Color Planning System for Product Design

Woojae Jung; Munsell Color Science Laboratory, Rochester Institute of Technology, Rochester, NY, USA

Abstract

“Why do users prefer a certain color for the product?” This paper introduces a Color Planning System that maps and models the relationship between color and emotion to enhance user preference in product design. By visualizing these associations, the system helps designers connect color and emotion relationships to user preferences. Instead of directly predicting color preference, which can make it difficult to identify influencing factors, the system provides a structured map and set of models that reveal how emotions associated with color influence user preference. This approach supports more informed and intuitive decisions in the design process.

Introduction

The objective of product design can be diverse, such as enhancing usability, visual appeal, or brand identity. Ultimately, however, the goal is to improve user preference. Preference is not only a subjective matter, but also difficult to interpret in terms of its underlying causes. While predicting preference may be feasible, uncovering its underlying mechanisms remains a challenge. This challenge makes it difficult for designers to understand why users prefer certain colors, even when the outcomes are predictable.

One of the most influential factors in user preference is color, a dominant visual cue that strongly impacts emotional response. In some cases, emotional associations with color appear to be widely shared. For instance, reddish hues are commonly linked to intense emotions, explaining their frequent use in warning signs like STOP signs. In other cases, emotional meaning is deliberately assigned, as in the Pantone Color of the Year, where specific hues are chosen to evoke and promote particular emotional themes. Figure 1 presents the 2025 Pantone Color, described on the official website as follows. As stated in the description, “answering our desire for comfort,” color selection is driven by intuition to evoke specific emotions.

“For 2025, the Pantone Color Institute selects PANTONE 17-1230 Mocha Mousse, a warming brown hue imbued with richness. It nurtures us with its suggestion of the delectable qualities of chocolate and coffee, answering our desire for comfort.”

FIGURE 1. COLOR OF THE YEAR 2025 PANTONE

In the introduction of Hanada’s (2018) paper, conflicting opinions on the dependency of color-emotion associations on gender and socio-cultural background are well summarized. In author’s opinion, while some emotions appear to be universally associated with certain colors, it is more appropriate to view these associations as being shaped by participants’ socioeconomic and cultural experiences since the difference continuously figured out (Murray & Deabler, 1957; Hupka et al., 1997; Ou et al., 2004a). More importantly, Schloss (2023) demonstrated that emotions associated with colors also depend on context. Thus, it is reasonable to conclude that color-emotion associations vary with both socio-cultural background and contextual factors. Therefore, applying associations derived from other studies without accounting for these influences may lead to misleading or contextually inappropriate interpretations.

Among empirical studies, Ou et al. (2004a) systematically assessed color-emotion associations using bipolar adjectives and identified key emotional dimensions through factor analysis. In a follow-up (2004b), they proposed three models to predict preference: one, via individual emotion ratings, two, using reduced emotional factors through principal component analysis (PCA), and three, directly from preference ratings. Although the direct model achieved the highest performance score, it lacked interpretability, making it unclear what underlying mechanisms drove the preferences.

In response to this limitation, the present study introduces a Color Planning System designed not as a high-accuracy predictor, but as a transparent framework to support designers’ decision making. The system models how color appearance attributes (lightness, chroma, and hue) influence emotional responses, and how these emotions relate to user preference. Rather than treating preference as a black-box output, this approach seeks to reveal the structure behind preference judgments and to enhance interpretability through visualization and regression modeling. A case study on office chair color is conducted to demonstrate how the system supports emotional interpretation of color choices in a design context.

Method

Step1. Color-Emotion Assessment

Sample selection and colorimetry measurement

To conduct the psychophysical experiment to generate data for Color Planning System, in first step, appropriate samples should be selected. When selecting samples, design elements that are not the focus should remain consistent, if the relationship between elements is not clearly defined and could potentially act as noise. Then, shape and transparency should be maintained consistently within the samples in the case of Color Planning System. Additionally, the sample set should encompass a wide range of colors that vary across the three color appearance attributes: lightness, chroma, and hue. Since the system will be developed based on this data, an insufficient dataset could limit its accuracy and generalizability, leading to incomplete or biased predictions. The colorimetry tristimulus values (XYZ) of the samples should be measured using the viewing condition which participants will observe during the assessment. During the colorimetry measurement, specular reflections should be avoided to ensure that the measured values correspond to the diffusely reflected light that observers primarily perceive. When evaluating the color of an object, observers often perceive it through diffusely reflected areas rather than specular reflections (Hardy, as cited in Berns, 2019).

