideline for assigning colors from a conventional palette to the concepts they fit the most.

Given that only a single congruent palette was tested on a map using one cartographic method, additional research is needed to explore the advantages of such palettes for other contexts of emotional mapping. It seems like a good idea to test the proposed color set and palette generator tool in application to an existing emotional mapping project like the interactive map by Pánek (2018) and investigate the effects on user experience and decision making. As the literature indicates the presence of color-concept associations other than associations with emotions, the development of other context-fitted categorical color palettes, in which colors are matched to concepts in a way that matches human associations, could be a possible research direction.

The use of maps in experiment 3

The design of experiments 1 and 2 of this study is similar to the studies conducted in psychology and psychophysics, in which the number of variables is minimized to isolate the one that is being studied. This approach is also common in cartography when a single aspect of map design is investigated, for example, the effect of the symbol size or shape (G. Ekman, Lindman, and William-Olsson 1961). Experiment 3 was different. Instead of demonstrating stand-alone color swatches or symbols, maps were used as stimuli. Even a minimalistic map of a fictional town is a complex visual system that tells stories and bears a lot of variables that can potentially affect the viewers' attention, interpretation, and behavior. From the semiological point of view, every map is a sign system, and its components are not perceived and interpreted individually (MacEachern 1995). Due to the interaction between all the symbols on a map, it is impossible to completely isolate the effects of the studied visual variable (colors used to display emotions) from the effects of the other symbols present on the map.

In addition to the spatial emotion data, the map in experiment 3 showed the main attractions of the town as pictorial symbols. According to the semiotic triad (Peirce 1991), the meaning (interpretation) of each sign is produced in the head of the viewer. As each observer has their own unique experience and associations that developed over time, the same sign observed by two people can, and often will, lead to rather different interpretations. Given this, the attraction symbols displayed on the map may be perceived and interpreted in different ways, affecting the attention and decision-making of the map users.

Each attraction shown on the map as well as the areas with emotional reviews should be also considered from the perspective of the geographic concept of place. Places, as defined by Cresswell (2008) are locations with meaning. In experiment 3 the whole town is a place, and all attractions and emotional areas are places too. Each attraction overlaps with a place defined by emotions, which can cause a mismatch between the personal association with the place defined by an attraction symbol and the corresponding emotional review. For example, a person may have some negative associations with a waterfront restaurant and will prefer to ignore any positive emotional reviews related to the restaurant present on the map.

As it is mentioned in chapter 2, the map itself and the process of interacting with a map can elicit an emotional response, bring associations and memories, and give ideas. This can be illustrated by the comments participants left in response to the question about their logic for designing the walking tour and in the optional survey feedback. It appears that the very use of a map can trigger memories: “I traveled many miles using road maps and miss them now.” The task of drawing a walking tour made some people imagine the scenario in which they would be actually walking around the town: “… I loved making a path on this map and envisioning walking to these locations with a group of friends.” Another participant expressed their inspiration for action and reflected on the related problems: “*Now I want to tour a town, but gas is too expensive.*” The thematic content of the map sparked thoughts about whether it is appropriate to demonstrate such data to the public: “… *I don't really see the appeal of a map that shows how people were feeling at certain locations based on social media posts. It would maybe be useful for the city itself to see how people react and how they could improve. But I don't think it would be something useful to give to the public. Showing the public what spots in the city made people feel disgusted or disappointed is not a very effective way to advertise.* …” It is intriguing, how a tour drawing task brought such a complex and debatable question, touching on the problem of the cartographic silence (Harley 1988). As if in contradiction to the last comment, one participant mentioned that negative places are also worth advertising: “*If I was designing my route completely independently I'd probably want to visit the negative places too to see what they were like.*” while another person seems to support the value of showing the emotions in exploring the town: “… *We often find that some of the best locations are found outside of the "engineered" tourist zones.*”

Using maps as stimuli in experiment 3 is a confounding factor, that like the variability of the viewing conditions, increases the possible variability in user responses and behavior. On the one hand, this reduces the reliability of the findings and additional research would be useful to confirm the observed effects of the use of the congruent colors. For example, conduct a similar experiment with positive and negative emotional reviews being attributed to other attractions. On the other hand, framing the task in a map-use context that is close to a possible real-world application implies a higher practical value of the results.

The scope and outcomes

This study builds upon and extends existing knowledge in the domains of psychology, cartography, and data visualization. It provides much-needed empirically-based guidelines for the informed use of color and for the design of more effective visual representations of spatial emotional data that facilitate comprehension and analysis of the information (Silva, Sousa Santos, and Madeira 2011). This study aimed to solve a pragmatic problem of identifying the cognitively congruent colors for optimization of displaying emotions on maps. The congruent colors were defined as matching subliminal human color-emotion associations, which were identified in a user experiment based on the color selections reported as representing for each emotion. Final color candidates for each emotion were calculated as geometric medians of clusters in selected colors plotted in a CIELab color space. The interpretability of each congruent color candidate was quantified and used to find the optimal color assignments. Given the many-to-many nature of relationship of the color to emotion associations, different congruent color palettes could be constructed, depending on the combination of emotions. The color assignment problem was solved mathematically, using the linear programming approach.

This solution was implemented as a web-app that generates cognitively congruent color palettes for the selected emotions. A sample congruent color palette for 8 emotions obtained using the web-app was compared to ColorBrewer qualitative set 1, a conventional cartographic color palette. The results demonstrate that the use of congruent colors can provide an advantage in user task performance, perceived difficulty, and can influence user decision making.

This research did not try to establish any universal color-emotion associations. Investigation of the personal or cultural differences and understanding the underlying mechanisms and patterns of color-emotion associations were out of the scope of present research. Possible differences in color-emotion associations between male and female participants or between younger and older participants were not considered. Three primary contributions are made: (1) an empirically derived set of cognitively congruent colors for 23 emotions, (2) an interactive web-app tool for automatic optimal color to emotion assignment, and (3) experimental analyses of map-based task performance under two different color-assignment conditions (congruent color palette and conventional cartographic color palette).

By estimating the associations between colors and a set of discrete emotion concepts and examining the influence of cognitive congruence on thematic map user experience, this study mainly contributes to the area of color-emotion associations and the emotional mapping branch of thematic cartography. Presented findings can be important both for academic and commercial contexts. It has been outlined in the literature that color-concept associations should be considered when designing color-coding systems for categorical data. The application of this idea to emotional mapping is a useful contribution to the existing knowledge because maps of emotions are valuable tools for studying human experience with space and place. Mapping of emotional landscapes, as advocated by human geographers and critical cartographers, makes geospatial practices more relevant to real-life (Kwan 2007; Pearce 2008).

Understanding what colors are congruent to each emotion can be useful to make informed decisions about the colormaps for mapping naturally emotional topics. In other words, cognitively congruent colors may serve as a basis for designing affectively congruent color palettes. The appropriate use of color in such cases may allow patterns to be easily observed while inducing the desired emotional response.

The broader impact of the outcomes of the current study is twofold. First, a developed tool for choosing colors for visualization of emotions can help researchers, cartographers, and designers create visualizations of emotions that put a lower cognitive load on the viewers. This could facilitate exploratory visual analysis and help emphasize and communicate the necessary information more accurately. Geographers who use emotional mapping for collecting data can use the color palette generator tool to provide the participants with color-coding systems that are easier to use. Researchers and geovisual analytics who explore big spatial datasets for extracting emotional information could benefit from more efficient data visualizations. Designers of user interfaces and human-computer interaction (HCI) specialists can also benefit from cognitively congruent palettes for emotional data. For example, such palettes may be helpful in development of web-based or mobile applications. The provided palette generator tool can be used as a guideline and assist nonprofessional cartographers and people dealing with emotional data visualization in diverse disciplines such as medicine, psychology, and graphic design. It can help with color choices for making their visualizations easier to read, explore and understand.

Next, an empirically tested cognitively congruent color set for visualizing emotions can serve as a basis for further research. As emotional mapping is a relatively new area of thematic cartography, there are no well-established design methods for showing emotions on maps. The effectiveness of different symbolization approaches could be evaluated in future work, using the provided color suggestions as a baseline for comparison. Knowledge of the influence of cognitive congruence of the color palette on user performance and preference for different kinds of emotional maps (e.g., choropleth) could provide further guidance to designers and cartographers. As demonstrated in this study and by Fuest et al. (2021), differences in cartographic designs can influence user decision-making. Thus, the suggested cognitively congruent colors can be used to investigate how colors on emotional maps influence viewers' opinions and decisions. This could be of special importance for maps made for and used by policymakers.

Limitations of the research

The reported results provide evidence of the importance of cognitive congruence of colors in emotional map design. However, as the literature recognizes, color associations may vary between cultures. This also applies to the emotional color connotations. The present study was limited to the United States residents, which provides some additional experimental control but at the same time limits the generalizability of the results. The communities with different cultural background may have noticeable differences in color preferences and associations even within one country. Given this, the presented findings can be applicable to the population of the

United States, but any available knowledge of color-concepts associations should be considered when making maps for a particular audience to avoid an improper color-emotion assignment. At the same time, suggested colors should be used with caution when making emotional maps and visualizations for an audience in countries other than the United States, or in the international mapping context. In such cases, the proposed cognitively congruent colors may serve as a starting point for making informed decisions about choosing and assigning colors to display emotions.

Individual variations in color preferences and associations are out of the focus of this research but are likely to introduce additional uncertainty in user color selections. However, this effect was at least partially mitigated by aggregating the submitted color choices with clustering algorithms, which smoothed the noise in the collected data. Given this, the suggested congruent color set does not consist of the only possible congruent colors but represents one of multiple possible variants. The palettes generated by the proposed tool should be considered as general recommendations, and not as rigid rules.

Based on the collected demographic data, the average age of the participants in all experiments was between 36 years old, ranging from 18 to 91, with most participants being from 18 to 40 years old. The samples for each experiment included approximately the same number of male and female participants, all native English speakers residing in the United States. It is important to note that this can only be considered a convenience sample. This sample has been drawn from a population of internet users who are aware of crowdsourcing platforms like Prolific and willing to participate in research surveys. Nevertheless, this sample is valid and provides a broader view of the studied matter than a common in behavior academic research sample drawn from the student population would. Sample sizes of about 100 people in experiments 1 and 2, and 200 people in experiment 3, can be considered as relatively small. Still, the obtained results provide useful idea about the color-emotion associations and the effect of the cognitive congruency on map use performance and experience. To attribute the presented findings to any particular target population, further research with a representative sample is needed.

Only participants with normal color vision were recruited for each experiment in the present research. They were also required to pass the Ishihara color vision test before proceeding to the main trial to ensure they met the requirement. This means that identified color-emotion associations may not be representative of people with color vision deficiencies, as they may associate emotions with different colors, which may also differ depending on the type of color blindness. It is worth mentioning that the congruent color palettes suggested by the palette generator tool may not be colorblind safe, with a higher chance for the palettes including greater number of classes. In cases when this property of the palette is necessary, a color blindness simulation tool should be applied to check a particular palette and adjust it if necessary. Given that the suggested cognitively congruent palettes may not provide the advantages in performance and perceived difficulty to people with color vision deficiencies, the use of a categorical palettes designed to be color blind safe may be a better fit in such cases.

The effects of congruent colors were tested using a dot density map. This thematic mapping technique is common for emotional mapping. However, the size of the colored symbol pays an important role in the way color is perceived by the viewers. The size of the symbol affects color discriminability (Stone, Szafir, and Setlur 2014) and user performance (Gramazio, Schloss, and Laidlaw 2014). The symbols on the dot map are quite small, and this gives a reason to assume that the influence of the congruent color on task performance and decision making demonstrated for the dot map, may not be the same for the other cartographic methods that use larger color symbols. Thus, the findings of the present research are only applicable to the dot density mapping.

Finally, the present research shares a limitation common to the online-based crowdsourced research – the lack of control of the environment for stimuli demonstration. It is possible that the difference in how colors look on different screens, under different lighting conditions, at different viewing distances, and from different viewing angles had increased the variability of responses in experiments 1 and 2 and interfered with the effect of congruent colors in experiment 3. At the same time, close to real-world viewing conditions add validity to the identified effects.

Conclusion

Maps and map-based services have become ubiquitous, and geovisual analytical tools help explore big spatial datasets. The growing interest in emotional cartography (Griffin and McQuoid 2012; Caquard and Griffin 2018) and research in data visualization (Lin et al. 2013; Setlur and Stone 2015) make the consideration of the colors used to display emotional data an important aspect of map design.

This study identified cognitively congruent colors for emotional mapping and examined the influence of such colors on thematic map task performance and user experience. The results demonstrate that on a map using cognitively congruent palette people perform the task faster and report lower perceived task difficulty. From the perspective of aesthetics, map with a congruent color palette was rated the same as the map using a conventional cartographic color palette. Provided empirical evidence of objective benefits of cognitively congruent color palettes supports the importance of considering cognitive congruence in cartographic color palette design in the context of emotional mapping.

The advantages of cognitively congruent color palettes for map-based task performance indicate that using congruent colors for mapping emotions can improve map use efficiency, which is one of the primary concerns of cartographers. The demonstrated ability of cognitively congruent colors to lower the perceived difficulty of a map-based task can be beneficial to the users of geovisual analytic tools, especially when working with big data or completing cognitively challenging tasks. Congruent color palettes can help in solving more complicated problems and processing larger amounts of information. They may be applicable in multiple mapping contexts, such as developing spatially enabled mobile applications, information visualizations in media, and visual analytics decision support systems.

The participants also demonstrated differences in decision-making, depending on the type of the color palette used on the map. Despite the lack of knowledge about the exact mechanism of influence of congruent colors on decision-making, the mere presence of this effect suggests the need for a more careful approach to map design. Testing different design variants to see which one provides a more desirable effect could be recommended as a responsible map design practice.

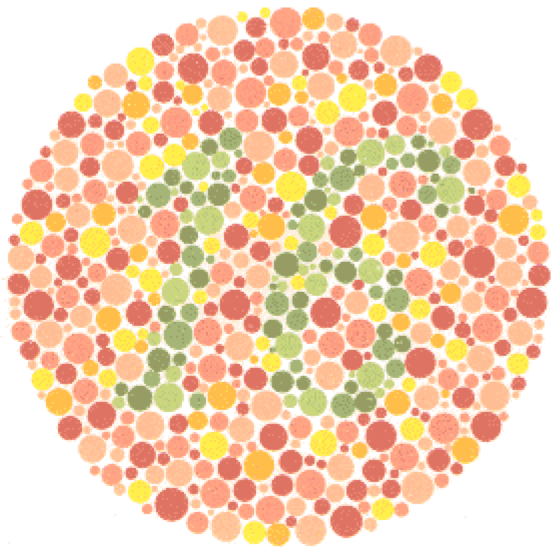
More research is necessary for deeper understanding of the behavioral impact of congruent colors. Multiple questions could be answered to help predicting the effect of different map designs on user experience and decisions. Such as whether the viewers of maps with congruent color design are likely to interact with the map more, whether they are more likely to believe its content, or whether they can better understand the information it contains.

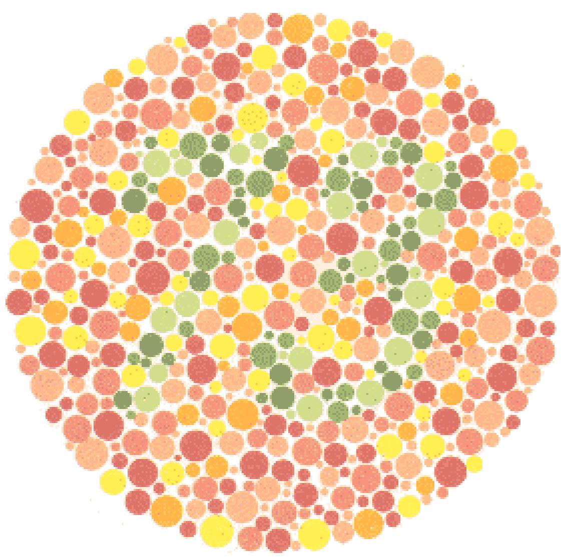
In closing, it is important to note that existing color conventions and principles of color mapping should not be ignored in favor of facilitating cognitive congruence. This study, however, advocates that connoted color meanings in general and color-emotion associations in particular influence map user experience, performance, and decision-making. Thus, it should be one of the essential design considerations in cartographic design and data visualization.

