A Computational Framework for Color Theory in Art Design: Integrating Classical Harmony Rules with User Perception and Interactive Optimization

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Abstract. Color theory plays a fundamental role in art design, influencing visual aesthetics, emotional communication, and brand identity. However, the translation of classical color principles (e.g., Itten's contrasts, Munsell's harmony) into computable and designer-friendly tools remains underexplored. To address this gap, this study proposes a computational framework that integrates classical color harmony rules with user-centric perception models for art design applications. The framework formalizes color features in HSV space, defines multi-dimensional harmony indices based on complementary, analogous, and triadic schemes, and constructs a color–emotion mapping model using regression analysis. An interactive genetic algorithm is introduced to iteratively optimize palettes according to designer preferences and task constraints. A comparative experiment involving 120 design tasks was conducted, comparing pure manual designer selection, pure AIGC-based color generation, and the proposed interactive method. Results show that the proposed framework achieves significantly higher objective harmony scores (0.87 vs. 0.52 and 0.68) and subjective user satisfaction (6.43/7 vs. 4.85/7 and 5.21/7), while reducing average iteration time by 53% relative to manual tuning. This study provides a quantifiable and practical bridge between classical color theory and digital art design practice.

Keywords: Color theory; Art design; Color harmony; User perception; Interactive genetic algorithm; AI-assisted design.

1 Introduction

Color is one of the most powerful visual elements in art design, directly affecting user emotion, attention, and decision-making. Despite the long history of color theory — from Goethe's psychological approach to Itten's seven contrasts and Munsell's systematic color space — its application in contemporary design workflows remains largely intuitive and experience-dependent [1]. Many digital design tools (e.g., Adobe Color) provide static harmony rules but fail to adapt to designer intent, task context, or subjective user preferences [2].

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Theoretical underpinnings. To move beyond a purely technical report-style description, our framework is explicitly grounded in two complementary theoretical traditions [3]. First, Gestalt psychology — particularly the principles of similarity, proximity, and continuity — suggests that visual harmony emerges when color elements form coherent, structured relationships rather than isolated features [4]. Classical harmony rules (complementary, analogous, triadic) can be reinterpreted as specific configurations of hue differences that reduce perceptual tension and enhance global coherence. Second, information aesthetics theory proposes that human preference for visual stimuli follows an inverted-U relationship between complexity and order; color palettes that are too random (high entropy) or too uniform (low entropy) both receive lower aesthetic ratings [5]. Our formalization of harmony scores (Eq. 1) operationalizes this principle by quantifying deviations from ideal geometric relationships, thereby balancing predictability and novelty. This theoretical grounding distinguishes our work from purely heuristic or black-box AI approaches.

Core theoretical contribution. Unlike prior work that either applies classical rules in a rigid template or abandons them entirely for data-driven generation, our framework maintains a continuous dialogue between theory and optimization: classical harmony rules provide the structural constraints (priors) that prevent degenerate solutions, while the interactive genetic algorithm allows designer preferences to modulate these constraints according to task-specific needs.

2 Literature Review

2.1 Classical Color Theory in Design

Color theory in art design originates from the works of Itten, Munsell, and Ostwald. Itten defined seven color contrasts (e.g., complementary, light-dark, cold-warm) that remain fundamental in visual composition [6]. Munsell's three-dimensional model (hue, value, chroma) provides a systematic basis for measuring color relationships. In design practice, complementary ($\Delta H \approx 180°$) and analogous ($\Delta H < 60°$) schemes are most frequently used for harmony [7].

2.2 Practical Teaching and Product Design Education

Several computational models have attempted to quantify harmony. Matsuda's color coordination templates and Cohen-Or's harmony optimization algorithm formalize harmony as a function of hue differences . More recently, data-driven approaches using large palette datasets have been proposed. However, these models rarely integrate designer interaction or task-specific emotional targets.A key limitation is that most computational models treat harmony as a static geometric property, ignoring the role of user perception, task context, and iterative refinement — gaps our framework directly addresses.

2.3 AIGC and Color Generation in Design

Generative models such as Stable Diffusion and Midjourney can produce aesthetically pleasing images but often fail to generate controllable, harmonious color palettes [8]. Text-to-color generation suffers from semantic ambiguity, and most outputs require extensive post-hoc adjustment. Critically, the low harmony of pure AIGC methods is not accidental but stems from their underlying architecture: these models learn marginal distributions of RGB or HSV values from large image datasets without explicit relational constraints. They predict pixel-level statistics but lack an understanding of color intervals (e.g., that $\Delta H \approx 180°$ defines complementarity). Consequently, generated palettes frequently produce near-opposite hues with slight deviations (e.g., 165° or 195°) that visually clash, or analogous hues that are too close to create sufficient contrast [9]. In other words, AIGC optimizes for realism or single-step prediction, not for the structural relationships that define perceptual harmony.This highlights the need for a hybrid framework that combines AI efficiency with human design knowledge and classical theory.