Semantic dimensions decision

In the second step, when selecting the semantic attributes, these should be represented as bipolar adjective pairs due to their various advantages (Osgood et al., 1957). Using bipolar adjective pairs helps observers establish their subjective criteria within a continuous semantic space. Moreover, by allowing observers to apply their own criteria, this approach enhances the reliability of semantic evaluations. These adjective pairs can be determined through a literature review, a user survey by target group, or consultations with experienced experts who share same background with users. After selecting the evaluating attributes, it is recommended to include a direct preference-evaluating attribute, such as Like-Dislike.

In Ou et al.'s (2004a) study on color-associated emotions, ten keyword pairs were used for assessment: Warm-Cool, Heavy-Light, Modern-Classical, Clean-Dirty, Active-Passive, Hard-Soft, Tense-Relaxed, Fresh-Stale, Masculine-Feminine, and Like-Dislike. These ten keywords, selected based on the three primary dimensions of evaluative, potency, and activity identified by Osgood et al. (1957), were used to assess emotions associated with color, and can therefore serve as a baseline for selecting semantic attributes in the Color Planning System.

Psychophysical experiment

In the third step, psychophysical experiments should be conducted using selected samples to collect user data. During these experiments, users are asked to evaluate the presented samples based on the given keywords using semantic scales, with participants assessing each sample according to a scaling method.

Several considerations should be taken into account when conducting the experiment. First, the viewing environment (e.g. illuminant and background) for the experiment should remain consistent. It is preferable to use an achromatic background, as a chromatic background can influence not only the associated emotions but also the color perception itself. Second, before starting the experiment, it is necessary to confirm that the participants' understanding of the evaluation keywords aligns with the intended meaning defined by the designer. Third, since a scaling method is used, it is advisable to have participants observe all the samples before the experiment begins. This helps prevent two potential issues: excessive reliance on moderate value and the overuse of maximum or minimum values. Lastly, it is preferable to present each semantic attribute in random order for assessment, rather than presenting all the attributes at once or in a fixed order. This approach helps prevent participants from finding correlations between emotions caused by the samples, ensuring that each evaluation remains independent and unaffected by previous assessments.

Step2. Color-Emotion Mapping

Data preprocessing

The factor reduction is done to create the color-emotion map. A normalization process should be applied before using the data for mapping and modeling to mitigate errors caused by variations in scaling among participants. Each participant's raw ratings for each stimulus across all semantic attributes should be standardization into Z-scores to account for individual differences in scaling range. Then, for each attribute, the individual Z-scores are aggregated across all participants for each stimulus, commonly using the arithmetic mean, though the median or other summary statistics can be applied.

Principal component analysis

After preprocessing, designers can visualize the results using two-dimensional or three-dimensional maps, employing PCA. After performing PCA, first, the latent of the principal components should be checked to ensure that the data depicted in two-dimensional or three-dimensional space can adequately explain the dataset. The threshold can be checked by examining whether the eigenvalue of the principal component (latent) is greater than 1 or if the cumulative variance ratio exceeds 0.8. Then, the color-emotion map can be computed based on the selected number of principal components. If the number of principal components exceeds three, visualization becomes challenging, and even if performed, it may not effectively explain the dataset. Third, the correlation matrix of variables can provide additional insights, particularly in identifying highly correlated color-associated emotions with user preferences. As a result of the mapping, the relationships between design elements and user feelings can be interpreted. Furthermore, labeling the principal components shown on the map can make interpretation easier.

Step3. Color-Emotion Modeling

Color appearance attributes computation

Through the results of color-emotion mapping, the relationship between color-emotion and user preference was identified. By modeling color-emotion relationships, color appearance attributes were used to understand how each attribute relates to each emotion. The correlation between color and emotion can be modeled using three color appearance dimensions: lightness, chroma, and hue. This approach helps guide the understanding of how each color appearance dimension contributes to emotions.

CIELAB is the most widely used color system for calculating color appearance dimensions for this purpose, as it has simple computational metrics. However, it should be noted that CIELAB cannot account for diverse viewing environments and provides the most accurate prediction of color appearance under lighting source having correlated color temperature of 6500K. Therefore, CIECAM16 is more appropriate, as it is the current recommended model and offers high accuracy in modeling color perception under various viewing environments without excessive complexity.