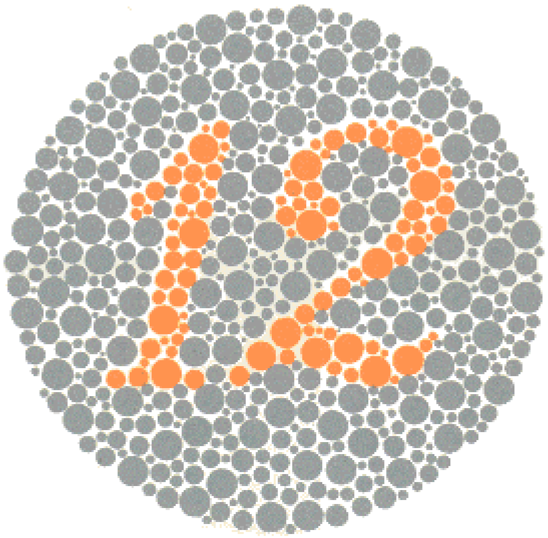
APPENDIX SECTION

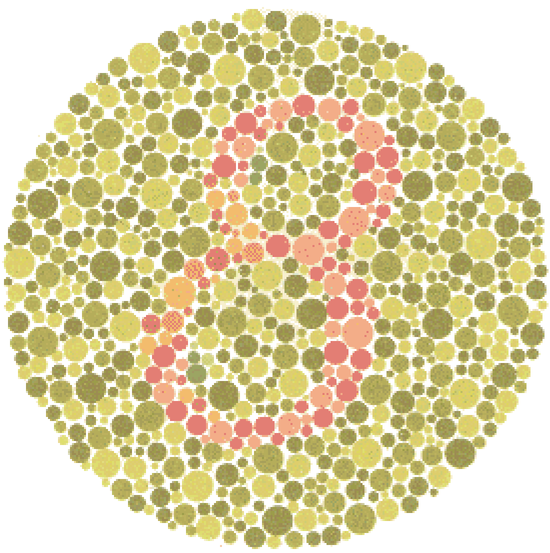
APPENDIX A: Resources used in experiments.

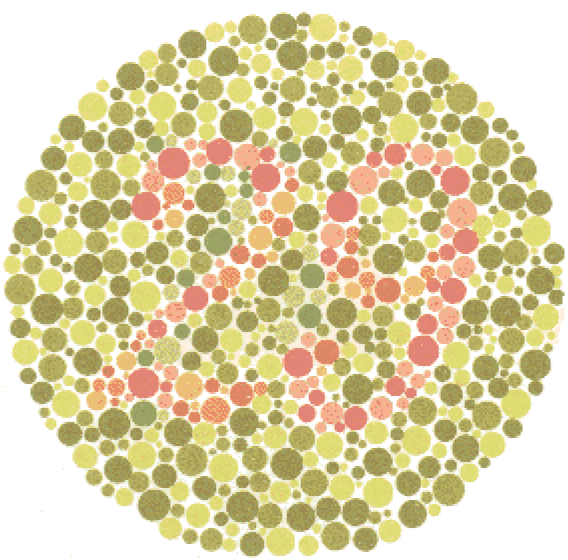
Experiment 1. Plates used for the Ishihara color vision test. Also available at: https://github.com/reirby/cognitively-congruent-color-palette-for-emotional-mapping

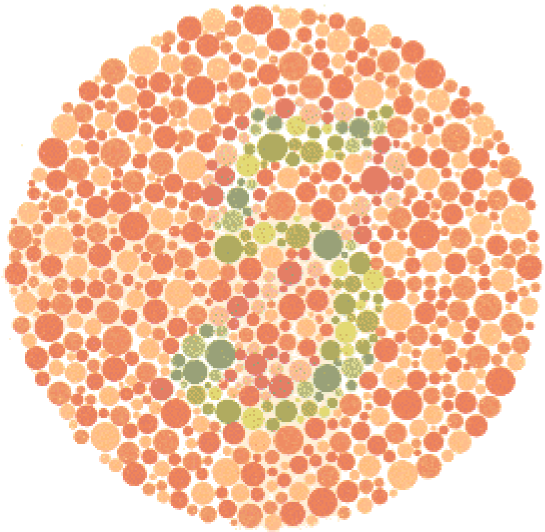


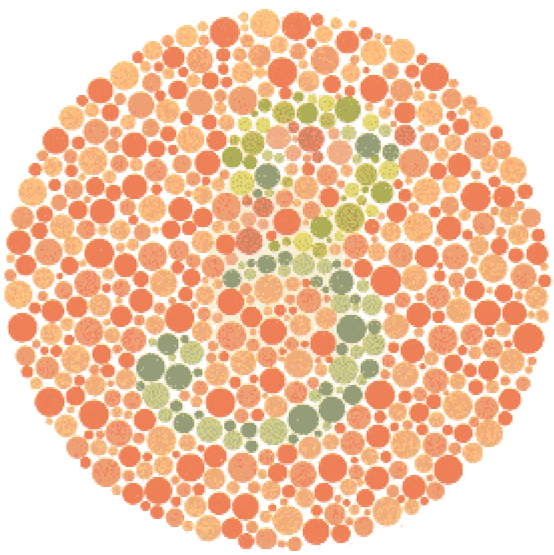


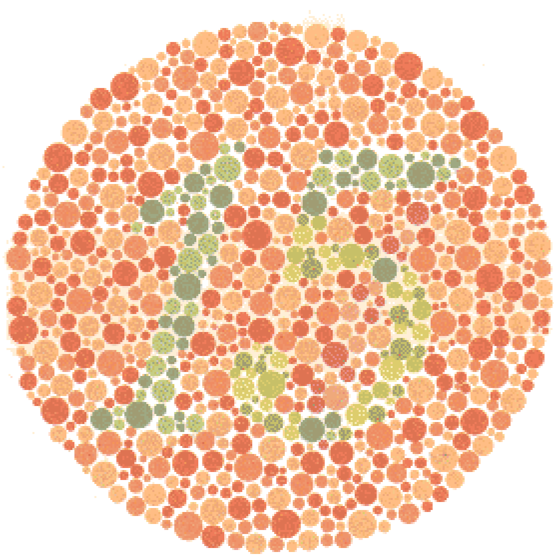


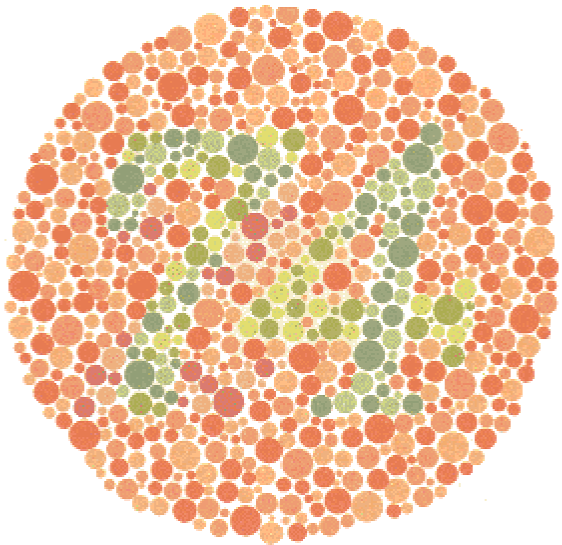


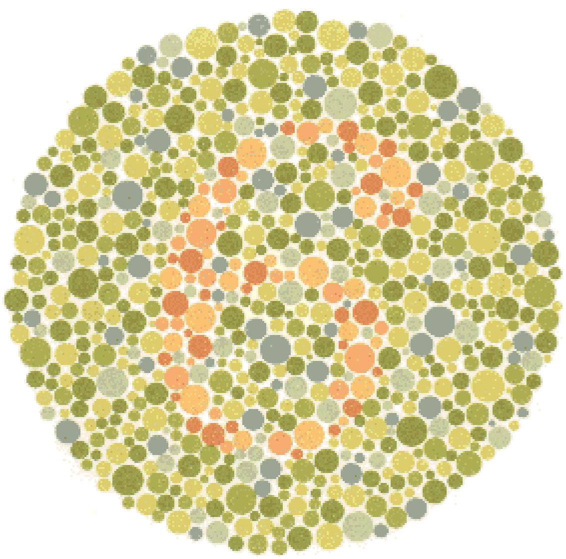


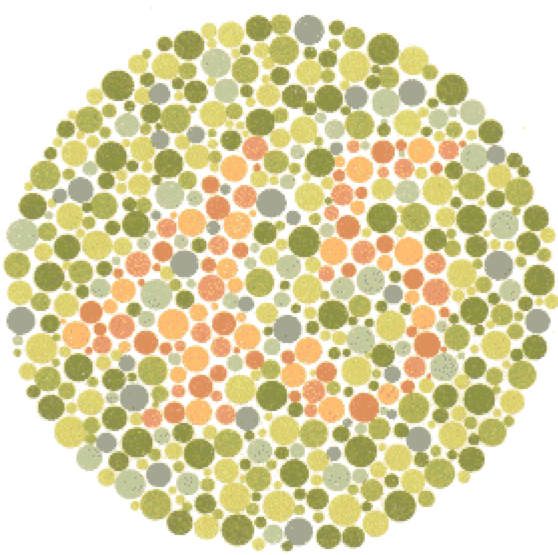


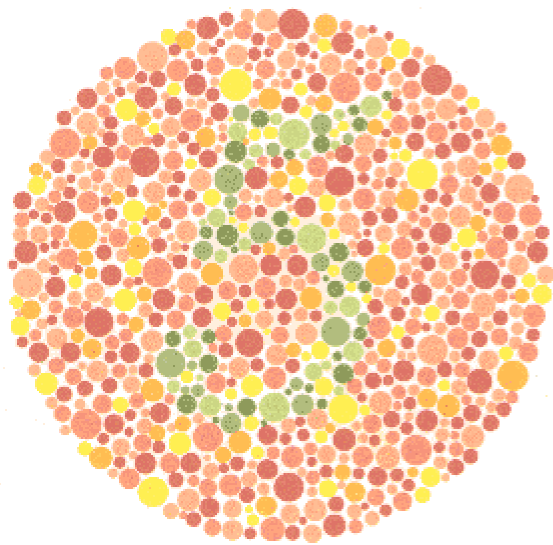












Experiment 3. Post task questionnaire.

Free text question:

1. What was your logic for designing the tour?

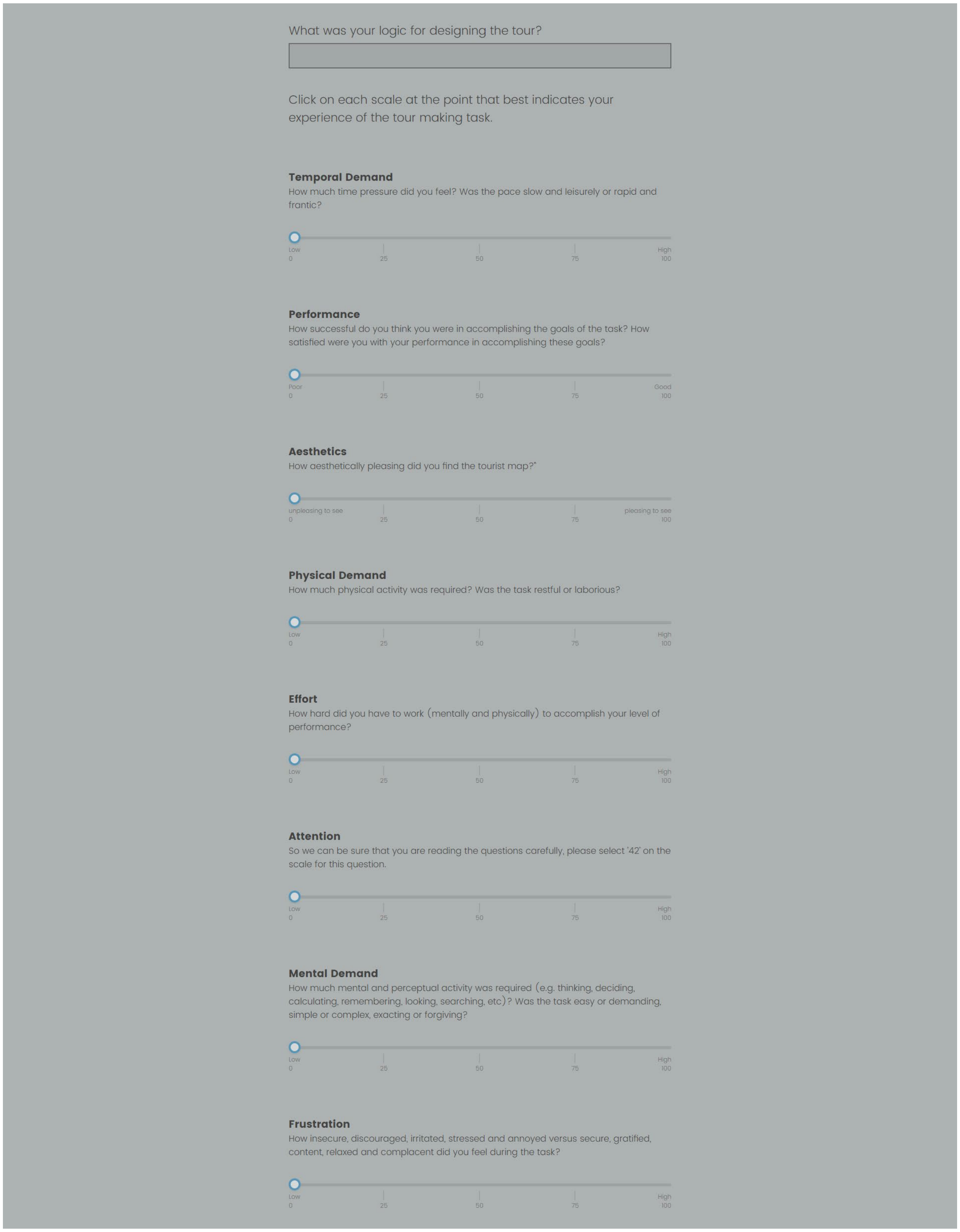
Range slider questions, values from 0 to 100:

1. Mental Demand. How much mental and perceptual activity was required (e.g., thinking, deciding, calculating, remembering, looking, searching, etc.)? Was the task easy or demanding, simple or complex, exacting or forgiving?
2. Physical Demand. How much physical activity was required? Was the task restful or laborious?
3. Temporal Demand. How much time pressure did you feel? Was the pace slow and leisurely or rapid and frantic?
4. Performance. How successful do you think you were in accomplishing the goals of the task? How satisfied were you with your performance in accomplishing these goals?
5. Effort. How hard did you have to work (mentally and physically) to accomplish

your level of performance?

6. Frustration. How insecure, discouraged, irritated, stressed and annoyed versus secure, gratified, content, relaxed and complacent did you feel during the task?
7. Attention. So we can be sure that you are reading the questions carefully, please select “42” on the scale for this question.
8. Aesthetics. How aesthetically pleasing did you find the tourist map?”

Experiment 3. The post-task questionnaire.



What was your logic for designing the tour?

Click on each scale at the point that best indicates your experience of the tour making task.

Temporal Demand
How much time pressure did you feel? Was the pace slow and leisurely or rapid and frantic?

Low 0 | 25 | 50 | 75 | High 100

Performance
How successful do you think you were in accomplishing the goals of the task? How satisfied were you with your performance in accomplishing these goals?

Poor 0 | 25 | 50 | 75 | Good 100

Aesthetics
How aesthetically pleasing did you find the tourist map?"

unpleasing to see 0 | 25 | 50 | 75 | pleasing to see 100

Physical Demand
How much physical activity was required? Was the task restful or laborious?

Low 0 | 25 | 50 | 75 | High 100

Effort
How hard did you have to work (mentally and physically) to accomplish your level of performance?

Low 0 | 25 | 50 | 75 | High 100

Attention
So we can be sure that you are reading the questions carefully, please select '42' on the scale for this question.

Low 0 | 25 | 50 | 75 | High 100

Mental Demand
How much mental and perceptual activity was required (e.g. thinking, deciding, calculating, remembering, looking, searching, etc)? Was the task easy or demanding, simple or complex, exacting or forgiving?

Low 0 | 25 | 50 | 75 | High 100

Frustration
How insecure, discouraged, irritated, stressed and annoyed versus secure, gratified, content, relaxed and complacent did you feel during the task?

Low 0 | 25 | 50 | 75 | High 100

APPENDIX B: Extended results.