2.4 Inefficiency of Manual Color Tuning

Manual color selection, despite its flexibility, suffers from specific, analyzable inefficiencies. First, designers lack quantitative feedback: they must rely on subjective “feeling” to judge harmony, leading to repeated trial-and-error cycles. Second, the adjustment space is high-dimensional (three channels per color × five colors = 15 dimensions), but human working memory can only manipulate a few variables simultaneously. Third, cognitive conflict arises when a designer attempts to satisfy multiple constraints (e.g., complementary base, sufficient value contrast, emotional tone) — each adjustment toward one goal often disrupts another, requiring backtracking. These factors explain why manual design in our experiment averaged 28.4 minutes per task, with large variance (SD = 6.2 min).

3 Methodology

3.1 Color Representation and Harmony Formalization

We represent each color in HSV space:

hue $H \in [0，360]$,saturation $S \in [0，1]$,value $V \in [0，1]$ A palette is defined as $P = \{[c_1, c_2, \ldots. c_n]\}$,typically with $n = 5$ for design tasks.

Based on Itten’s harmony rules, we define three harmony types:

Complementary harmony: Two colors with hue difference $\Delta H \approx 180°$.Deviation measured as $D_{comp} = min(\Delta H - 180|，360 - |(\Delta H - 180|)$.

Analogous harmony: Colors with hue differences $\Delta H \leq 60$.Mean deviation $D_{anal} = \frac{2}{n（n-1）} \sum_{i<j} \min(|\Delta H_{ij}|, 360-|H_{ij})$.

Triadic harmony: Three colors with hue difference≈120.Deviation $D_{tri} = \sum_{k=1}^{3} min(|H_{k,ideal}|, 360 - |\ldots|)$.

The overall Harmony Score HtotalHtotal is defined as:

$$D_{total} = 1 - \frac{1}{3}\left[\frac{D_{comp}}{180} + \frac{D_{anal}}{60} + \frac{D_{tri}}{120}\right]$$

where smaller deviations yield H_{total} close to 1.

3.2 Color–Emotion Mapping Model

To enable emotion-oriented design, we construct a linear regression model mapping color features to three emotional dimensions: Pleasant, Energetic, and Elegant. Training data are collected from 50 designers rating 200 palettes. Features include mean hue, saturation contrast (standard deviation of S), value contrast, and harmony score.

The prediction for emotion dimension ee is:

$$E_e = \beta_0 + \beta_1 H + \beta_2 o\mathrm{S} = \beta_3 o\mathrm{V} + \beta_4 o H_{total} + \mathcal{E}$$

Coefficients are estimated via ordinary least squares (R^2=0.71 on validation set).

3.3 Interactive Genetic Algorithm for Palette Optimization

To incorporate designer preference, we adopt an interactive genetic algorithm (IGA).

Initialization: Generate 20 random palettes respecting harmony rules (Eq. 1 > 0.5).

Fitness: Designer rates each palette on a 1–7 scale (7 = best).

Fitness = normalized rating.

Selection: Roulette wheel selection based on fitness.

Crossover: Blend crossover on hue values with probability 0.7.

Mutation: Gaussian perturbation (σ=15 for hue, 0.1 for S/V) with probability 0.1.

Termination: After 5 generations or designer approval.

The IGA runs within a Python-based interface, and each iteration takes approximately 2–3 minutes.

4 Experiments and Comparative Analysis

4.1 Experimental Setup

A total of 120 design tasks (posters, UI interfaces, packaging, illustrations) were assigned to 12 designers (average 5 years experience). Three methods were compared:

Group A (Manual): Designers manually select colors using Photoshop/Adobe Color, no AI assistance.

Group B (Pure AIGC): Stable Diffusion + ControlNet generates palettes from text prompts (e.g., “vibrant summer poster”), no post-adjustment.

Group C (Proposed): Interactive genetic algorithm with harmony initialization and emotion prediction feedback.

Each task was completed by three different designers across groups to avoid learning effects. Evaluation metrics included:

Objective Harmony Score: $H_{total}$from Eq. (1).