Single attribute color-emotion models

In color-emotion modeling, we employed a quadratic function to fit the relationships of lightness and chroma with emotion, as this approach effectively captures their complex associations. Given that color perception follows a sigmoidal pattern, like the compressive relationship between lightness and luminance, it is reasonable to assume that the relationship between lightness and emotion may also be nonlinear. Also, nonlinear characteristics have already been observed in the relationship between image naturalness and colorfulness (De Ridder et al., 1995), suggesting that the correlation between color and emotion is also unlikely to be strictly linear. Therefore, a quadratic function was chosen to better model these color appearance attributes and emotion association.

$$
\begin{aligned}
f(Lightness) &= \beta_0 + \beta_1 \cdot Lightness + \beta_2 \cdot Lightness^2 \\
f(Chroma) &= \beta_0 + \beta_1 \cdot Choma + \beta_2 \cdot Chorma^2
\end{aligned}
$$

In case of hue, since it is expressed in degrees ranging from $0°$ to $360°$, colors with a hue value of $0°$ and $360°$ are identical due to the cyclic property. To accommodate this, the hue values were transformed into cylindrical coordinates using cosine and sine transformations, using $\cos(hue)$, $\sin(hue)$, $\cos(2 \cdot hue)$, and $\sin(2 \cdot hue)$ to capture both the first and second harmonic components. By incorporating these components, the model can address the issue that complementary colors do not always evoke opposite emotions. For instance, while yellow may be predicted to have a modern image, its complementary color, blue, might not necessarily be predicted as non-modern.

$$f(Hue) = \beta_0 + \beta_1 \cdot \cos(hue) + \beta_2 \cdot \sin(hue) + \beta_3 \cdot \cos(2 \cdot hue) + \beta_4 \cdot \sin(2 \cdot hue)$$

While it is true that a single attribute alone cannot fully represent color, and at least three dimensions are necessary to specify color appearance under a particular viewing environment, the challenge lies in understanding how individual attributes relate to emotion. Although this influence depends on the sample sets used, certain tendencies can still be observed even when using a single attribute for modeling. This approach is justified by Ou et al. (2004a), who demonstrated that selective use of specific attributes that excluding unrelated ones, can effectively model color-emotion associations.

Multiple attributes color-emotion models

Although some emotions may correspond to a single color dimension, emotional responses are more appropriately understood as reactions to color as an integrated percept, which is defined across multiple dimensions. Therefore, three color appearance attributes are used together to model the color–emotion associations. Although this model makes it difficult to interpret the individual contribution of each attribute through coefficients, it is intended to provide better prediction of the associated emotion. In this purpose, suggested model from Schloss et al. (2017) using cylindrical coordinates incorporated lightness, chroma, and hue, along with the 1st and 2nd harmonic components to model preference are used for modeling.. The methodology for using these harmonic components in color-emotion modeling is well illustrated in Fig. 2 of Schloss et al. (2017). Even when multiple attributes are considered, it can still be difficult to capture a clear relationship with color. This may suggest that some emotions are inherently weakly associated with color, or that these associations vary significantly across individuals.

$$f(Color) = \beta_0 + \beta_1 \cdot Lightness + \beta_2 \cdot Chroma + \beta_3 \cdot \cos(hue - 1^{st}\ component) + \beta_4 \cdot \cos(2 \cdot (hue - 2^{nd}\ component))$$

Prediction model decision

In conclusion, four equations are derived for each color associated emotion. Since the primary objective of the Color Planning System is guide the selection of colors that evoke specific emotional responses, color-emotion models using a single attribute, despite their relatively low performance, are still visualized to help designers make a rough estimation of emotional associations for each color appearance dimension. In practice, the prediction for a new color is determined by the best performing model, identified by the highest R^2.

Although all semantic attributes, including preference, were modeled using the same modeling framework and evaluated with predictive metrics such as R^2, their roles within the system's interpretive structure differ. Emotional attributes are treated as mediators that link color appearance to user response, while preference is interpreted as a composite evaluation that can be explained through those emotional impressions. Thus, while preference is technically predicted alongside other attributes, the system emphasizes its interpretability through the emotional reasoning path, rather than isolating it as a standalone construct.