Experiment 1. All interactive 3D scatterplots are available at:

https://github.com/reirby/cognitively-congruent-color-palette-for-emotional-mapping

Experiment 1. Results of post-hoc t-tests for "L" color dimension.

group1	group2	p	p.signif	p.adj	p.adj.signif
amusement	anger	0.000	****	0.000	****
amusement	annoyance	0.000	****	0.000	****
anger	annoyance	0.002	**	0.438	ns
amusement	awe	0.131	ns	1.000	ns
anger	awe	0.000	****	0.000	****
annoyance	awe	0.000	****	0.000	****
amusement	boredom	0.000	****	0.000	****
anger	boredom	0.000	****	0.003	**
annoyance	boredom	0.148	ns	1.000	ns
awe	boredom	0.000	****	0.004	**
amusement	confusion	0.000	****	0.000	****
anger	confusion	0.000	****	0.005	**
annoyance	confusion	0.242	ns	1.000	ns
awe	confusion	0.000	****	0.000	***
boredom	confusion	0.749	ns	1.000	ns
amusement	contempt	0.000	****	0.000	****
anger	contempt	0.372	ns	1.000	ns
annoyance	contempt	0.024	*	1.000	ns
awe	contempt	0.000	****	0.000	****
boredom	contempt	0.000	***	0.089	ns
confusion	contempt	0.001	***	0.180	ns
amusement	contentment	0.227	ns	1.000	ns
anger	contentment	0.000	****	0.000	****
annoyance	contentment	0.000	****	0.000	****
awe	contentment	0.773	ns	1.000	ns
boredom	contentment	0.000	****	0.001	**
confusion	contentment	0.000	****	0.000	***
contempt	contentment	0.000	****	0.000	****
amusement	disappointment	0.000	****	0.000	****
anger	disappointment	0.764	ns	1.000	ns
annoyance	disappointment	0.001	***	0.145	ns
awe	disappointment	0.000	****	0.000	****
boredom	disappointment	0.000	****	0.001	***
confusion	disappointment	0.000	****	0.001	**

contempt	disappointment	0.231	ns	1.000	ns
contentment	disappointment	0.000	****	0.000	****
amusement	disgust	0.000	****	0.000	****
anger	disgust	0.382	ns	1.000	ns
annoyance	disgust	0.000	****	0.013	*
awe	disgust	0.000	****	0.000	****
boredom	disgust	0.000	****	0.000	****
confusion	disgust	0.000	****	0.000	****
contempt	disgust	0.074	ns	1.000	ns
contentment	disgust	0.000	****	0.000	****
disappointment	disgust	0.567	ns	1.000	ns
amusement	elation	0.279	ns	1.000	ns
anger	elation	0.000	****	0.000	****
annoyance	elation	0.000	****	0.000	****
awe	elation	0.665	ns	1.000	ns
boredom	elation	0.000	****	0.001	***
confusion	elation	0.000	****	0.000	****
contempt	elation	0.000	****	0.000	****
contentment	elation	0.890	ns	1.000	ns
disappointment	elation	0.000	****	0.000	****
disgust	elation	0.000	****	0.000	****
amusement	embarrassment	0.000	****	0.000	****
anger	embarrassment	0.000	****	0.000	****
annoyance	embarrassment	0.025	*	1.000	ns
awe	embarrassment	0.000	***	0.030	*
boredom	embarrassment	0.501	ns	1.000	ns
confusion	embarrassment	0.298	ns	1.000	ns
contempt	embarrassment	0.000	****	0.002	**
contentment	embarrassment	0.000	****	0.011	*
disappointment	embarrassment	0.000	****	0.000	****
disgust	embarrassment	0.000	****	0.000	****
elation	embarrassment	0.000	****	0.005	**
amusement	fear	0.000	****	0.000	****
anger	fear	0.228	ns	1.000	ns
annoyance	fear	0.000	****	0.003	**
awe	fear	0.000	****	0.000	****
boredom	fear	0.000	****	0.000	****
confusion	fear	0.000	****	0.000	****
contempt	fear	0.034	*	1.000	ns
contentment	fear	0.000	****	0.000	****
disappointment	fear	0.365	ns	1.000	ns

disgust	fear	0.735	ns	1.000	ns
elation	fear	0.000	****	0.000	****
embarrassment	fear	0.000	****	0.000	****
amusement	grief	0.000	****	0.000	****
anger	grief	0.000	****	0.000	****
annoyance	grief	0.000	****	0.000	****
awe	grief	0.000	****	0.000	****
boredom	grief	0.000	****	0.000	****
confusion	grief	0.000	****	0.000	****
contempt	grief	0.000	****	0.000	****
contentment	grief	0.000	****	0.000	****
disappointment	grief	0.000	****	0.000	****
disgust	grief	0.000	****	0.000	****
elation	grief	0.000	****	0.000	****
embarrassment	grief	0.000	****	0.000	****
fear	grief	0.000	****	0.000	****
amusement	happiness	0.301	ns	1.000	ns
anger	happiness	0.000	****	0.000	****
annoyance	happiness	0.000	****	0.000	****
awe	happiness	0.010	*	1.000	ns
boredom	happiness	0.000	****	0.000	****
confusion	happiness	0.000	****	0.000	****
contempt	happiness	0.000	****	0.000	****
contentment	happiness	0.025	*	1.000	ns
disappointment	happiness	0.000	****	0.000	****
disgust	happiness	0.000	****	0.000	****
elation	happiness	0.033	*	1.000	ns
embarrassment	happiness	0.000	****	0.000	****
fear	happiness	0.000	****	0.000	****
grief	happiness	0.000	****	0.000	****
amusement	interest	0.018	*	1.000	ns
anger	interest	0.000	****	0.000	****
annoyance	interest	0.000	****	0.000	****
awe	interest	0.384	ns	1.000	ns
boredom	interest	0.001	***	0.117	ns
confusion	interest	0.000	****	0.017	*
contempt	interest	0.000	****	0.000	****
contentment	interest	0.250	ns	1.000	ns
disappointment	interest	0.000	****	0.000	****
disgust	interest	0.000	****	0.000	****
elation	interest	0.193	ns	1.000	ns

embarrassment	interest	0.003	**	0.707	ns
fear	interest	0.000	****	0.000	****
grief	interest	0.000	****	0.000	****
happiness	interest	0.001	***	0.154	ns
amusement	joy	0.996	ns	1.000	ns
anger	joy	0.000	****	0.000	****
annoyance	joy	0.000	****	0.000	****
awe	joy	0.126	ns	1.000	ns
boredom	joy	0.000	****	0.000	****
confusion	joy	0.000	****	0.000	****
contempt	joy	0.000	****	0.000	****
contentment	joy	0.221	ns	1.000	ns
disappointment	joy	0.000	****	0.000	****
disgust	joy	0.000	****	0.000	****
elation	joy	0.272	ns	1.000	ns
embarrassment	joy	0.000	****	0.000	****
fear	joy	0.000	****	0.000	****
grief	joy	0.000	****	0.000	****
happiness	joy	0.299	ns	1.000	ns
interest	joy	0.017	*	1.000	ns
amusement	pride	0.000	****	0.000	***
anger	pride	0.000	****	0.000	****
annoyance	pride	0.009	**	1.000	ns
awe	pride	0.001	***	0.122	ns
boredom	pride	0.299	ns	1.000	ns
confusion	pride	0.155	ns	1.000	ns
contempt	pride	0.000	****	0.000	***
contentment	pride	0.000	***	0.047	*
disappointment	pride	0.000	****	0.000	****
disgust	pride	0.000	****	0.000	****
elation	pride	0.000	****	0.022	*
embarrassment	pride	0.703	ns	1.000	ns
fear	pride	0.000	****	0.000	****
grief	pride	0.000	****	0.000	****
happiness	pride	0.000	****	0.000	****
interest	pride	0.009	**	1.000	ns
joy	pride	0.000	****	0.000	***
amusement	relief	0.189	ns	1.000	ns
anger	relief	0.000	****	0.000	****
annoyance	relief	0.000	****	0.000	****
awe	relief	0.849	ns	1.000	ns

boredom	relief	0.000	****	0.002	**
confusion	relief	0.000	****	0.000	***
contempt	relief	0.000	****	0.000	****
contentment	relief	0.921	ns	1.000	ns
disappointment	relief	0.000	****	0.000	****
disgust	relief	0.000	****	0.000	****
elation	relief	0.810	ns	1.000	ns
embarrassment	relief	0.000	****	0.015	*
fear	relief	0.000	****	0.000	****
grief	relief	0.000	****	0.000	****
happiness	relief	0.018	*	1.000	ns
interest	relief	0.291	ns	1.000	ns
joy	relief	0.183	ns	1.000	ns
pride	relief	0.000	***	0.064	ns
amusement	sadness	0.000	****	0.000	****
anger	sadness	0.002	**	0.444	ns
annoyance	sadness	0.000	****	0.000	****
awe	sadness	0.000	****	0.000	****
boredom	sadness	0.000	****	0.000	****
confusion	sadness	0.000	****	0.000	****
contempt	sadness	0.000	****	0.014	*
contentment	sadness	0.000	****	0.000	****
disappointment	sadness	0.005	**	1.000	ns
disgust	sadness	0.021	*	1.000	ns
elation	sadness	0.000	****	0.000	****
embarrassment	sadness	0.000	****	0.000	****
fear	sadness	0.049	*	1.000	ns
grief	sadness	0.001	***	0.116	ns
happiness	sadness	0.000	****	0.000	****
interest	sadness	0.000	****	0.000	****
joy	sadness	0.000	****	0.000	****
pride	sadness	0.000	****	0.000	****
relief	sadness	0.000	****	0.000	****
amusement	serenity	0.083	ns	1.000	ns
anger	serenity	0.000	****	0.000	****
annoyance	serenity	0.000	****	0.000	****
awe	serenity	0.799	ns	1.000	ns
boredom	serenity	0.000	****	0.015	*
confusion	serenity	0.000	****	0.002	**
contempt	serenity	0.000	****	0.000	****
contentment	serenity	0.592	ns	1.000	ns

disappointment	serenity	0.000	****	0.000	****
disgust	serenity	0.000	****	0.000	****
elation	serenity	0.497	ns	1.000	ns
embarrassment	serenity	0.000	***	0.103	ns
fear	serenity	0.000	****	0.000	****
grief	serenity	0.000	****	0.000	****
happiness	serenity	0.006	**	1.000	ns
interest	serenity	0.548	ns	1.000	ns
joy	serenity	0.079	ns	1.000	ns
pride	serenity	0.002	**	0.375	ns
relief	serenity	0.660	ns	1.000	ns
sadness	serenity	0.000	****	0.000	****
amusement	shame	0.000	****	0.000	****
anger	shame	0.874	ns	1.000	ns
annoyance	shame	0.001	***	0.207	ns
awe	shame	0.000	****	0.000	****
boredom	shame	0.000	****	0.001	***
confusion	shame	0.000	****	0.002	**
contempt	shame	0.286	ns	1.000	ns
contentment	shame	0.000	****	0.000	****
disappointment	shame	0.883	ns	1.000	ns
disgust	shame	0.466	ns	1.000	ns
elation	shame	0.000	****	0.000	****
embarrassment	shame	0.000	****	0.000	****
fear	shame	0.286	ns	1.000	ns
grief	shame	0.000	****	0.000	****
happiness	shame	0.000	****	0.000	****
interest	shame	0.000	****	0.000	****
joy	shame	0.000	****	0.000	****
pride	shame	0.000	****	0.000	****
relief	shame	0.000	****	0.000	****
sadness	shame	0.003	**	0.630	ns
serenity	shame	0.000	****	0.000	****
amusement	surprise	0.276	ns	1.000	ns
anger	surprise	0.000	****	0.000	****
annoyance	surprise	0.000	****	0.000	****
awe	surprise	0.670	ns	1.000	ns
boredom	surprise	0.000	****	0.001	***
confusion	surprise	0.000	****	0.000	****
contempt	surprise	0.000	****	0.000	****
contentment	surprise	0.895	ns	1.000	ns

disappointment	surprise	0.000	****	0.000	****
disgust	surprise	0.000	****	0.000	****
elation	surprise	0.995	ns	1.000	ns
embarrassment	surprise	0.000	****	0.005	**
fear	surprise	0.000	****	0.000	****
grief	surprise	0.000	****	0.000	****
happiness	surprise	0.032	*	1.000	ns
interest	surprise	0.195	ns	1.000	ns
joy	surprise	0.270	ns	1.000	ns
pride	surprise	0.000	****	0.023	*
relief	surprise	0.815	ns	1.000	ns
sadness	surprise	0.000	****	0.000	****
serenity	surprise	0.501	ns	1.000	ns
shame	surprise	0.000	****	0.000	****

Experiment 1. Results of post-hoc t-tests for "a" color dimension.

group1	group2	p	p.signif	p.adj	p.adj.signif
amusement	anger	0.000	****	0.000	****
amusement	annoyance	0.004	**	1.000	ns
anger	annoyance	0.000	****	0.000	****
amusement	awe	0.312	ns	1.000	ns
anger	awe	0.000	****	0.000	****
annoyance	awe	0.000	****	0.023	*
amusement	boredom	0.038	*	1.000	ns
anger	boredom	0.000	****	0.000	****
annoyance	boredom	0.000	****	0.000	***
awe	boredom	0.258	ns	1.000	ns
amusement	confusion	0.144	ns	1.000	ns
anger	confusion	0.000	****	0.000	****
annoyance	confusion	0.000	****	0.004	**
awe	confusion	0.635	ns	1.000	ns
boredom	confusion	0.506	ns	1.000	ns
amusement	contempt	0.099	ns	1.000	ns
anger	contempt	0.000	****	0.000	****
annoyance	contempt	0.226	ns	1.000	ns
awe	contempt	0.007	**	1.000	ns
boredom	contempt	0.000	***	0.071	ns
confusion	contempt	0.002	**	0.508	ns
amusement	contentment	0.001	***	0.199	ns
anger	contentment	0.000	****	0.000	****
annoyance	contentment	0.000	****	0.000	****

awe	contentment	0.017	*	1.000	ns
boredom	contentment	0.259	ns	1.000	ns
confusion	contentment	0.061	ns	1.000	ns
contempt	contentment	0.000	****	0.000	***
amusement	disappointment	0.090	ns	1.000	ns
anger	disappointment	0.000	****	0.000	****
annoyance	disappointment	0.000	****	0.001	**
awe	disappointment	0.477	ns	1.000	ns
boredom	disappointment	0.656	ns	1.000	ns
confusion	disappointment	0.818	ns	1.000	ns
contempt	disappointment	0.001	***	0.220	ns
contentment	disappointment	0.100	ns	1.000	ns
amusement	disgust	0.001	**	0.262	ns
anger	disgust	0.000	****	0.000	****
annoyance	disgust	0.000	****	0.000	****
awe	disgust	0.021	*	1.000	ns
boredom	disgust	0.298	ns	1.000	ns
confusion	disgust	0.074	ns	1.000	ns
contempt	disgust	0.000	****	0.000	***
contentment	disgust	0.922	ns	1.000	ns
disappointment	disgust	0.119	ns	1.000	ns
amusement	elation	0.057	ns	1.000	ns
anger	elation	0.000	****	0.000	****
annoyance	elation	0.318	ns	1.000	ns
awe	elation	0.003	**	0.820	ns
boredom	elation	0.000	****	0.025	*
confusion	elation	0.001	***	0.199	ns
contempt	elation	0.820	ns	1.000	ns
contentment	elation	0.000	****	0.000	****
disappointment	elation	0.000	***	0.080	ns
disgust	elation	0.000	****	0.000	****
amusement	embarrassment	0.000	****	0.001	***
anger	embarrassment	0.000	****	0.000	****
annoyance	embarrassment	0.066	ns	1.000	ns
awe	embarrassment	0.000	****	0.000	****
boredom	embarrassment	0.000	****	0.000	****
confusion	embarrassment	0.000	****	0.000	****
contempt	embarrassment	0.002	**	0.603	ns
contentment	embarrassment	0.000	****	0.000	****
disappointment	embarrassment	0.000	****	0.000	****
disgust	embarrassment	0.000	****	0.000	****

elation	embarrassment	0.004	**	1.000	ns
amusement	fear	0.024	*	1.000	ns
anger	fear	0.000	****	0.000	****
annoyance	fear	0.540	ns	1.000	ns
awe	fear	0.001	***	0.247	ns
boredom	fear	0.000	****	0.006	**
confusion	fear	0.000	***	0.054	ns
contempt	fear	0.548	ns	1.000	ns
contentment	fear	0.000	****	0.000	****
disappointment	fear	0.000	****	0.020	*
disgust	fear	0.000	****	0.000	****
elation	fear	0.704	ns	1.000	ns
embarrassment	fear	0.014	*	1.000	ns
amusement	grief	0.122	ns	1.000	ns
anger	grief	0.000	****	0.000	****
annoyance	grief	0.000	****	0.004	**
awe	grief	0.565	ns	1.000	ns
boredom	grief	0.581	ns	1.000	ns
confusion	grief	0.915	ns	1.000	ns
contempt	grief	0.002	**	0.416	ns
contentment	grief	0.083	ns	1.000	ns
disappointment	grief	0.905	ns	1.000	ns
disgust	grief	0.099	ns	1.000	ns
elation	grief	0.001	***	0.163	ns
embarrassment	grief	0.000	****	0.000	****
fear	grief	0.000	***	0.045	*
amusement	happiness	0.102	ns	1.000	ns
anger	happiness	0.000	****	0.000	****
annoyance	happiness	0.000	****	0.002	**
awe	happiness	0.525	ns	1.000	ns
boredom	happiness	0.597	ns	1.000	ns
confusion	happiness	0.880	ns	1.000	ns
contempt	happiness	0.001	**	0.258	ns
contentment	happiness	0.081	ns	1.000	ns
disappointment	happiness	0.934	ns	1.000	ns
disgust	happiness	0.097	ns	1.000	ns
elation	happiness	0.000	***	0.094	ns
embarrassment	happiness	0.000	****	0.000	****
fear	happiness	0.000	****	0.024	*
grief	happiness	0.968	ns	1.000	ns
amusement	interest	0.189	ns	1.000	ns