Subjective Satisfaction: 7-point Likert scale (1=very dissatisfied, 7=very satisfied).

Emotion Matching: Difference between predicted and desired emotion scores.

Time Efficiency: Total design time (minutes).

4.2 Results

The experimental results show clear differentiation among the three groups across all four metrics: objective harmony score, subjective satisfaction, emotion matching error, and design time. Overall, the proposed interactive genetic algorithm framework (Group C) outperforms both pure AIGC generation (Group B) and pure manual design (Group A) on all quality-related indicators (objective harmony, subjective satisfaction, and emotion matching accuracy). Specifically, Group C achieves the highest objective harmony score (0.87) and the highest subjective satisfaction (6.43) among the three groups. In contrast, pure AIGC (Group B), despite being the fastest in design time (averaging only 4.5 minutes), yields the lowest objective harmony (0.52) and the lowest subjective satisfaction (4.85), confirming the inherent deficiency of unconstrained generative models in color coordination. Pure manual design (Group A) outperforms pure AIGC in quality but takes the longest time (averaging 28.4 minutes), indicating a significant inefficiency. The specific values and standard deviations for each metric are detailed in Table 1.

Table 1. Summarizes the main results.

Metric	Group A (Manual)	Group B (Pure AIGC)	Group C (Proposed)
Objective Harmony Score (H)	0.68 ± 0.12	0.52 ± 0.18	**0.87 ± 0.09**
Subjective Satisfaction (1–7)	5.21 ± 0.85	4.85 ± 1.02	6.43 ± 0.61
Emotion Matching Error	1.12 ± 0.34	1.58 ± 0.47	0.68 ± 0.25
Total Design Time (min)	28.4 ± 6.2	**4.5 ± 1.3**	13.2 ± 3.8

To further verify whether the above differences are statistically significant, we conducted one- way analyses of variance (ANOVA) on the four metrics. The results show that the between- group differences for all metrics are highly significant ($p < 0.001$), indicating that the performance gaps across workflows are not due to random fluctuation. The detailed F- values and p- values are presented in Table 2.

Table 2. One-way ANOVA results across three groups.

Metric	F-value	p-value	Significance
Harmony Score	24.36	<0.001	**
Subjective Satisfaction	31.82	<0.001	**
Emotion Matching Error	18.47	<0.001	**
Design Time	156.73	<0.001	**

4.3 Discussion

The results reveal three key findings.Beyond the summary, we analyze the underlying causes of performance differences.

Pure AIGC yields low harmony (0.52) because generative models lack explicit relational constraints: they learn probable color co-occurrences, not harmonious ones. For instance, near-complementary pairs ($\Delta H = 155°/205°$) are statistically common in natural images but perceptually jarring in flat design. Training on unfiltered internet data also reproduces average, not ideal, designs, and generic prompts provide no task-specific guidance.

Manual design is inefficient (28.4 min avg) due to three bottlenecks: exploratory search (15–25 palettes with manual sliders), conflict resolution (complementarity often reduces value contrast, breaking emotional alignment), and lack of convergence feedback, causing over-iteration.

Our framework achieves 0.87 harmony and 6.43 satisfaction—not by rigid classical rules but by integrating them as a multi-objective deviation penalty within an interactive evolutionary loop. Designer ratings override the geometric score when needed (e.g., for intentional off-complementary brand colors), and an emotion regression model guides affective targeting, cutting cognitive load. This yields 53% time saving (28.4 → 13.2 minutes).

5 Conclusion

This study presented a computational framework that bridges classical color theory with modern art design practice through harmony formalization, emotion modeling, and interactive optimization. By grounding our approach in Gestalt psychology and information aesthetics, we moved beyond a mere technical integration to a theoretically coherent design support system. The framework transforms Itten's and Munsell's principles into measurable indices and integrates them into a designer-in-the-loop genetic algorithm. We further provided a detailed analysis of why pure AIGC methods fail (lack of relational constraints, training on average aesthetics) and why manual design is inefficient (trial-and-error, high-dimensional adjustment, conflict resolution). Experimental results demonstrate that the proposed method significantly outperforms both pure manual and pure AIGC approaches in harmony quality, user satisfaction, and emotion matching, while substantially reducing design time compared to manual workflows.

The main contribution lies in providing a quantifiable, interactive, and theory-grounded tool for color design in art and design education and professional practice. Future work will extend the framework to support dynamic color adaptation for motion graphics and virtual reality environments, as well as incorporate larger-scale emotion datasets and non-linear emotion models (e.g., neural networks) to capture more complex affective interactions.

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