Case Study: Color of Office Chair

Experimental setting

As a case study, the author conducted psychophysical experiment to gather data on color–emotion associations for an office chair. Four graduate students from the Munsell Color Science Laboratory participated in the experiment. The participants evaluated color samples ($2.5 \times 3.8\ cm$) selected from the BEHR Premium Floor Coatings color guide brochure, presented under a lighting cabinet with a gray background. The spectral characteristics of the lighting source are shown in Figure 2. Before the evaluation began, all color samples were shown to the participants. To ensure contextual evaluation, they were asked to imagine each color applied to an office chair, aided by the image. The question posed for the assessment was: "Rate the emotion you feel from this color, assuming it is the color of your office chair." Participants rated the semantic attributes in a pseudorandomized order using a semantic scale ranging from 0 to 10, where 5 indicated a moderate value that does not convey a emotional inclination along the semantic scale. The attribute pairs were selected with reference to Ou et al. (2004a) with some modification and are listed in Table 1.

Sample patches were measured using spectroradiometer, CR-250, under a lighting cabinet. Figure 3 illustrates the measurement geometry, approximately $0°:45°$, which was chosen to minimize specular reflections that might be generated by the patch surface. XYZ values were computed from the measured spectral radiance using the CIE 1931 standard observer and are presented in Table 2. The text column shows patch colors in the sRGB, transformed from the measured XYZ values. Figure 4 shows the chromaticity diagram of the measured samples. To compute the color appearance attributes, CIECAM16 was used. A perfect reflecting diffuser was employed to measure the illuminant characteristics and served as the reference white.

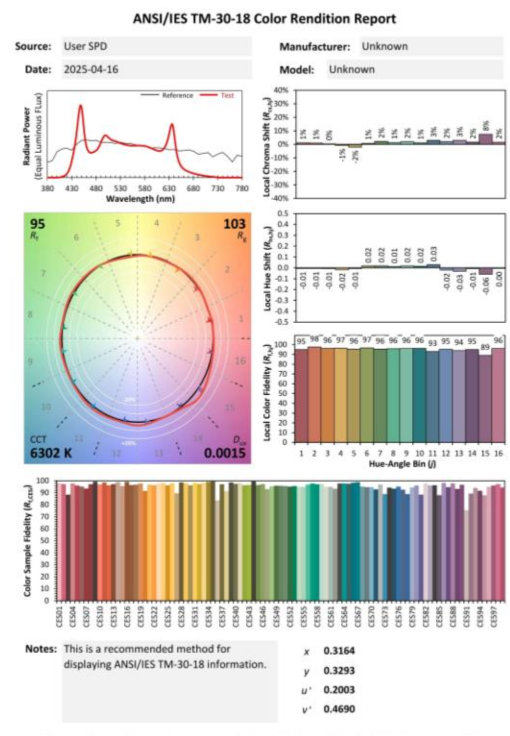

FIGURE 2. TM-30 REPORT OF LIGHTING SOURCE

Table 1. Used semantic attributes for assessment

Warm	-	Cool
Modern	-	Classic
Clean	-	Messy
Active	-	Passive
Hard	-	Soft
Tense	-	Calm
Natural	-	Artificial
Like	-	Dislike

Figure 3. Measurement geometry

Table 2. Color appearance attributes of samples

	X	Y	Z
Alpine sky	516.40	535.00	546.40
Black	189.50	212.40	194.60
Blue	276.20	295.80	346.70
Cafe iruna	488.97	508.47	540.33
Clay terrace	522.67	546.67	442.03
Dark walnut	296.20	294.33	242.90
Deep galaxy	232.70	202.77	142.80
Elemental green	203.17	203.40	195.33
Grain	304.43	336.10	251.50
Green	347.43	351.43	428.33
Ice white	317.70	332.47	349.23
Iron ore	448.73	474.07	525.13
Moss covered	575.00	601.90	578.43
Orange	159.17	190.80	285.23
Patio green	478.93	486.40	460.80
Pools of blue	448.37	479.03	575.87
Red	138.07	164.83	100.77
Rich brown	140.30	116.30	71.78
Royal red	553.00	576.40	526.60
Sea cave	473.10	510.50	477.33
Terrace view	149.23	154.90	181.10
Tarnished silver	501.00	514.23	369.83
White cloud	335.53	337.40	212.97
Yellow	401.17	331.57	206.30