anger	interest	0.000	****	0.000	****
annoyance	interest	0.000	****	0.006	**
awe	interest	0.759	ns	1.000	ns
boredom	interest	0.399	ns	1.000	ns
confusion	interest	0.862	ns	1.000	ns
contempt	interest	0.003	**	0.738	ns
contentment	interest	0.037	*	1.000	ns
disappointment	interest	0.682	ns	1.000	ns
disgust	interest	0.046	*	1.000	ns
elation	interest	0.001	**	0.292	ns
embarrassment	interest	0.000	****	0.000	****
fear	interest	0.000	***	0.080	ns
grief	interest	0.779	ns	1.000	ns
happiness	interest	0.741	ns	1.000	ns
amusement	joy	0.572	ns	1.000	ns
anger	joy	0.000	****	0.000	****
annoyance	joy	0.020	*	1.000	ns
awe	joy	0.112	ns	1.000	ns
boredom	joy	0.009	**	1.000	ns
confusion	joy	0.042	*	1.000	ns
contempt	joy	0.271	ns	1.000	ns
contentment	joy	0.000	****	0.020	*
disappointment	joy	0.023	*	1.000	ns
disgust	joy	0.000	***	0.027	*
elation	joy	0.178	ns	1.000	ns
embarrassment	joy	0.000	****	0.007	**
fear	joy	0.087	ns	1.000	ns
grief	joy	0.035	*	1.000	ns
happiness	joy	0.027	*	1.000	ns
interest	joy	0.058	ns	1.000	ns
amusement	pride	0.004	**	0.990	ns
anger	pride	0.000	****	0.000	****
annoyance	pride	0.992	ns	1.000	ns
awe	pride	0.000	****	0.021	*
boredom	pride	0.000	****	0.000	***
confusion	pride	0.000	****	0.004	**
contempt	pride	0.226	ns	1.000	ns
contentment	pride	0.000	****	0.000	****
disappointment	pride	0.000	****	0.001	**
disgust	pride	0.000	****	0.000	****
elation	pride	0.319	ns	1.000	ns

embarrassment	pride	0.063	ns	1.000	ns
fear	pride	0.543	ns	1.000	ns
grief	pride	0.000	****	0.003	**
happiness	pride	0.000	****	0.001	**
interest	pride	0.000	****	0.006	**
joy	pride	0.019	*	1.000	ns
amusement	relief	0.000	***	0.051	ns
anger	relief	0.000	****	0.000	****
annoyance	relief	0.000	****	0.000	****
awe	relief	0.006	**	1.000	ns
boredom	relief	0.144	ns	1.000	ns
confusion	relief	0.026	*	1.000	ns
contempt	relief	0.000	****	0.000	****
contentment	relief	0.732	ns	1.000	ns
disappointment	relief	0.046	*	1.000	ns
disgust	relief	0.658	ns	1.000	ns
elation	relief	0.000	****	0.000	****
embarrassment	relief	0.000	****	0.000	****
fear	relief	0.000	****	0.000	****
grief	relief	0.038	*	1.000	ns
happiness	relief	0.036	*	1.000	ns
interest	relief	0.015	*	1.000	ns
joy	relief	0.000	****	0.004	**
pride	relief	0.000	****	0.000	****
amusement	sadness	0.218	ns	1.000	ns
anger	sadness	0.000	****	0.000	****
annoyance	sadness	0.000	****	0.012	*
awe	sadness	0.804	ns	1.000	ns
boredom	sadness	0.381	ns	1.000	ns
confusion	sadness	0.825	ns	1.000	ns
contempt	sadness	0.004	**	1.000	ns
contentment	sadness	0.037	*	1.000	ns
disappointment	sadness	0.651	ns	1.000	ns
disgust	sadness	0.045	*	1.000	ns
elation	sadness	0.002	**	0.454	ns
embarrassment	sadness	0.000	****	0.000	****
fear	sadness	0.001	***	0.133	ns
grief	sadness	0.746	ns	1.000	ns
happiness	sadness	0.708	ns	1.000	ns
interest	sadness	0.958	ns	1.000	ns
joy	sadness	0.072	ns	1.000	ns

pride	sadness	0.000	****	0.011	*
relief	sadness	0.015	*	1.000	ns
amusement	serenity	0.044	*	1.000	ns
anger	serenity	0.000	****	0.000	****
annoyance	serenity	0.000	****	0.000	***
awe	serenity	0.300	ns	1.000	ns
boredom	serenity	0.890	ns	1.000	ns
confusion	serenity	0.583	ns	1.000	ns
contempt	serenity	0.000	***	0.067	ns
contentment	serenity	0.186	ns	1.000	ns
disappointment	serenity	0.749	ns	1.000	ns
disgust	serenity	0.217	ns	1.000	ns
elation	serenity	0.000	****	0.022	*
embarrassment	serenity	0.000	****	0.000	****
fear	serenity	0.000	****	0.005	**
grief	serenity	0.665	ns	1.000	ns
happiness	serenity	0.684	ns	1.000	ns
interest	serenity	0.462	ns	1.000	ns
joy	serenity	0.009	**	1.000	ns
pride	serenity	0.000	****	0.000	***
relief	serenity	0.095	ns	1.000	ns
sadness	serenity	0.442	ns	1.000	ns
amusement	shame	0.880	ns	1.000	ns
anger	shame	0.000	****	0.000	****
annoyance	shame	0.002	**	0.586	ns
awe	shame	0.386	ns	1.000	ns
boredom	shame	0.052	ns	1.000	ns
confusion	shame	0.186	ns	1.000	ns
contempt	shame	0.070	ns	1.000	ns
contentment	shame	0.001	**	0.306	ns
disappointment	shame	0.118	ns	1.000	ns
disgust	shame	0.002	**	0.403	ns
elation	shame	0.038	*	1.000	ns
embarrassment	shame	0.000	****	0.000	***
fear	shame	0.015	*	1.000	ns
grief	shame	0.158	ns	1.000	ns
happiness	shame	0.135	ns	1.000	ns
interest	shame	0.241	ns	1.000	ns
joy	shame	0.470	ns	1.000	ns
pride	shame	0.002	**	0.557	ns
relief	shame	0.000	***	0.081	ns

sadness	shame	0.274	ns	1.000	ns
serenity	shame	0.059	ns	1.000	ns
amusement	surprise	0.027	*	1.000	ns
anger	surprise	0.000	****	0.000	****
annoyance	surprise	0.496	ns	1.000	ns
awe	surprise	0.001	**	0.279	ns
boredom	surprise	0.000	****	0.007	**
confusion	surprise	0.000	***	0.062	ns
contempt	surprise	0.587	ns	1.000	ns
contentment	surprise	0.000	****	0.000	****
disappointment	surprise	0.000	****	0.023	*
disgust	surprise	0.000	****	0.000	****
elation	surprise	0.749	ns	1.000	ns
embarrassment	surprise	0.011	*	1.000	ns
fear	surprise	0.950	ns	1.000	ns
grief	surprise	0.000	***	0.051	ns
happiness	surprise	0.000	***	0.027	*
interest	surprise	0.000	***	0.091	ns
joy	surprise	0.096	ns	1.000	ns
pride	surprise	0.499	ns	1.000	ns
relief	surprise	0.000	****	0.000	****
sadness	surprise	0.001	***	0.151	ns
serenity	surprise	0.000	****	0.006	**
shame	surprise	0.017	*	1.000	ns

Experiment 1. Results of post-hoc t-tests for “b” color dimension.

group1	group2	p	p.signif	p.adj	p.adj.signif
amusement	anger	0.000	****	0.000	****
amusement	annoyance	0.001	***	0.163	ns
anger	annoyance	0.033	*	1.000	ns
amusement	awe	0.005	**	1.000	ns
anger	awe	0.000	****	0.000	****
annoyance	awe	0.000	****	0.000	****
amusement	boredom	0.014	*	1.000	ns
anger	boredom	0.000	****	0.000	****
annoyance	boredom	0.000	****	0.000	****
awe	boredom	0.849	ns	1.000	ns
amusement	confusion	0.798	ns	1.000	ns
anger	confusion	0.000	****	0.000	****
annoyance	confusion	0.002	**	0.447	ns
awe	confusion	0.002	**	0.593	ns

boredom	confusion	0.007	**	1.000	ns
amusement	contempt	0.406	ns	1.000	ns
anger	contempt	0.000	****	0.001	***
annoyance	contempt	0.010	*	1.000	ns
awe	contempt	0.000	***	0.069	ns
boredom	contempt	0.001	**	0.303	ns
confusion	contempt	0.569	ns	1.000	ns
amusement	contentment	0.005	**	1.000	ns
anger	contentment	0.000	****	0.000	****
annoyance	contentment	0.000	****	0.000	****
awe	contentment	0.957	ns	1.000	ns
boredom	contentment	0.811	ns	1.000	ns
confusion	contentment	0.002	**	0.555	ns
contempt	contentment	0.000	***	0.066	ns
amusement	disappointment	0.000	***	0.050	ns
anger	disappointment	0.000	****	0.000	****
annoyance	disappointment	0.000	****	0.000	****
awe	disappointment	0.331	ns	1.000	ns
boredom	disappointment	0.270	ns	1.000	ns
confusion	disappointment	0.000	****	0.020	*
contempt	disappointment	0.000	****	0.001	**
contentment	disappointment	0.363	ns	1.000	ns
amusement	disgust	0.016	*	1.000	ns
anger	disgust	0.002	**	0.429	ns
annoyance	disgust	0.310	ns	1.000	ns
awe	disgust	0.000	****	0.000	****
boredom	disgust	0.000	****	0.001	***
confusion	disgust	0.033	*	1.000	ns
contempt	disgust	0.116	ns	1.000	ns
contentment	disgust	0.000	****	0.000	****
disappointment	disgust	0.000	****	0.000	****
amusement	elation	0.104	ns	1.000	ns
anger	elation	0.000	****	0.000	****
annoyance	elation	0.000	****	0.000	***
awe	elation	0.230	ns	1.000	ns
boredom	elation	0.349	ns	1.000	ns
confusion	elation	0.062	ns	1.000	ns
contempt	elation	0.014	*	1.000	ns
contentment	elation	0.215	ns	1.000	ns
disappointment	elation	0.031	*	1.000	ns
disgust	elation	0.000	****	0.012	*

amusement	embarrassment	0.946	ns	1.000	ns
anger	embarrassment	0.000	****	0.000	****
annoyance	embarrassment	0.000	***	0.118	ns
awe	embarrassment	0.006	**	1.000	ns
boredom	embarrassment	0.016	*	1.000	ns
confusion	embarrassment	0.746	ns	1.000	ns
contempt	embarrassment	0.366	ns	1.000	ns
contentment	embarrassment	0.005	**	1.000	ns
disappointment	embarrassment	0.000	***	0.060	ns
disgust	embarrassment	0.013	*	1.000	ns
elation	embarrassment	0.117	ns	1.000	ns
amusement	fear	0.753	ns	1.000	ns
anger	fear	0.000	****	0.000	****
annoyance	fear	0.000	***	0.047	*
awe	fear	0.012	*	1.000	ns
boredom	fear	0.030	*	1.000	ns
confusion	fear	0.570	ns	1.000	ns
contempt	fear	0.251	ns	1.000	ns
contentment	fear	0.012	*	1.000	ns
disappointment	fear	0.001	***	0.158	ns
disgust	fear	0.006	**	1.000	ns
elation	fear	0.189	ns	1.000	ns
embarrassment	fear	0.804	ns	1.000	ns
amusement	grief	0.000	****	0.009	**
anger	grief	0.000	****	0.000	****
annoyance	grief	0.000	****	0.000	****
awe	grief	0.145	ns	1.000	ns
boredom	grief	0.119	ns	1.000	ns
confusion	grief	0.000	****	0.003	**
contempt	grief	0.000	****	0.000	***
contentment	grief	0.165	ns	1.000	ns
disappointment	grief	0.622	ns	1.000	ns
disgust	grief	0.000	****	0.000	****
elation	grief	0.009	**	1.000	ns
embarrassment	grief	0.000	****	0.010	*
fear	grief	0.000	***	0.030	*
amusement	happiness	0.030	*	1.000	ns
anger	happiness	0.001	***	0.183	ns
annoyance	happiness	0.207	ns	1.000	ns
awe	happiness	0.000	****	0.000	***
boredom	happiness	0.000	****	0.002	**

confusion	happiness	0.058	ns	1.000	ns
contempt	happiness	0.185	ns	1.000	ns
contentment	happiness	0.000	****	0.000	***
disappointment	happiness	0.000	****	0.000	****
disgust	happiness	0.805	ns	1.000	ns
elation	happiness	0.000	***	0.033	*
embarrassment	happiness	0.025	*	1.000	ns
fear	happiness	0.013	*	1.000	ns
grief	happiness	0.000	****	0.000	****
amusement	interest	0.241	ns	1.000	ns
anger	interest	0.000	****	0.000	****
annoyance	interest	0.000	****	0.001	***
awe	interest	0.097	ns	1.000	ns
boredom	interest	0.171	ns	1.000	ns
confusion	interest	0.155	ns	1.000	ns
contempt	interest	0.044	*	1.000	ns
contentment	interest	0.091	ns	1.000	ns
disappointment	interest	0.009	**	1.000	ns
disgust	interest	0.000	***	0.075	ns
elation	interest	0.647	ns	1.000	ns
embarrassment	interest	0.266	ns	1.000	ns
fear	interest	0.390	ns	1.000	ns
grief	interest	0.002	**	0.577	ns
happiness	interest	0.001	***	0.190	ns
amusement	joy	0.943	ns	1.000	ns
anger	joy	0.000	****	0.000	****
annoyance	joy	0.001	***	0.190	ns
awe	joy	0.004	**	0.922	ns
boredom	joy	0.011	*	1.000	ns
confusion	joy	0.852	ns	1.000	ns
contempt	joy	0.443	ns	1.000	ns
contentment	joy	0.003	**	0.862	ns
disappointment	joy	0.000	***	0.033	*
disgust	joy	0.018	*	1.000	ns
elation	joy	0.087	ns	1.000	ns
embarrassment	joy	0.888	ns	1.000	ns
fear	joy	0.697	ns	1.000	ns
grief	joy	0.000	****	0.005	**
happiness	joy	0.034	*	1.000	ns
interest	joy	0.209	ns	1.000	ns
amusement	pride	0.053	ns	1.000	ns

anger	pride	0.000	****	0.000	****
annoyance	pride	0.000	****	0.000	****
awe	pride	0.373	ns	1.000	ns
boredom	pride	0.518	ns	1.000	ns
confusion	pride	0.030	*	1.000	ns
contempt	pride	0.006	**	1.000	ns
contentment	pride	0.350	ns	1.000	ns
disappointment	pride	0.065	ns	1.000	ns
disgust	pride	0.000	****	0.003	**
elation	pride	0.757	ns	1.000	ns
embarrassment	pride	0.061	ns	1.000	ns
fear	pride	0.105	ns	1.000	ns
grief	pride	0.021	*	1.000	ns
happiness	pride	0.000	****	0.009	**
interest	pride	0.443	ns	1.000	ns
joy	pride	0.043	*	1.000	ns
amusement	relief	0.000	***	0.064	ns
anger	relief	0.000	****	0.000	****
annoyance	relief	0.000	****	0.000	****
awe	relief	0.381	ns	1.000	ns
boredom	relief	0.311	ns	1.000	ns
confusion	relief	0.000	***	0.026	*
contempt	relief	0.000	****	0.002	**
contentment	relief	0.417	ns	1.000	ns
disappointment	relief	0.915	ns	1.000	ns
disgust	relief	0.000	****	0.000	****
elation	relief	0.039	*	1.000	ns
embarrassment	relief	0.000	***	0.077	ns
fear	relief	0.001	***	0.202	ns
grief	relief	0.546	ns	1.000	ns
happiness	relief	0.000	****	0.000	****
interest	relief	0.012	*	1.000	ns
joy	relief	0.000	***	0.043	*
pride	relief	0.078	ns	1.000	ns
amusement	sadness	0.000	****	0.000	****
anger	sadness	0.000	****	0.000	****
annoyance	sadness	0.000	****	0.000	****
awe	sadness	0.000	****	0.000	****
boredom	sadness	0.000	****	0.000	***
confusion	sadness	0.000	****	0.000	****
contempt	sadness	0.000	****	0.000	****

contentment	sadness	0.000	****	0.000	***
disappointment	sadness	0.000	****	0.010	**
disgust	sadness	0.000	****	0.000	****
elation	sadness	0.000	****	0.000	****
embarrassment	sadness	0.000	****	0.000	****
fear	sadness	0.000	****	0.000	****
grief	sadness	0.000	***	0.095	ns
happiness	sadness	0.000	****	0.000	****
interest	sadness	0.000	****	0.000	****
joy	sadness	0.000	****	0.000	****
pride	sadness	0.000	****	0.000	****
relief	sadness	0.000	****	0.005	**
amusement	serenity	0.000	****	0.000	****
anger	serenity	0.000	****	0.000	****
annoyance	serenity	0.000	****	0.000	****
awe	serenity	0.011	*	1.000	ns
boredom	serenity	0.010	*	1.000	ns
confusion	serenity	0.000	****	0.000	****
contempt	serenity	0.000	****	0.000	****
contentment	serenity	0.014	*	1.000	ns
disappointment	serenity	0.124	ns	1.000	ns
disgust	serenity	0.000	****	0.000	****
elation	serenity	0.000	***	0.052	ns
embarrassment	serenity	0.000	****	0.000	****
fear	serenity	0.000	****	0.000	***
grief	serenity	0.309	ns	1.000	ns
happiness	serenity	0.000	****	0.000	****
interest	serenity	0.000	****	0.008	**
joy	serenity	0.000	****	0.000	****
pride	serenity	0.001	***	0.166	ns
relief	serenity	0.096	ns	1.000	ns
sadness	serenity	0.009	**	1.000	ns
amusement	shame	0.406	ns	1.000	ns
anger	shame	0.000	****	0.000	****
annoyance	shame	0.000	****	0.005	**
awe	shame	0.046	*	1.000	ns
boredom	shame	0.092	ns	1.000	ns
confusion	shame	0.280	ns	1.000	ns
contempt	shame	0.096	ns	1.000	ns
contentment	shame	0.043	*	1.000	ns
disappointment	shame	0.003	**	0.856	ns

disgust	shame	0.001	**	0.275	ns
elation	shame	0.424	ns	1.000	ns
embarrassment	shame	0.443	ns	1.000	ns
fear	shame	0.606	ns	1.000	ns
grief	shame	0.001	***	0.188	ns
happiness	shame	0.003	**	0.638	ns
interest	shame	0.731	ns	1.000	ns
joy	shame	0.363	ns	1.000	ns
pride	shame	0.267	ns	1.000	ns
relief	shame	0.004	**	1.000	ns
sadness	shame	0.000	****	0.000	****
serenity	shame	0.000	****	0.002	**
amusement	surprise	0.642	ns	1.000	ns
anger	surprise	0.000	****	0.000	****
annoyance	surprise	0.000	****	0.023	*
awe	surprise	0.018	*	1.000	ns
boredom	surprise	0.041	*	1.000	ns
confusion	surprise	0.472	ns	1.000	ns
contempt	surprise	0.192	ns	1.000	ns
contentment	surprise	0.016	*	1.000	ns
disappointment	surprise	0.001	***	0.242	ns
disgust	surprise	0.004	**	0.925	ns
elation	surprise	0.240	ns	1.000	ns
embarrassment	surprise	0.690	ns	1.000	ns
fear	surprise	0.882	ns	1.000	ns
grief	surprise	0.000	***	0.047	*
happiness	surprise	0.008	**	1.000	ns
interest	surprise	0.473	ns	1.000	ns
joy	surprise	0.588	ns	1.000	ns
pride	surprise	0.138	ns	1.000	ns
relief	surprise	0.001	**	0.309	ns
sadness	surprise	0.000	****	0.000	****
serenity	surprise	0.000	****	0.000	***
shame	surprise	0.710	ns	1.000	ns

Experiment 2. Contingency table of counts for each color emotion pair.

color	amusement	anger	annoyance	awe	boredom	confusion	contempt	contentment	disappointment	disgust	elation	embarrassment	fear	grief	happiness	interest	joy	pride	relief	sadness	serenity	shame	surprise	none
#e23dc2	20	1	6	5	1	10	2	5	0	0	14	3	0	0	23	13	33	23	2	1	2	2	30	2
#f080f1	22	1	6	11	0	3	0	5	2	1	17	1	0	1	25	13	34	17	8	1	1	0	28	7
#eda4b3	24	1	3	5	2	1	0	9	2	1	16	11	0	0	25	12	41	17	3	0	12	4	13	5
#eeb8e0	18	0	2	10	1	2	1	9	0	1	14	3	0	0	32	14	34	24	3	0	11	1	13	6
#62202b	1	23	17	4	8	3	8	9	7	9	1	5	4	5	3	7	2	9	1	7	3	7	1	14
#9b1c45	6	17	17	5	2	3	10	5	6	4	4	7	3	3	8	19	11	9	4	4	8	4	6	13
#ac1011	2	67	35	2	0	0	16	0	3	11	1	6	13	4	5	9	4	4	0	5	1	6	6	1
#dc2265	20	7	9	8	0	4	2	4	1	0	12	3	0	1	26	15	29	15	1	0	4	3	22	10

#8ce7f7	#34b0f4	#4290ac	#ebe049	#f9b308	#e5914e	#f07723	#c94949	#ef2119
11	14	4	22	14	14	18	7	7
0	0	0	0	1	2	4	38	53
0	5	0	12	18	7	14	21	32
5	11	10	11	8	4	11	2	4
1	1	6	1	2	1	1	4	0
1	0	2	2	8	11	7	3	3
2	1	2	1	2	5	2	10	13
12	12	30	4	6	7	1	5	1
0	1	2	0	1	1	2	4	6
0	1	0	4	3	2	3	2	5
24	22	5	28	23	15	14	2	3
0	0	0	1	3	2	3	9	12
0	1	0	3	7	2	3	8	11
0	0	3	0	0	1	0	1	2
32	31	21	28	26	16	19	7	2
21	20	18	13	7	15	16	9	3
32	27	15	46	33	22	16	4	2
7	5	5	11	13	8	9	3	4
18	11	18	2	0	4	2	0	0
1	4	5	2	1	0	1	2	1
28	25	37	1	3	7	1	1	0
0	0	0	2	3	2	1	8	2
11	14	7	21	15	9	21	7	18
6	1	5	2	2	16	7	11	3

#838586	#6e6c68	#3fad41	#767928	#465838	#424326	#ada8ff	#91a3cf	#c9f1ec
0	0	12	2	1	1	12	3	7
1	3	0	0	3	5	0	0	0
5	1	6	6	6	4	2	1	1
1	1	3	0	4	2	11	6	11
49	47	1	8	7	8	2	7	7
10	8	2	6	4	4	5	2	3
2	3	6	10	7	6	2	1	1
6	7	16	7	15	15	15	28	16
14	18	4	7	10	16	0	3	0
5	3	10	39	22	26	2	1	0
0	0	12	1	1	1	17	5	16
2	3	4	9	3	4	1	1	0
5	9	2	6	2	6	0	0	1
17	27	3	3	2	12	0	8	0
0	0	18	3	6	1	14	7	14
2	3	26	5	9	6	13	11	13
0	0	16	2	3	0	19	9	17
0	0	4	2	1	0	7	4	3
6	2	7	6	7	7	12	18	18
28	27	0	3	4	12	3	15	2
6	3	11	8	22	8	23	40	35
6	10	5	5	4	12	2	1	0
1	1	11	0	2	3	14	2	9
8	6	7	15	12	14	4	6	9

#070808	#282a36	#40718f	#204c6e	#eee3e8	#a0a1a5
0	1	2	1	9	1
12	11	0	2	1	0
4	2	1	2	2	3
2	0	4	1	10	1
9	15	6	10	11	43
5	5	7	2	5	9
10	7	3	6	0	5
3	8	26	27	14	16
17	14	9	7	1	12
9	9	0	2	2	2
1	0	2	2	3	0
3	0	0	0	2	0
30	25	4	3	0	2
48	38	9	12	0	12
0	1	8	2	9	2
4	3	9	4	7	2
2	1	4	2	14	0
0	2	5	4	8	1
4	2	13	12	11	6
33	36	27	25	2	17
2	3	32	33	20	13
12	14	0	2	1	8
1	2	1	0	8	1
5	8	8	10	17	15

Experiment 2. Multiple-response hypergeometric tests per cell. Each value is a percentage of participants who selected the emotion as represented by the corresponding color. Highlighted cells denote a significant (α = 5%) multiple-response hypergeometric test per cell.

	#e23dc2	#f080f1	#eda4b3	#eeb8e0	#62202b	#9b1c45	#ac1011	#dc2265
amuseme	21.28	23.4	25.53	19.15	1.06	6.38	2.13	21.28
anger	1.06	1.06	1.06	0	24.47	18.09	71.28	7.45
annoyanc	6.38	6.38	3.19	2.13	18.09	18.09	37.23	9.57
awe	5.32	11.7	5.32	10.64	4.26	5.32	2.13	8.51
boredom	1.06	0	2.13	1.06	8.51	2.13	0	0
confusion	10.64	3.19	1.06	2.13	3.19	3.19	0	4.26
contempt	2.13	0	0	1.06	8.51	10.64	17.02	2.13
contentm	5.32	5.32	9.57	9.57	9.57	5.32	0	4.26
disappoin	0	2.13	2.13	0	7.45	6.38	3.19	1.06
disgust	0	1.06	1.06	1.06	9.57	4.26	11.7	0
elation	14.89	18.09	17.02	14.89	1.06	4.26	1.06	12.77
embarrass	3.19	1.06	11.7	3.19	5.32	7.45	6.38	3.19
fear	0	0	0	0	4.26	3.19	13.83	0
grief	0	1.06	0	0	5.32	3.19	4.26	1.06
happiness	24.47	26.6	26.6	34.04	3.19	8.51	5.32	27.66
interest	13.83	13.83	12.77	14.89	7.45	20.21	9.57	15.96
joy	35.11	36.17	43.62	36.17	2.13	11.7	4.26	30.85
none	2.13	7.45	5.32	6.38	14.89	13.83	1.06	10.64
pride	24.47	18.09	18.09	25.53	9.57	9.57	4.26	15.96
relief	2.13	8.51	3.19	3.19	1.06	4.26	0	1.06
sadness	1.06	1.06	0	0	7.45	4.26	5.32	0
serenity	2.13	1.06	12.77	11.7	3.19	8.51	1.06	4.26
shame	2.13	0	4.26	1.06	7.45	4.26	6.38	3.19
surprise	31.91	29.79	13.83	13.83	1.06	6.38	6.38	23.4

#91a3cf	#c9f1ec	#8ce7f7	#34b0f4	#4290ac	#ebe049	#f9b308	#e5914e	#f07723	#c94949	#ef2119
3.19	7.45	11.7	14.89	4.26	23.4	14.89	14.89	19.15	7.45	7.45
0	0	0	0	0	0	1.06	2.13	4.26	40.43	56.38
1.06	1.06	0	5.32	0	12.77	19.15	7.45	14.89	22.34	34.04
6.38	11.7	5.32	11.7	10.64	11.7	8.51	4.26	11.7	2.13	4.26
7.45	7.45	1.06	1.06	6.38	1.06	2.13	1.06	1.06	4.26	0
2.13	3.19	1.06	0	2.13	2.13	8.51	11.7	7.45	3.19	3.19
1.06	1.06	2.13	1.06	2.13	1.06	2.13	5.32	2.13	10.64	13.83
29.79	17.02	12.77	12.77	31.91	4.26	6.38	7.45	1.06	5.32	1.06
3.19	0	0	1.06	2.13	0	1.06	1.06	2.13	4.26	6.38
1.06	0	0	1.06	0	4.26	3.19	2.13	3.19	2.13	5.32
5.32	17.02	25.53	23.4	5.32	29.79	24.47	15.96	14.89	2.13	3.19
1.06	0	0	0	0	1.06	3.19	2.13	3.19	9.57	12.77
0	1.06	0	1.06	0	3.19	7.45	2.13	3.19	8.51	11.7
8.51	0	0	0	3.19	0	0	1.06	0	1.06	2.13
7.45	14.89	34.04	32.98	22.34	29.79	27.66	17.02	20.21	7.45	2.13
11.7	13.83	22.34	21.28	19.15	13.83	7.45	15.96	17.02	9.57	3.19
9.57	18.09	34.04	28.72	15.96	48.94	35.11	23.4	17.02	4.26	2.13
6.38	9.57	6.38	1.06	5.32	2.13	2.13	17.02	7.45	11.7	3.19
4.26	3.19	7.45	5.32	5.32	11.7	13.83	8.51	9.57	3.19	4.26
19.15	19.15	19.15	11.7	19.15	2.13	0	4.26	2.13	0	0
15.96	2.13	1.06	4.26	5.32	2.13	1.06	0	1.06	2.13	1.06
42.55	37.23	29.79	26.6	39.36	1.06	3.19	7.45	1.06	1.06	0
1.06	0	0	0	0	2.13	3.19	2.13	1.06	8.51	2.13
2.13	9.57	11.7	14.89	7.45	22.34	15.96	9.57	22.34	7.45	19.15

#40718f	#204c6e	#eee3e8	#a0a1a5	#838586	#6e6c68	#3fad41	#767928	#465838	#424326	#ada8ff
2.13	1.06	9.57	1.06	0	0	12.77	2.13	1.06	1.06	12.77
0	2.13	1.06	0	1.06	3.19	0	0	3.19	5.32	0
1.06	2.13	2.13	3.19	5.32	1.06	6.38	6.38	6.38	4.26	2.13
4.26	1.06	10.64	1.06	1.06	1.06	3.19	0	4.26	2.13	11.7
6.38	10.64	11.7	45.74	52.13	50	1.06	8.51	7.45	8.51	2.13
7.45	2.13	5.32	9.57	10.64	8.51	2.13	6.38	4.26	4.26	5.32
3.19	6.38	0	5.32	2.13	3.19	6.38	10.64	7.45	6.38	2.13
27.66	28.72	14.89	17.02	6.38	7.45	17.02	7.45	15.96	15.96	15.96
9.57	7.45	1.06	12.77	14.89	19.15	4.26	7.45	10.64	17.02	0
0	2.13	2.13	2.13	5.32	3.19	10.64	41.49	23.4	27.66	2.13
2.13	2.13	3.19	0	0	0	12.77	1.06	1.06	1.06	18.09
0	0	2.13	0	2.13	3.19	4.26	9.57	3.19	4.26	1.06
4.26	3.19	0	2.13	5.32	9.57	2.13	6.38	2.13	6.38	0
9.57	12.77	0	12.77	18.09	28.72	3.19	3.19	2.13	12.77	0
8.51	2.13	9.57	2.13	0	0	19.15	3.19	6.38	1.06	14.89
9.57	4.26	7.45	2.13	2.13	3.19	27.66	5.32	9.57	6.38	13.83
4.26	2.13	14.89	0	0	0	17.02	2.13	3.19	0	20.21
8.51	10.64	18.09	15.96	8.51	6.38	7.45	15.96	12.77	14.89	4.26
5.32	4.26	8.51	1.06	0	0	4.26	2.13	1.06	0	7.45
13.83	12.77	11.7	6.38	6.38	2.13	7.45	6.38	7.45	7.45	12.77
28.72	26.6	2.13	18.09	29.79	28.72	0	3.19	4.26	12.77	3.19
34.04	35.11	21.28	13.83	6.38	3.19	11.7	8.51	23.4	8.51	24.47
0	2.13	1.06	8.51	6.38	10.64	5.32	5.32	4.26	12.77	2.13
1.06	0	8.51	1.06	1.06	1.06	11.7	0	2.13	3.19	14.89

#070808	0	12.77	4.26	2.13	9.57	5.32	10.64	3.19	18.09	9.57	1.06	3.19	31.91	51.06	0	4.26	2.13	5.32	0	4.26	35.11	2.13	12.77	1.06
#282a36	1.06	11.7	2.13	0	15.96	5.32	7.45	8.51	14.89	9.57	0	0	26.6	40.43	1.06	3.19	1.06	8.51	2.13	2.13	38.3	3.19	14.89	2.13

Experiment 2. Probabilities of color being interpreted as a particular emotion, obtained by multinomial logistic regression.

	amuseme	anger	annoyanc	awe	boredom	confusion	contempt	contentm	disappoin	disgust	elation	embarrass	fear	grief	happiness	interest	joy	pride	relief	sadness	serenity	shame	surprise
#e23dc2	0.1019	0.0051	0.0303	0.0254	0.0051	0.0508	0.0104	0.0253	0.0001	0.0001	0.0725	0.0150	0.0000	0.0000	0.1167	0.0669	0.1689	0.1165	0.0097	0.0051	0.0105	0.0100	0.1540
#f080f1	0.1118	0.0052	0.0305	0.0559	0.0000	0.0152	0.0000	0.0248	0.0100	0.0051	0.0870	0.0050	0.0000	0.0052	0.1268	0.0660	0.1724	0.0866	0.0410	0.0051	0.0053	0.0000	0.1409
#eda4b3	0.1182	0.0050	0.0146	0.0249	0.0101	0.0049	0.0001	0.0448	0.0099	0.0049	0.0790	0.0538	0.0000	0.0001	0.1232	0.0598	0.2030	0.0844	0.0153	0.0000	0.0596	0.0201	0.0643
#eeb8e0	0.0948	0.0000	0.0105	0.0518	0.0052	0.0101	0.0054	0.0477	0.0000	0.0052	0.0730	0.0148	0.0000	0.0000	0.1623	0.0726	0.1735	0.1262	0.0156	0.0000	0.0582	0.0053	0.0675
#62202b	0.0068	0.1609	0.1169	0.0280	0.0560	0.0210	0.0555	0.0624	0.0479	0.0630	0.0070	0.0353	0.0280	0.0354	0.0202	0.0484	0.0140	0.0621	0.0066	0.0487	0.0207	0.0483	0.0069
#9b1c45	0.0364	0.1009	0.1044	0.0308	0.0122	0.0182	0.0605	0.0300	0.0367	0.0249	0.0244	0.0423	0.0179	0.0184	0.0483	0.1135	0.0671	0.0546	0.0255	0.0239	0.0486	0.0243	0.0363
#ac1011	0.0096	0.3363	0.1749	0.0096	0.0001	0.0001	0.0809	0.0000	0.0145	0.0544	0.0051	0.0304	0.0644	0.0198	0.0244	0.0453	0.0196	0.0201	0.0001	0.0246	0.0052	0.0299	0.0306