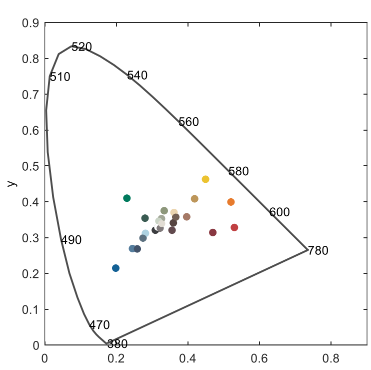

Figure 4. Sample colors

Results

Map and Models

The analysis results for color-emotion mapping are depicted through Figure 5-8. Figure 5 presents a Pareto chart of the PCA results. In this analysis, the eigenvalues of the first three principal components are 1.5855, 0.9606, and 0.7089, respectively. The cumulative contribution of the first two components accounts for 66% of the total variance, while the first three components together explain 84%. Figure 6 and Figure 7 visualized the map in two-dimensional and three-dimensional spaces using different number of principal components. Table 3 shows the coefficients of each variable for first three principal components. Through color-emotion map and correlation matrix (Figure 8), we can find out that color preference of this participant is most correlated with the Tense-Calm, Clean-Messy, and Hard-Soft with correlation coefficient of -0.7387, 0.6509, and -0.5998, respectively. It means color preference of office chair can be increased of intriguing calm, clean, and soft emotions. As an additional note, Elemental green is most liked and Orange is most disliked.

Table 3. Eigenvectors of each variable

	PC1	PC2	PC3
Warm-Cool	0.1237	0.7534	0.3137
Modern-Classic	-0.0706	-0.2529	0.5213
Clean-Messy	-0.2493	-0.3154	0.2269
Active-Passive	0.085	0.0777	0.6361
Hard-Soft	0.5593	-0.1307	-0.2783
Tense-Relaxed	0.5443	-0.0111	0.0035
Natural-Artificial	-0.3981	0.4628	-0.2943
Like-Dislike	-0.378	-0.1776	-0.0981

As described, R^2 was used as criterion for selecting the prediction model. In this case study, all emotions were predicted using a multiple attributes model, $f(Color)$, achieved R^2 of 0.6527, 0.5513, 0.5108, and 0.7156, respectively for Clean-Messy, Hard-Soft, Tense-Calm, and Like-Dislike. Although models using a single color attribute showed relatively low performance, their fitted curves were also visualized to help designers make approximate judgments about emotional tendencies associated with each color appearance dimension. The fitted models for the three color-associated emotions most highly correlated with preference, along with like–dislike itself, are presented in Figures 9 to 11. In these figures, the line represents the model's predicted values, while the colored points indicate the empirical values, with point colors approximately matching the actual sample colors.

The graphs reveal several trends: the feeling of 'clean' can be evoked by either low or high lightness; 'hard' tends to be associated with low lightness; and 'tense' appears to be triggered by high chroma. These findings suggest that, to promote positive emotional responses such as cleanliness, softness, and calmness and thereby enhance user preference, office chairs in the Munsell Color Science Laboratory should use colors with high lightness and avoid high chroma levels to be preferred by graduate students.

Example of usage

Imagine the Munsell Color Science Laboratory selecting a new office chair color from four options, as shown in Table 4. Using colorimetric measurements under the same conditions as in the experiment, we can compute color appearance attributes and estimate color-emotion associations as Z-scores using the prediction model. Based on the computed values shown in Table 5, Silverberry should be selected as it is expected to be the most preferred, evoking strong cleanliness, softness, and weak calmness.