#c9f1ec	#8ce7f7	#34b0f4	#4290ac	#ebe049	#f9b308	#e5914e	#f07723	#c94949	#ef2119	#dc2265
0.0399	0.0536	0.0683	0.0212	0.1028	0.0716	0.0891	0.1065	0.0447	0.0376	0.1075
0.0000	0.0000	0.0000	0.0000	0.0000	0.0051	0.0132	0.0224	0.2435	0.2890	0.0384
0.0057	0.0001	0.0241	0.0001	0.0565	0.0923	0.0443	0.0828	0.1331	0.1723	0.0477
0.0634	0.0238	0.0534	0.0522	0.0510	0.0398	0.0262	0.0645	0.0117	0.0220	0.0424
0.0400	0.0048	0.0050	0.0311	0.0047	0.0100	0.0063	0.0059	0.0257	0.0000	0.0000
0.0170	0.0047	0.0001	0.0102	0.0090	0.0406	0.0695	0.0415	0.0184	0.0163	0.0208
0.0060	0.0095	0.0051	0.0110	0.0048	0.0104	0.0317	0.0121	0.0627	0.0700	0.0111
0.0917	0.0586	0.0566	0.1585	0.0190	0.0305	0.0441	0.0060	0.0313	0.0055	0.0212
0.0000	0.0000	0.0050	0.0103	0.0000	0.0051	0.0063	0.0114	0.0253	0.0335	0.0054
0.0000	0.0001	0.0050	0.0000	0.0191	0.0148	0.0126	0.0180	0.0125	0.0277	0.0001
0.0930	0.1174	0.1055	0.0262	0.1286	0.1168	0.0960	0.0835	0.0129	0.0167	0.0649
0.0001	0.0001	0.0001	0.0001	0.0046	0.0148	0.0123	0.0179	0.0569	0.0648	0.0157
0.0058	0.0000	0.0050	0.0000	0.0138	0.0352	0.0123	0.0182	0.0519	0.0601	0.0000
0.0000	0.0000	0.0000	0.0159	0.0000	0.0000	0.0063	0.0000	0.0064	0.0106	0.0054
0.0796	0.1556	0.1513	0.1112	0.1314	0.1321	0.1018	0.1128	0.0443	0.0107	0.1403
0.0745	0.1000	0.0975	0.0951	0.0601	0.0360	0.0955	0.0949	0.0573	0.0159	0.0808
0.0974	0.1571	0.1315	0.0783	0.2146	0.1669	0.1394	0.0951	0.0260	0.0109	0.1577
0.0174	0.0333	0.0243	0.0261	0.0507	0.0660	0.0520	0.0540	0.0190	0.0213	0.0799
0.1041	0.0869	0.0526	0.0958	0.0087	0.0001	0.0257	0.0112	0.0001	0.0001	0.0052
0.0120	0.0048	0.0190	0.0267	0.0099	0.0051	0.0000	0.0060	0.0131	0.0055	0.0000
0.2001	0.1362	0.1216	0.1934	0.0048	0.0151	0.0448	0.0061	0.0066	0.0000	0.0210
0.0000	0.0000	0.0000	0.0000	0.0093	0.0147	0.0129	0.0060	0.0522	0.0109	0.0154
0.0520	0.0531	0.0689	0.0366	0.0966	0.0767	0.0576	0.1233	0.0443	0.0983	0.1190

#204c6e	#eee3e8	#a0a1a5	#838586	#6e6c68	#3fad41	#767928	#465838	#424326	#ada8ff	#91a3cf
0.0063	0.0650	0.0064	0.0000	0.0000	0.0669	0.0141	0.0068	0.0063	0.0686	0.0181
0.0129	0.0072	0.0000	0.0061	0.0171	0.0001	0.0000	0.0199	0.0315	0.0000	0.0000
0.0128	0.0143	0.0197	0.0301	0.0057	0.0335	0.0443	0.0417	0.0251	0.0116	0.0057
0.0044	0.0710	0.0044	0.0040	0.0038	0.0173	0.0008	0.0279	0.0117	0.0626	0.0347
0.0618	0.0789	0.2755	0.2977	0.2662	0.0055	0.0584	0.0489	0.0502	0.0116	0.0409
0.0124	0.0355	0.0577	0.0613	0.0459	0.0109	0.0424	0.0279	0.0252	0.0282	0.0112
0.0369	0.0000	0.0318	0.0122	0.0173	0.0328	0.0720	0.0480	0.0373	0.0119	0.0060
0.1702	0.0996	0.1024	0.0365	0.0402	0.0883	0.0503	0.1037	0.0941	0.0852	0.1616
0.0432	0.0072	0.0783	0.0833	0.1026	0.0219	0.0500	0.0691	0.0997	0.0000	0.0173
0.0125	0.0139	0.0127	0.0301	0.0175	0.0569	0.2830	0.1512	0.1645	0.0114	0.0058
0.0127	0.0220	0.0000	0.0000	0.0000	0.0666	0.0073	0.0070	0.0064	0.0977	0.0284
0.0001	0.0135	0.0001	0.0115	0.0174	0.0228	0.0658	0.0203	0.0256	0.0056	0.0057
0.0184	0.0000	0.0123	0.0304	0.0517	0.0104	0.0434	0.0134	0.0373	0.0000	0.0000
0.0745	0.0000	0.0762	0.1014	0.1547	0.0169	0.0217	0.0138	0.0772	0.0000	0.0467
0.0125	0.0647	0.0128	0.0000	0.0000	0.1005	0.0210	0.0409	0.0063	0.0791	0.0407
0.0249	0.0493	0.0130	0.0119	0.0171	0.1455	0.0360	0.0631	0.0375	0.0733	0.0629
0.0126	0.1001	0.0000	0.0000	0.0000	0.0896	0.0138	0.0210	0.0001	0.1069	0.0521
0.0251	0.0569	0.0064	0.0000	0.0000	0.0231	0.0151	0.0068	0.0000	0.0402	0.0231
0.0748	0.0791	0.0378	0.0365	0.0107	0.0402	0.0444	0.0482	0.0444	0.0684	0.1044
0.1545	0.0148	0.1087	0.1698	0.1529	0.0001	0.0215	0.0274	0.0750	0.0166	0.0868
0.2038	0.1423	0.0845	0.0355	0.0174	0.0611	0.0584	0.1510	0.0505	0.1293	0.2302
0.0127	0.0072	0.0526	0.0353	0.0559	0.0281	0.0363	0.0278	0.0758	0.0117	0.0059
0.0000	0.0573	0.0065	0.0062	0.0059	0.0608	0.0000	0.0144	0.0185	0.0801	0.0117

#070808	#282a36	#40718f
0.0007	0.0049	0.0112
0.0565	0.0549	0.0000
0.0199	0.0090	0.0057
0.0180	0.0006	0.0230
0.0421	0.0757	0.0342
0.0244	0.0248	0.0410
0.0469	0.0351	0.0175
0.0141	0.0397	0.1513
0.0797	0.0695	0.0530
0.0418	0.0449	0.0001
0.0028	0.0000	0.0115
0.0153	0.0000	0.0001
0.1401	0.1256	0.0235
0.2274	0.1947	0.0519
0.0005	0.0049	0.0465
0.0206	0.0152	0.0528
0.0065	0.0048	0.0231
0.0008	0.0097	0.0290
0.0195	0.0091	0.0764
0.1564	0.1824	0.1576
0.0069	0.0152	0.1849
0.0563	0.0701	0.0001
0.0026	0.0092	0.0058

LITERATURE CITED

Amhorst, Mary Lynn D, and J Reed. 1986. “Clothing Color Value and Facial Expression: Effects on Evaluations of Female Job Applicants.” *Social Behavior and Personality: An International Journal* 14, no. 1: 89–98.

Anderson, Cary L, and Anthony C. Robinson. 2021. “Affective Congruence in Visualization Design: Influences on Reading Categorical Maps.” *IEEE Transactions on Visualization and Computer Graphics*, 1–1. https://doi.org/10.1109/TVCG.2021.3050118.

Ankerst, Mihael, Markus M Breunig, Hans-Peter Kriegel, and Jörg Sander. 1999. “OPTICS: Ordering Points to Identify the Clustering Structure.” *ACM Sigmod Record* 28, no. 2: 49–60.

Ashkezari-Toussi, Soheila, Mohammad Kamel, and Hadi Sadoghi-Yazdi. 2019. “Emotional Maps Based on Social Networks Data to Analyze Cities Emotional Structure and Measure Their Emotional Similarity.” *Cities* 86, no. March (March): 113–24. https://doi.org/10.1016/j.cities.2018.09.009.

Barrett, Lisa Feldman. 1998. “Discrete Emotions or Dimensions? The Role of Valence Focus and Arousal Focus.” *Cognition & Emotion* 12, no. 4 (July): 579–99. https://doi.org/10.1080/026999398379574.

———. 2017. *How Emotions Are Made: The Secret Life of the Brain*. Houghton Mifflin Harcourt.

Bartram, Lyn, Abhisekh Patra, and Maureen Stone. 2017. “Affective Color in Visualization.” In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, 1364–74. Denver Colorado USA: ACM. https://doi.org/10.1145/3025453.3026041.

Bergner, BS, and P Zeile. 2012. “Ist Barrierefreiheit Messbar?” *Planerin*, no. 3.

Bertin, Jacques. 1983. *Semiology of Graphics*. University of Wisconsin Press.

Bleisch, Susanne, and Daria Hollenstein. 2018. “Exploratory Geovisualizations for Supporting the Qualitative Analysis and Synthesis of Place-Related Emotion Data.” *Cartographic Perspectives*, no. 91: 30-46-30–46. https://doi.org/10.14714/CP91.1437.

Borkin, M., K. Gajos, A. Peters, D. Mitsouras, S. Melchionna, F. Rybicki, C. Feldman, and H. Pfister. 2011. “Evaluation of Artery Visualizations for Heart Disease Diagnosis.” *IEEE Transactions on Visualization and Computer Graphics* 17, no. 12 (December): 2479–88. https://doi.org/10.1109/TVCG.2011.192.

Borland, David, and Russell M. Taylor Ii. 2007. “Rainbow Color Map (Still) Considered Harmful.” *IEEE Computer Graphics and Applications* 27, no. 2 (March): 14–17. https://doi.org/10.1109/MCG.2007.323435.

Boronine, Alexei. 2022. “HSLuv - Human-Friendly HSL.” HSLuv - Human-Friendly HSL. 2022. https://www.hsluv.org/.

Bostan, Laura-Ana-Maria, and Roman Klinger. 2018. "An Analysis of Annotated Corpora for Emotion Classification in Text." In *Proceedings of the 27th International Conference on Computational Linguistics*, 2104–19. Santa Fe, New Mexico, USA: Association for Computational Linguistics. https://aclanthology.org/C18-1179.

Brainard, David H. 2003. "Color Appearance and Color Difference Specification." *The Science of Color* 2, no. 191–216: 5.

Brewer, Cynthia A. 1994. "Guidelines for Use of the Perceptual Dimensions of Color for Mapping and Visualization." In , 2171:54–63. International Society for Optics and Photonics.

Brewer, Cynthia A. 1996. "Guidelines for Selecting Colors for Diverging Schemes on Maps." *The Cartographic Journal* 33, no. 2 (December): 79–86. https://doi.org/10.1179/caj.1996.33.2.79.

Brewer, Cynthia A., Geoffrey W. Hatchard, and Mark A. Harrower. 2003. "ColorBrewer in Print: A Catalog of Color Schemes for Maps." *Cartography and Geographic Information Science* 30, no. 1 (January): 5–32. https://doi.org/10.1559/152304003100010929.

Brewer, Cynthia A., Alan M. MacEachren, Linda W. Pickle, and Douglas Herrmann. 1997. "Mapping Mortality: Evaluating Color Schemes for Choropleth Maps." *Annals of the Association of American Geographers* 87, no. 3 (September): 411–38. https://doi.org/10.1111/1467-8306.00061.

Brown, Brené. 2021. *Atlas of the Heart: Mapping Meaningful Connection and the Language of Human Experience*. Random House.

Cabanac, Michel. 2002. "What Is Emotion?" *Behavioural Processes* 60, no. 2 (November): 69–83. https://doi.org/10.1016/S0376-6357(02)00078-5.

"Cambridge English Dictionary: Meanings & Definitions." n.d. Accessed June 16, 2022. https://dictionary.cambridge.org/dictionary/english/.

Caquard, Sébastien, and William Cartwright. 2014. "Narrative Cartography: From Mapping Stories to the Narrative of Maps and Mapping." *The Cartographic Journal* 51, no. 2 (May): 101–6. https://doi.org/10.1179/0008704114Z.000000000130.

Caquard, Sébastien, and Amy Griffin. 2018. "Mapping Emotional Cartography." *Cartographic Perspectives*, no. 91: 4-16-4–16. https://doi.org/10.14714/CP91.1551.

Caragea, Cornelia, Anna Cinzia Squicciarini, Sam Stehle, Kishore Neppalli, and Andrea H Tapia. 2014. "Mapping Moods: Geo-Mapped Sentiment Analysis during Hurricane Sandy." In . Citeseer.

Christen, Markus, Peter Brugger, and Sara Irina Fabrikant. 2021. "Susceptibility of Domain Experts to Color Manipulation Indicate a Need for Design Principles in Data Visualization." *PLOS ONE* 16, no. 2 (February): e0246479. https://doi.org/10.1371/journal.pone.0246479.

Cohen, Jacob. 1988. "Statistical Power Analysis for the Behavioral Sciences." 0805802835.

———. 1992. "Statistical Power Analysis." *Current Directions in Psychological Science* 1, no. 3 (June): 98–101. https://doi.org/10.1111/1467-8721.ep10768783.

Coppin, Géraldine, and David Sander. 2016a. "1 - Theoretical Approaches to Emotion and Its Measurement." In *Emotion Measurement*, edited by Herbert L. Meiselman, 3–30. Woodhead Publishing. https://doi.org/10.1016/B978-0-08-100508-8.00001-1.

———. 2016b. "Theoretical Approaches to Emotion and Its Measurement." In *Emotion Measurement*, edited by Herbert L. Meiselman, 3–30. Woodhead Publishing. https://doi.org/10.1016/B978-0-08-100508-8.00001-1.

Cowen, Alan S, Hillary Anger Elfenbein, Petri Laukka, and Dacher Keltner. 2019. "Mapping 24 Emotions Conveyed by Brief Human Vocalization." *American Psychologist* 74, no. 6: 698.

Cowen, Alan S., and Dacher Keltner. 2017. "Self-Report Captures 27 Distinct Categories of Emotion Bridged by Continuous Gradients." *Proceedings of the National Academy of Sciences* 114, no. 38 (September): E7900–7909. https://doi.org/10.1073/pnas.1702247114.

———. 2020. "What the Face Displays: Mapping 28 Emotions Conveyed by Naturalistic Expression." *American Psychologist* 75, no. 3: 349–64. https://doi.org/10.1037/amp0000488.

———. 2021. "Semantic Space Theory: A Computational Approach to Emotion." *Trends in Cognitive Sciences* 25, no. 2 (February): 124–36. https://doi.org/10.1016/j.tics.2020.11.004.

Cowen, Alan S., Dacher Keltner, Florian Schroff, Brendan Jou, Hartwig Adam, and Gautam Prasad. 2021. "Sixteen Facial Expressions Occur in Similar Contexts Worldwide." *Nature* 589, no. 7841 (January): 251–57. https://doi.org/10.1038/s41586-020-3037-7.

Cowen, Alan, Disa Sauter, Jessica L Tracy, and Dacher Keltner. 2019. "Mapping the Passions: Toward a High-Dimensional Taxonomy of Emotional Experience and Expression." *Psychological Science in the Public Interest* 20, no. 1: 69–90.

Cresswell, Tim. 2008. "Place: Encountering Geography as Philosophy." *Geography* 93, no. 3: 132–39.

Curtis, Jacqueline W, Ellen Shiau, Bryce Lowery, David Sloane, Karen Hennigan, and Andrew Curtis. 2014. "The Prospects and Problems of Integrating Sketch Maps with Geographic Information Systems to Understand Environmental Perception: A Case Study of Mapping Youth Fear in Los Angeles Gang Neighborhoods." *Environment and Planning B: Planning and Design* 41, no. 2 (April): 251–71. https://doi.org/10.1068/b38151.

Cyr, Dianne, Milena Head, and Hector Larios. 2010. "Colour Appeal in Website Design within and across Cultures: A Multi-Method Evaluation." *International Journal of Human-Computer Studies* 68, no. 1–2 (January): 1–21. https://doi.org/10.1016/j.ijhcs.2009.08.005.

D'andrade, R., and M. Egan. 1974. "The Colors of Emotion1." *American Ethnologist* 1, no. 1: 49–63. https://doi.org/10.1525/ae.1974.1.1.02a00030.

Dean, Angela, Daniel Voss, and Danel Draguljic. 2017. *Design and Analysis of Experiments*. 2nd ed. Springer Texts in Statistics. Springer International Publishing. https://doi.org/10.1007/978-3-319-52250-0.

Demir, Ümit. 2020. "Investigation of Color-Emotion Associations of the University Students." *Color Research & Application* 45, no. 5: 871–84. https://doi.org/10.1002/col.22522.

Demszky, Dorottya, Dana Movshovitz-Attias, Jeongwoo Ko, Alan Cowen, Gaurav Nemade, and Sujith Ravi. 2020. "GoEmotions: A Dataset of Fine-Grained Emotions." In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, 4040–54. Online: Association for Computational Linguistics. https://doi.org/10.18653/v1/2020.acl-main.372.

Dent, Borden, J Torguson, and T Hodler. 2008. *Thematic Map Design*. McGraw-Hill New York, New York, NY.

Duan, Lian, Lida Xu, Feng Guo, Jun Lee, and Baopin Yan. 2007. "A Local-Density Based Spatial Clustering Algorithm with Noise." *Information Systems*, Special Issue on Intelligent Information Processing, 32, no. 7 (November): 978–86. https://doi.org/10.1016/j.is.2006.10.006.

Ekman, Gosta, Ralf Lindman, and William William-Olsson. 1961. "A Psychophysical Study of Cartographic Symbols." *Perceptual and Motor Skills* 13, no. 3: 355–68.

Ekman, Paul, and Wallace V Friesen. 1971. "Constants across Cultures in the Face and Emotion." *Journal of Personality and Social Psychology* 17, no. 2: 124.

———. 1986. "A New Pan-Cultural Facial Expression of Emotion." *Motivation and Emotion* 10, no. 2: 159–68.

Elliot, Andrew J., and Markus A. Maier. 2012. "Chapter Two - Color-in-Context Theory." In *Advances in Experimental Social Psychology*, edited by Patricia Devine and Ashby Plant, 45:61–125. Academic Press. https://doi.org/10.1016/B978-0-12-394286-9.00002-0.

———. 2014. "Color Psychology: Effects of Perceiving Color on Psychological Functioning in Humans." *Annual Review of Psychology* 65, no. 1: 95–120. https://doi.org/10.1146/annurev-psych-010213-115035.

Elliot, Andrew J., Markus A. Maier, Arlen C. Moller, Ron Friedman, and Jörg Meinhardt. 2007. "Color and Psychological Functioning: The Effect of Red on Performance Attainment." *Journal of Experimental Psychology: General* 136, no. 1: 154–68. https://doi.org/10.1037/0096-3445.136.1.154.

Ester, Martin, Hans-Peter Kriegel, Jörg Sander, and Xiaowei Xu. 1996. "A Density-Based Algorithm for Discovering Clusters in Large Spatial Databases with Noise." In *kdd*, 96:226–31.

Fathullah, Afif, and Katharine Willis. 2018. "Engaging the Senses: The Potential of Emotional Data for Participation in Urban Planning." *Urban Science* 2, no. 4 (September): 98. https://doi.org/10.3390/urbansci2040098.

Faul, Franz, Edgar Erdfelder, Albert-Georg Lang, and Axel Buchner. 2007. "G*Power 3: A Flexible Statistical Power Analysis Program for the Social, Behavioral, and Biomedical Sciences." *Behavior Research Methods* 39, no. 2 (May): 175–91. https://doi.org/10.3758/BF03193146.

Fontaine, Johnny R.J., Klaus R. Scherer, Etienne B. Roesch, and Phoebe C. Ellsworth. 2007. "The World of Emotions Is Not Two-Dimensional." *Psychological Science* 18, no. 12 (December): 1050–57. https://doi.org/10.1111/j.1467-9280.2007.02024.x.

Fuest, Stefan, Susanne Grüner, Mark Vollrath, and Monika Sester. 2021. "Evaluating the Effectiveness of Different Cartographic Design Variants for Influencing Route Choice." *Cartography and Geographic Information Science* 48, no. 2 (March): 169–85. https://doi.org/10.1080/15230406.2020.1855251.

Fugate, Jennifer Marie Binzak, and Courtny L Franco. 2019. "What Color Is Your Anger? Assessing Color-Emotion Pairings in English Speakers." *Frontiers in Psychology* 10: 206.

Gartner, Georg. 2012. "Putting Emotions in Maps–The Wayfinding Example." *New Zealand: New Zealand Cartographic Society*, 61–65.

Gerrig, Richard J., and Philip G. Zimbardo. 2008. *Psychology and Life*. Eighteenth edition. Boston, Mass: Pearson Education / Allyn and Bacon.

Gilbert, Avery N, Alan J Fridlund, and Laurie A Lucchina. 2016. "The Color of Emotion: A Metric for Implicit Color Associations." *Food Quality and Preference* 52: 203–10.

Gobron, Stephane, Junghyun Ahn, Georgios Paltoglou, Michael Thelwall, and Daniel Thalmann. 2010. "From Sentence to Emotion: A Real-Time Three-Dimensional Graphics Metaphor of Emotions Extracted from Text." *The Visual Computer* 26, no. 6–8 (June): 505–19. https://doi.org/10.1007/s00371-010-0446-x.

Goodhew, Stephanie C., and Evan Kidd. 2020. "Bliss Is Blue and Bleak Is Grey: Abstract Word-Colour Associations Influence Objective Performance Even When Not Task Relevant." *Acta Psychologica* 206, no. May (May): 103067. https://doi.org/10.1016/j.actpsy.2020.103067.

Gramazio, Connor C., David H. Laidlaw, and Karen B. Schloss. 2017. "Colorgorical: Creating Discriminable and Preferable Color Palettes for Information Visualization." *IEEE Transactions on Visualization and Computer Graphics* 23, no. 1 (January): 521–30. https://doi.org/10.1109/TVCG.2016.2598918.

Gramazio, Connor C, Karen B Schloss, and David H Laidlaw. 2014. "The Relation between Visualization Size, Grouping, and User Performance." *IEEE Transactions on Visualization and Computer Graphics* 20, no. 12: 1953–62.

Graybill, Jessica K. 2013. "Mapping an Emotional Topography of an Ecological Homeland: The Case of Sakhalin Island, Russia." *Emotion, Space and Society* 8, no. August (August): 39–50. https://doi.org/10.1016/j.emospa.2012.09.005.

Griffin, Amy L, and Julia McQuoid. 2012. "At the Intersection of Maps and Emotion: The Challenge of Spatially Representing Experience." *Kartographische Nachrichten* 62, no. 6: 291–99.

Griffin, Amy L., Travis White, Carolyn Fish, Beate Tomio, Haosheng Huang, Claudia Robbi Sluter, João Vitor Meza Bravo, et al. 2017. "Designing across Map Use Contexts: A Research Agenda." *International Journal of Cartography* 3, no. sup1 (October): 90–114. https://doi.org/10.1080/23729333.2017.1315988.

Gupta, Neeraja, Luca Rigotti, and Alistair Wilson. 2021. "The Experimenters' Dilemma: Inferential Preferences over Populations." *ArXiv:2107.05064 [Econ, q-Fin]*, July (July). http://arxiv.org/abs/2107.05064.

Guthier, Benjamin, Rajwa Alharthi, Rana Abaalkhail, and Abdulmotaleb El Saddik. 2014. "Detection and Visualization of Emotions in an Affect-Aware City." In *Proceedings of the 1st International Workshop on Emerging Multimedia Applications and Services for Smart Cities - EMASC '14*, 23–28. Orlando, Florida, USA: ACM Press. https://doi.org/10.1145/2661704.2661708.

Hamann, Stephan. 2012. "Mapping Discrete and Dimensional Emotions onto the Brain: Controversies and Consensus." *Trends in Cognitive Sciences* 16, no. 9 (September): 458–66. https://doi.org/10.1016/j.tics.2012.07.006.

Hanada, Mitsuhiko. 2018. "Correspondence Analysis of Color–Emotion Associations." *Color Research & Application* 43, no. 2: 224–37. https://doi.org/10.1002/col.22171.

Hao, Ming C, Christian Rohrdantz, Halldor Janetzko, Daniel A Keim, Umeshwar Dayal, Lars erik Haug, Meichun Hsu, and Florian Stoffel. 2013. "Visual Sentiment Analysis of Customer Feedback Streams Using Geo-Temporal Term Associations." *Information Visualization* 12, no. 3–4 (July): 273–90. https://doi.org/10.1177/1473871613481691.

Harley, J Brian. 1988. "Silences and Secrecy: The Hidden Agenda of Cartography in Early Modern Europe." *Imago Mundi* 40, no. 1: 57–76.

Harmon-Jones, Eddie, Cindy Harmon-Jones, and Elizabeth Summerell. 2017. "On the Importance of Both Dimensional and Discrete Models of Emotion." *Behavioral Sciences* 7, no. 4: 66.

Harrower, Mark, and Cynthia A. Brewer. 2003. "ColorBrewer.Org: An Online Tool for Selecting Colour Schemes for Maps." *The Cartographic Journal* 40, no. 1 (June): 27–37. https://doi.org/10.1179/000870403235002042.

Hart, Sandra G, and Moffett Field. 2006. "NASA-Task Load Index (NASA-TLX); 20 Years Later." In In *Proceedings of the human factors and ergonomics society annual meeting*, 50:904–8. Sage publications Sage CA: Los Angeles, CA.

Hart, Sandra G, and Lowell E Staveland. 1988. "Development of NASA-TLX (Task Load Index): Results of Empirical and Theoretical Research." In *Advances in Psychology*, 52:139–83. Elsevier.

Hart, Sandra G, and Christopher D Wickens. 1990. "Workload Assessment and Prediction." In *Manprint*, 257–96. Springer.

Hauthal, Eva, and Dirk Burghardt. 2013. "Extraction of Location-Based Emotions from Photo Platforms." In *Progress in Location-Based Services*, edited by Jukka M. Krisp, 3–28. Lecture Notes in Geoinformation and Cartography. Berlin, Heidelberg: Springer. https://doi.org/10.1007/978-3-642-34203-5_1.

Heer, Jeffrey, and Michael Bostock. 2010. "Crowdsourcing Graphical Perception: Using Mechanical Turk to Assess Visualization Design," 10.

Hemphill, Michael. 1996. "A Note on Adults' Color–Emotion Associations." *The Journal of Genetic Psychology* 157, no. 3: 275–80.

Hill, Russell A., and Robert A. Barton. 2005. "Red Enhances Human Performance in Contests." *Nature* 435, no. 7040 (May): 293–293. https://doi.org/10.1038/435293a.

Höffken, Stefan, Johann Wilhelm, Dennis Groß, Benjamin S Bergner, and Peter Zeile. 2014. "EmoCycling–Analysen von Radwegen Mittels Humansensorik Und Wearable Computing." In *REAL CORP 2014–PLAN IT SMART! Clever Solutions for Smart Cities. Proceedings of 19th International Conference on Urban Planning, Regional Development and Information Society*, 851–60. CORP–Competence Center of Urban and Regional Planning.

Huang, H., G. Gartner, S. Klettner, and M. Schmidt. 2014. "Considering Affective Responses towards Environments for Enhancing Location Based Services." *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences* XL–4, no. April (April): 93–96. https://doi.org/10.5194/isprsarchives-XL-4-93-2014.

Hulland, John, and Jeff Miller. 2018. ""Keep on Turkin'"?" *Journal of the Academy of Marketing Science* 46, no. 5 (September): 789–94. https://doi.org/10.1007/s11747-018-0587-4.

Jacobs, Laurence, Charles Keown, Reginald Worthley, and Kyung-Il Ghymn. 1991. "Cross-cultural Colour Comparisons: Global Marketers Beware!" *International Marketing Review* 8, no. 3 (January). https://doi.org/10.1108/02651339110137279.

Jain, Anil K. 2010. "Data Clustering: 50 Years beyond K-Means." *Pattern Recognition Letters*, Award winning papers from the 19th International Conference on Pattern Recognition (ICPR), 31, no. 8 (June): 651–66. https://doi.org/10.1016/j.patrec.2009.09.011.

James, William. 1884. “What Is Emotion?” *Mind* os-IX, no. 34 (April): 188–205. https://doi.org/10.1093/mind/os-IX.34.188.

Jonauskaite, Domicele, Ahmad Abu-Akel, Nele Dael, Daniel Oberfeld, Ahmed M Abdel-Khalek, Abdulrahman S Al-Rasheed, Jean-Philippe Antonietti, Victoria Bogushevskaya, Amer Chamseddine, and Eka Chkonia. 2020. “Universal Patterns in Color-Emotion Associations Are Further Shaped by Linguistic and Geographic Proximity.” *Psychological Science* 31, no. 10: 1245–60.

Kang, Yuhao, Qingyuan Jia, Song Gao, Xiaohuan Zeng, Yueyao Wang, Stephan Angsuesser, Yu Liu, Xinyue Ye, and Teng Fei. 2019. “Extracting Human Emotions at Different Places Based on Facial Expressions and Spatial Clustering Analysis.” *Transactions in GIS* 23, no. 3 (June): 450–80. https://doi.org/10.1111/tgis.12552.

Kaya, Naz, and Helen H Epps. 2004. “Relationship between Color and Emotion: A Study of College Students.” *College Student Journal* 38, no. 3: 396–405.

Keltner, Dacher, Jessica Tracy, Disa A Sauter, Daniel C Cordaro, and Galen McNeil. 2016. “Expression of Emotion.” *Handbook of Emotions* 4: 236–49.

Kim, Jeongmi (Jamie), and Daniel R. Fesenmaier. 2015. “Measuring Emotions in Real Time: Implications for Tourism Experience Design.” *Journal of Travel Research* 54, no. 4 (July): 419–29. https://doi.org/10.1177/0047287514550100.

Kinoshita, Sachiko, Luke Mills, and Dennis Norris. 2018. “The Semantic Stroop Effect Is Controlled by Endogenous Attention.” *Journal of Experimental Psychology. Learning, Memory, and Cognition* 44, no. 11 (November): 1730–42. https://doi.org/10.1037/xlm0000552.

Klettner, Silvia. 2020. “Form Follows Content: An Empirical Study on Symbol-Content (In) Congruences in Thematic Maps.” *ISPRS International Journal of Geo-Information* 9, no. 12: 719.

Klettner, Silvia, and Georg Gartner. 2012. *Modelling Affective Responses to Space*. na.

Kliger, Doron, and Dalia Gilad. 2012. “Red Light, Green Light: Color Priming in Financial Decisions.” *The Journal of Socio-Economics* 41, no. 5 (October): 738–45. https://doi.org/10.1016/j.socec.2012.07.003.

Kragel, Philip A., Marianne C. Reddan, Kevin S. LaBar, and Tor D. Wager. 2019. “Emotion Schemas Are Embedded in the Human Visual System.” *Science Advances* 5, no. 7 (July): eaaw4358. https://doi.org/10.1126/sciadv.aaw4358.

Kramer, Oliver. 2016. “Scikit-Learn.” In *Machine Learning for Evolution Strategies*, 45–53. Springer.

Kuhn, Harold W. 1955. “The Hungarian Method for the Assignment Problem.” *Naval Research Logistics Quarterly* 2, no. 1-2: 83–97.

Kwan, Mei-Po. 2007. “Affecting Geospatial Technologies: Toward a Feminist Politics of Emotion*.” *The Professional Geographer* 59, no. 1 (February): 22–34. https://doi.org/10.1111/j.1467-9272.2007.00588.x.

Lambert, Nicolas, and Christine Zanin. 2020. *Practical Handbook of Thematic Cartography: Principles, Methods, and Applications*. CRC Press.

Lee, Sungkil, Mike Sips, and Hans-Peter Seidel. 2013. "Perceptually Driven Visibility Optimization for Categorical Data Visualization." *IEEE Transactions on Visualization and Computer Graphics* 19, no. 10 (October): 1746–57. https://doi.org/10.1109/TVCG.2012.315.

Lin, Sharon, Julie Fortuna, Chinmay Kulkarni, Maureen Stone, and Jeffrey Heer. 2013. "Selecting Semantically-Resonant Colors for Data Visualization." *Computer Graphics Forum* 32, no. 3pt4: 401–10. https://doi.org/10.1111/cgf.12127.

Liu, Qiliang, Min Deng, Yan Shi, and Jiaqiu Wang. 2012. "A Density-Based Spatial Clustering Algorithm Considering Both Spatial Proximity and Attribute Similarity." *Computers & Geosciences* 46, no. September (September): 296–309. https://doi.org/10.1016/j.cageo.2011.12.017.

Loughin, Thomas M, and Peter N Scherer. 1998. "Testing for Association in Contingency Tables with Multiple Column Responses." *Biometrics*, 630–37.

Lu, Yafeng, Xia Hu, Feng Wang, Shamanth Kumar, Huan Liu, and Ross Maciejewski. 2015. "Visualizing Social Media Sentiment in Disaster Scenarios." In *Proceedings of the 24th International Conference on World Wide Web*, 1211–15. Florence Italy: ACM. https://doi.org/10.1145/2740908.2741720.

Luo, M Ronnier, Guihua Cui, and Bryan Rigg. 2001. "The Development of the CIE 2000 Colour-difference Formula: CIEDE2000." *Color Research & Application: Endorsed by Inter-Society Color Council, The Colour Group (Great Britain), Canadian Society for Color, Color Science Association of Japan, Dutch Society for the Study of Color, The Swedish Colour Centre Foundation, Colour Society of Australia, Centre Français de La Couleur* 26, no. 5: 340–50.

Lutabingwa, J, and CJ Auriacombe. 2007. "Data Analysis in Quantitative Research." *Journal of Public Administration* 42, no. 6: 528–48.