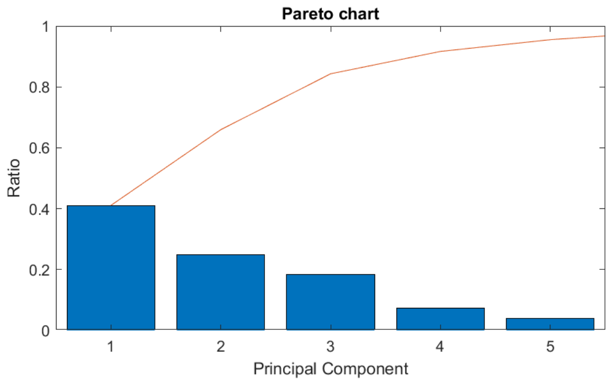

Figure 5. Pareto chart of principal component

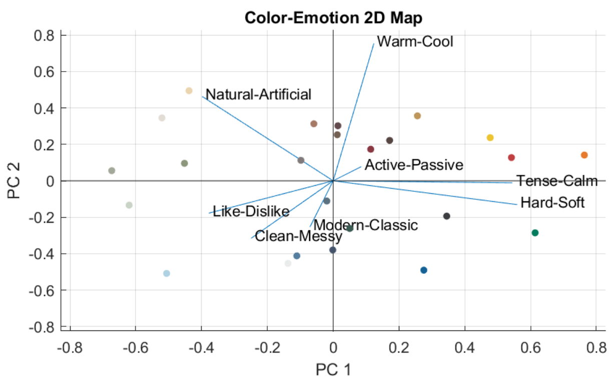

Figure 6. Two-dimensional color-emotion map

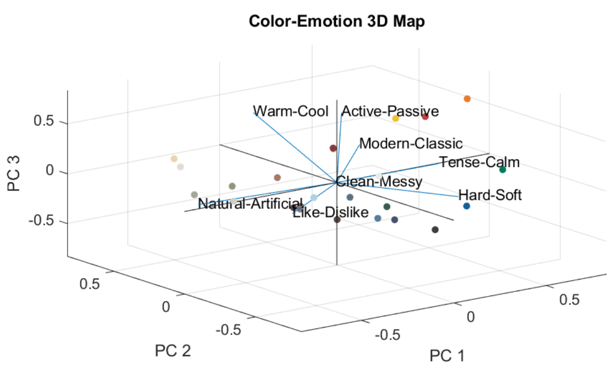

Figure 7. Three-dimensional color-emotion map

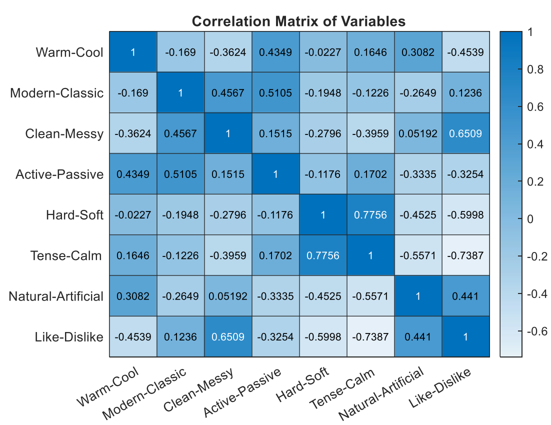

Figure 8. Correlation matrix of variables

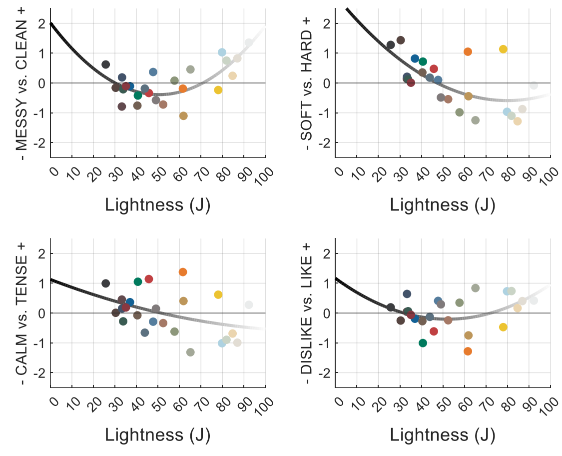

Figure 9. Lightness models

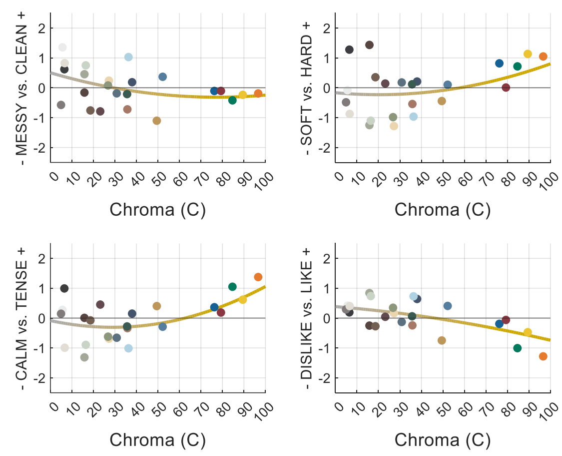

Figure 10. Chroma models

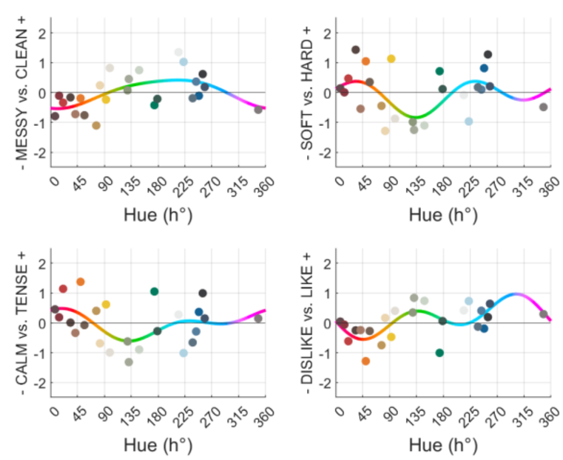

Figure 11. Hue models

Table 4. Color appearance attributes of test samples

	J	C	h
Silverberry	73.74	16.68	290°
Coral serenade	73.13	63.12	32°
Moss point green	52.13	42.30	130°
Victorian pewter	51.22	10.38	256°

TABLE 5. PREDICTED COLOR-EMOTION VALUES

	S	Cs	Mpg	Vp
Clean-Messy	0.8324	-0.0392	-0.1477	0.5175
Hard-Soft	-1.0194	-0.1148	-0.3566	-0.0636
Tense-Calm	-0.2937	0.3545	-0.3091	-0.2598
Like-Dislike	1.2844	-0.3266	0.0928	0.6914

Conclusion

This study introduces a Color Planning System that visualizes and models the relationship between color appearance, emotion, and preference. The primary goal of this work is not to optimize predictive performance, but to provide a transparent and interpretable framework that supports product design decisions involving color selection. By constructing models that link color appearance attributes to emotional responses and mapping these associations, the system enables designers to make more informed, emotion-aware color choices. The system consists of the following three steps:

Step 1. Color-Emotion Assessment
1. Sample preparation and colorimetry measurement
2. Semantic adjective pairs selection
3. Psychophysical evaluation with target users

Step 2. Color-Emotion Mapping
4. Preprocess the experimental data
5. Principal component analysis for visualizing color–emotion associations

Step 3. Color-Emotion Modeling
6. Regression modeling to estimate emotional responses from color appearance attributes

This structured framework supports designers by making emotional reasoning behind color preference for product more accessible and explainable, especially in preferred-based design.

Discussion

A case study involving office chair color evaluation was conducted to demonstrate how the system can be applied in a realistic design scenario. Although the sample size was small and limited to graduate students in the Munsell Color Science Laboratory, this population was intentionally selected as an expert group, capable of evaluating subtle color-emotion associations based on their knowledge of color science and experience with psychophysical experimentation. The purpose of the case study was not to generalize population-level trends, but to test and illustrate the interpretability and functionality of the system under controlled, expert conditions.

The system incorporates regression models to predict emotional responses from color appearance attributes, and R^2 values are provided to show how well the models capture observed variation. However, the goal is not solely aimed at maximizing accuracy. While improved predictive performance is certainly desirable, it is not pursued at the expense of interpretability. Overly dependent or opaque models may undermine practical usability, especially in design contexts where understanding the rationale behind a recommendation is essential. Therefore, the system favors models that offer meaningful, explainable associations, even if their statistical fit is not optimal.

Future work should expand the system to evaluate multi-color compositions, explore its application in more diverse user groups, and integrate product renderings to reduce the abstraction gap between color patches and real-world stimuli. By maintaining a focus on interpretability, the system aims to remain a usable and insightful tool for designers seeking to incorporate emotion-driven reasoning into their color choices.

Data availability

https://github.com/woojr/color_planning_system

Although the shared code uses CIELAB, the analysis and modeling in this case study are based on CIECAM16. The author did not request permission to redistribute the CIECAM16 implementation, which is why it is not included in the public repository.

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