MacDonald, Lindsay W. 1999. "Using Color Effectively in Computer Graphics." *IEEE Computer Graphics and Applications* 19, no. 4: 20–35.

MacEachern, AM. 1995. "How Maps Work: Representation, Visualization and Design." In *How Maps Work: Representation, Visualization and Design*. Guilford Press, NY, distributed by Longman outside N. America.

MacLeod, Colin M. 1991. "Half a Century of Research on the Stroop Effect: An Integrative Review." *Psychological Bulletin* 109, no. 2: 163.

Maddrell, Avril. 2016. "Mapping Grief. A Conceptual Framework for Understanding the Spatial Dimensions of Bereavement, Mourning and Remembrance." *Social & Cultural Geography* 17, no. 2 (February): 166–88. https://doi.org/10.1080/14649365.2015.1075579.

Mahieu, Benjamin, Pascal Schlich, Michel Visalli, and Hervé Cardot. 2021. "A Multiple-Response Chi-Square Framework for the Analysis of Free-Comment and Check-All-That-Apply Data." *Food Quality and Preference* 93: 104256.

Marey, Hatem M, Noura A Semary, and Sameh S Mandour. 2015. "Ishihara Electronic Color Blindness Test: An Evaluation Study." *Ophthalmology Research: An International Journal*, 67–75.

Matei, SORIN, Sandra J. Ball-Rokeach, and Jack Linchuan Qiu. 2001. "Fear and Misperception of Los Angeles Urban Space: A Spatial-Statistical Study of Communication-Shaped Mental Maps." *Communication Research* 28, no. 4 (August): 429–63. https://doi.org/10.1177/009365001028004004.

"Medieval Fantasy City Generator by Watabou." 2022. Itch.Io. 2022. https://watabou.itch.io/medieval-fantasy-city-generator.

Mehta, Ravi, and Rui Juliet Zhu. 2009. "Blue or Red? Exploring the Effect of Color on Cognitive Task Performances." *Science* 323, no. 5918: 1226–29.

Miller, Sarah. 2001. "Workload Measures." *National Advanced Driving Simulator. Iowa City, United States*.

Misue, Kazuo, and Kiyohisa Taguchi. 2015. "Development of Emotion-Weather Maps." *Procedia Computer Science* 60: 292–301.

Mitchell, Lewis, Morgan R. Frank, Kameron Decker Harris, Peter Sheridan Dodds, and Christopher M. Danforth. 2013. "The Geography of Happiness: Connecting Twitter Sentiment and Expression, Demographics, and Objective Characteristics of Place." Edited by Angel Sánchez. *PLoS ONE* 8, no. 5 (May): e64417. https://doi.org/10.1371/journal.pone.0064417.

Mitchell, Stuart, Michael OSullivan, and Iain Dunning. 2011. "PuLP: A Linear Programming Toolkit for Python." *The University of Auckland, Auckland, New Zealand* 65.

Mody, Ruturaj N., Katharine S. Willis, and Roland Kerstein. 2009. "WiMo: Location-Based Emotion Tagging." In *Proceedings of the 8th International Conference on Mobile and Ubiquitous Multimedia - MUM '09*, 1–4. Cambridge, United Kingdom: ACM Press. https://doi.org/10.1145/1658550.1658564.

Mohammad, Saif M. 2013. "Even the Abstract Have Colour: Consensus in Word-Colour Associations." *ArXiv:1309.5391 [Cs]*, September (September). http://arxiv.org/abs/1309.5391.

Mohammad, Saif M. 2016. "Sentiment Analysis: Detecting Valence, Emotions, and Other Affectual States from Text." In *Emotion Measurement*, 201–37. Elsevier.

Mokrzycki, Wojciech, and Maciej Tatol. 2011. "Color Difference Delta E - A Survey." *Machine Graphics and Vision* 20, no. April (April): 383–411.

Moller, Arlen C., Andrew J. Elliot, and Markus A. Maier. 2009. "Basic Hue-Meaning Associations." *Emotion*, 898–902.

Muehlenhaus, Ian. 2012. "If Looks Could Kill: The Impact of Different Rhetorical Styles on Persuasive Geocommunication." *The Cartographic Journal* 49, no. 4 (November): 361–75. https://doi.org/10.1179/1743277412Y.0000000032.

Munzner, Tamara. 2014. “Map Color and Other Channels.” In *Visualization Analysis and Design*, 218–42. CRC press.

Naor-Raz, Galit, Michael J Tarr, and Daniel Kersten. 2003. “Is Color an Intrinsic Property of Object Representation?” *Perception* 32, no. 6 (June): 667–80. https://doi.org/10.1068/p5050.

Nguyen, Vu Dung, Blesson Varghese, and Adam Barker. 2013. “The Royal Birth of 2013: Analysing and Visualising Public Sentiment in the UK Using Twitter.” In *2013 IEEE International Conference on Big Data*, 46–54. https://doi.org/10.1109/BigData.2013.6691669.

Nijdam, Niels A. 2009. “Mapping Emotion to Color.” *Book Mapping Emotion to Color*, 2–9.

Nold, Christian. 2009. *Emotional Cartography: Technologies of the Self*. Place of publication not identified .: publisher not identified.

Olsen, Chris, and DMM St George. 2004. “Cross-Sectional Study Design and Data Analysis.” *College Entrance Examination Board* 26, no. 03: 2006.

Or, Calvin Kalun, and Hailiang Wang. 2014. “Color-Concept Associations: A Cross-Occupational and -Cultural Study and Comparison.” *Color Research & Application* 39, no. December (December). https://doi.org/10.1002/col.21832.

Ortony, Andrew, and Terence J Turner. 1990. “What’s Basic about Basic Emotions?” *Psychological Review* 97, no. 3: 315.

Ou, Li-Chen, M. Ronnier Luo, Andrée Woodcock, and Angela Wright. 2004. “A Study of Colour Emotion and Colour Preference. Part I: Colour Emotions for Single Colours.” *Color Research & Application* 29, no. 3: 232–40. https://doi.org/10.1002/col.20010.

Ou, Li-Chen, Yinqiu Yuan, Tetsuya Sato, Wen-Yuan Lee, Ferenc Szabó, Suchitra Sueeprasan, and Rafael Huertas. 2018. “Universal Models of Colour Emotion and Colour Harmony.” *Color Research & Application* 43, no. 5: 736–48. https://doi.org/10.1002/col.22243.

Padilla, Lace M., Sarah H. Creem-Regehr, Mary Hegarty, and Jeanine K. Stefanucci. 2018. “Decision Making with Visualizations: A Cognitive Framework across Disciplines.” *Cognitive Research: Principles and Implications* 3, no. 1 (July): 29. https://doi.org/10.1186/s41235-018-0120-9.

Palmer, S. E., and K. B. Schloss. 2010. “An Ecological Valence Theory of Human Color Preference.” *Proceedings of the National Academy of Sciences* 107, no. 19 (May): 8877–82. https://doi.org/10.1073/pnas.0906172107.

Pánek, Jiři. 2018. “Emotional Maps: Participatory Crowdsourcing of Citizens´ Perceptions of Their Urban Environment.” *Cartographic Perspectives*, no. 91 (May): 17-29-17–29. https://doi.org/10.14714/CP91.1419.

Pánek, Jiří, and Karl Benediktsson. 2017. “Emotional Mapping and Its Participatory Potential: Opinions about Cycling Conditions in Reykjavík, Iceland.” *Cities* 61, no. January (January): 65–73. https://doi.org/10.1016/j.cities.2016.11.005.

Pánek, Jiří, Vít Pászto, and Lukáš Marek. 2017. “Mapping Emotions: Spatial Distribution of Safety Perception in the City of Olomouc.” In *The Rise of Big Spatial Data*, edited by Igor Ivan, Alex Singleton, Jiří Horák, and Tomáš Inspektor, 211–24. Lecture Notes in Geoinformation and Cartography. Cham: Springer International Publishing. https://doi.org/10.1007/978-3-319-45123-7_16.

Pearce, Margaret Wickens. 2008. “Framing the Days: Place and Narrative in Cartography.” *Cartography and Geographic Information Science* 35, no. 1 (January): 17–32. https://doi.org/10.1559/152304008783475661.

Peer, Eyal, David M Rothschild, Zak Evernden, Andrew Gordon, and Ekaterina Damer. 2021a. “MTurk, Prolific or Panels? Choosing the Right Audience for Online Research.” *Choosing the Right Audience for Online Research (January 10, 2021)*.

Peer, Eyal, David M. Rothschild, Zak Evernden, Andrew Gordon, and Ekaterina Damer. 2021b. “Data Quality of Platforms and Panels for Online Behavioral Research,” January (January). https://doi.org/10.2139/ssrn.3765448.

Peirce, Charles Sanders. 1991. *Peirce on Signs: Writings on Semiotic*. UNC Press Books.

Peterson, Gretchen. 2020. *GIS Cartography: A Guide to Effective Map Design*. CRC Press.

Plutchik, Robert. 2001. “The Nature of Emotions: Human Emotions Have Deep Evolutionary Roots, a Fact That May Explain Their Complexity and Provide Tools for Clinical Practice.” *American Scientist* 89, no. 4: 344–50.

Rathore, Ragini, Zachary Leggon, Laurent Lessard, and Karen B. Schloss. 2020. “Estimating Color-Concept Associations from Image Statistics.” *IEEE Transactions on Visualization and Computer Graphics* 26, no. 1 (January): 1226–35. https://doi.org/10.1109/TVCG.2019.2934536.

Resch, Bernd, Anja Summa, Günther Sagl, Peter Zeile, and Jan-Philipp Exner. 2015. “Urban Emotions—Geo-Semantic Emotion Extraction from Technical Sensors, Human Sensors and Crowdsourced Data.” In *Progress in Location-Based Services 2014*, edited by Georg Gartner and Haosheng Huang, 199–212. Lecture Notes in Geoinformation and Cartography. Cham: Springer International Publishing. https://doi.org/10.1007/978-3-319-11879-6_14.

Rod, Jan Ketil. 2001. “How The Monosemic Graphics Go Polysemic.” *Cartographic Perspectives*, no. 38: 7–18.

Rogowitz, B.E., and L.A. Treinish. 1998. “Data Visualization: The End of the Rainbow.” *IEEE Spectrum* 35, no. 12 (December): 52–59. https://doi.org/10.1109/6.736450.

Rogowitz, Bernice E., Lloyd A. Treinish, and Steve Bryson. 1996. “How Not to Lie with Visualization.” *Computers in Physics* 10, no. 3: 268. https://doi.org/10.1063/1.4822401.

Sacharin, Vera, Katja Schlegel, and Klaus R Scherer. 2012. “Geneva Emotion Wheel Rating Study.”

Samsel, Francesca, Terece L Turton, Phillip Wolfram, and Roxana Bujack. 2017. “Intuitive Colormaps for Environmental Visualization.” In , 55–59.

Sander, D. 2013. "Models of Emotion: The Affective Neuroscience Approach." *The Cambridge Handbook of Human Affective Neuroscience*, 5–53.

Schanda, János. 2007. *Colorimetry: Understanding the CIE System*. John Wiley & Sons.

Scherer, Klaus R. 2005. "What Are Emotions? And How Can They Be Measured?" *Social Science Information* 44, no. 4 (December): 695–729. https://doi.org/10.1177/0539018405058216.

Scherer, Klaus R, Vera Shuman, Johnny Fontaine, and Cristina Soriano. 2013. "The GRID Meets the Wheel: Assessing Emotional Feeling via Self-Report." *Components of Emotional Meaning: A Sourcebook*.

Schloss, Karen B., Connor C. Gramazio, Allison T. Silverman, Madeline L. Parker, and Audrey S. Wang. 2019. "Mapping Color to Meaning in Colormap Data Visualizations." *IEEE Transactions on Visualization and Computer Graphics* 25, no. 1 (January): 810–19. https://doi.org/10.1109/TVCG.2018.2865147.

Schloss, Karen B., Laurent Lessard, Charlotte S. Walmsley, and Kathleen Foley. 2018. "Color Inference in Visual Communication: The Meaning of Colors in Recycling." *Cognitive Research: Principles and Implications* 3, no. 1 (December): 5. https://doi.org/10.1186/s41235-018-0090-y.

Schrijver, Alexander. 1998. *Theory of Linear and Integer Programming*. John Wiley & Sons.

"Scikit-Learn: Machine Learning in Python." 2022. 2022. https://scikit-learn.org/stable/.

Setlur, Vidya, and Maureen C Stone. 2015. "A Linguistic Approach to Categorical Color Assignment for Data Visualization." *IEEE Transactions on Visualization and Computer Graphics* 22, no. 1: 698–707.

Setlur, Vidya, and Maureen C. Stone. 2016. "A Linguistic Approach to Categorical Color Assignment for Data Visualization." *IEEE Transactions on Visualization and Computer Graphics* 22, no. 1 (January): 698–707. https://doi.org/10.1109/TVCG.2015.2467471.

Sharma, Gaurav, Wencheng Wu, and Edul N. Dalal. 2005. "The CIEDE2000 Color-Difference Formula: Implementation Notes, Supplementary Test Data, and Mathematical Observations." *Color Research & Application* 30, no. 1: 21–30. https://doi.org/10.1002/col.20070.

Sheehan, Kim Bartel. 2018. "Crowdsourcing Research: Data Collection with Amazon's Mechanical Turk." *Communication Monographs* 85, no. 1 (January): 140–56. https://doi.org/10.1080/03637751.2017.1342043.

Shuman, Vera, Katja Schlegel, and Klaus Scherer. 2015. "Geneva Emotion Wheel Rating Study."

Silva, Samuel, Beatriz Sousa Santos, and Joaquim Madeira. 2011. "Using Color in Visualization: A Survey." *Computers & Graphics*, Virtual Reality in Brazil, 35, no. 2 (April): 320–33. https://doi.org/10.1016/j.cag.2010.11.015.

Smith, Tiffany Watt. 2015. *The Book of Human Emotions: An Encyclopedia of Feeling from Anger to Wanderlust*. Profile Books.

Stone, Maureen, Danielle Albers Szafir, and Vidya Setlur. 2014. "An Engineering Model for Color Difference as a Function of Size." In , 2014:253–58. Society for Imaging Science and Technology.

Stroop, J Ridley. 1935. "Studies of Interference in Serial Verbal Reactions." *Journal of Experimental Psychology* 18, no. 6: 643.

Suk, Hyeon-Jeong, and Hans Irtel. 2010. "Emotional Response to Color across Media." *Color Research & Application* 35, no. 1: 64–77. https://doi.org/10.1002/col.20554.

Tham, Diana Su Yun, Paul T Sowden, Alexandra Grandison, Anna Franklin, Anna Kai Win Lee, Michelle Ng, Juhyun Park, Weiguo Pang, and Jingwen Zhao. 2020. "A Systematic Investigation of Conceptual Color Associations." *Journal of Experimental Psychology: General* 149, no. 7: 1311.

Thyng, Kristen M., Chad A. Greene, Robert D. Hetland, Heather M. Zimmerle, and Steven F. DiMarco. 2016. "True Colors of Oceanography: Guidelines for Effective and Accurate Colormap Selection." *Oceanography* 29, no. 3: 9–13.

Urdan, Timothy C. 2016. *Statistics in Plain English*. Routledge.

Vardi, Yehuda, and Cun-Hui Zhang. 2000. "The Multivariate L1-Median and Associated Data Depth." *Proceedings of the National Academy of Sciences* 97, no. 4: 1423–26.

Volker, Martin A. 2006. "Reporting Effect Size Estimates in School Psychology Research." *Psychology in the Schools* 43, no. 6: 653–72. https://doi.org/10.1002/pits.20176.

White, Travis M., Terry A. Slocum, and Dave McDermott. 2017. "Trends and Issues in the Use of Quantitative Color Schemes in Refereed Journals." *Annals of the American Association of Geographers* 107, no. 4 (July): 829–48. https://doi.org/10.1080/24694452.2017.1293503.

Williams, H Paul. 2013. *Model Building in Mathematical Programming*. John Wiley & Sons.

Yamazaki, Atsuko K. 2010. "An Analysis of Background-Color Effects on the Scores of a Computer-Based English Test." In , 630–36. Springer.

Zeile, Peter, Stefan Höffken, and Georgios Papastefanou. 2009. *Mapping People?–The Measurement of Physiological Data in City Areas and the Potential Benefit for Urban Planning*. na.

Zeile, Peter, Bernd Resch, Jan-Philipp Exner, and Günther Sagl. 2015. "Urban Emotions: Benefits and Risks in Using Human Sensory Assessment for the Extraction of Contextual Emotion Information in Urban Planning." In *Planning Support Systems and Smart Cities*, edited by Stan Geertman, Joseph Ferreira, Robert Goodspeed, and John Stillwell, 209–25. Lecture Notes in Geoinformation and Cartography. Cham: Springer International Publishing. https://doi.org/10.1007/978-3-319-18368-8_11.

Zhou, Liang, and Charles D. Hansen. 2016. "A Survey of Colormaps in Visualization." *IEEE Transactions on Visualization and Computer Graphics* 22, no. 8 (August): 2051–69. https://doi.org/10.1109/TVCG.2015.2489649.