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Research on the Application of Painting Art in Textile Color Design

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Article

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ABSTRACT

The application of fine art to textile pattern design has historically been a subjective process. This research establishes a quantitative methodology to inform computer-aided design (CAD) in textile printing, using Impressionist painting as a case study. The study employs digital image processing and CIE Lab colorimetry to systematically analyze and extract color palettes from source artworks. A k-means clustering algorithm defines these palettes, which are then translated into five distinct surface patterns (G1-G5), incorporating specific control conditions designed to decouple color from structure. A consumer preference analysis (N=120) was conducted to evaluate the aesthetic appeal and color harmony of the resulting stimuli. Results from a repeated measures ANOVA indicate that while color palette was held constant, the pattern simulating the "broken color" technique (Design B) achieved significantly higher appeal (p < 0.001) compared to both the structure-agnostic entropy baseline (Design E) and the traditional commercial control (Design D). This study concludes that algorithmic structural organization plays an important role in shaping aesthetic preference under constant color conditions, providing a reliable framework for developing innovative textile products.*

KEYWORDS

digital textile printing, textile coloration, computer-aided textile design (CATD), textile pattern, impressionism

INTRODUCTION

Color is a fundamental pillar of textile design, serving as one of the most powerful tools for conveying emotion, creating aesthetic appeal, and defining market trends [1,2]. The textile industry continually seeks novel sources of inspiration to drive innovation and meet evolving consumer demands. Historically, the world of fine art has been a boundless reservoir of inspiration for textile designers, offering a rich tapestry of color combinations, compositional structures, and thematic concepts [3,4]. The process of translating the visual language of a painting onto the medium of fabric, however, is fraught with challenges. It often remains an intuitive, qualitative exercise, contingent upon the individual designer's artistic sensibility and interpretation. While this approach can yield remarkable results, it also introduces a high degree of subjectivity and unpredictability, making it difficult to establish a consistent and replicable design methodology.

The advent of digital technologies in both art analysis and textile production presents an unprecedented opportunity to introduce scientific rigor into this creative process [5,6]. Digital image processing allows for the deconstruction of an artwork's color composition with mathematical precision, while digital textile printing enables the faithful reproduction of complex and nuanced color palettes onto fabric [7-9]. This technological convergence makes it possible to move beyond simple imitation and toward a more profound and analytical application of artistic principles in textile design. By quantifying the core colorimetric properties of a specific art movement, designers can make more informed decisions, ensuring that the resulting textile products capture the authentic essence of the source inspiration.

This research focuses specifically on the Impressionist movement as a case study. Impressionism, with its revolutionary emphasis on the changing qualities of light, its use of vibrant and often unmixed colors, and its characteristic "broken color" brushwork, offers a particularly rich and complex field for color analysis. The movement's masters, such as Claude Monet, sought to capture the sensory effect of a scene rather than its objective details, a philosophy that resonates deeply with the affective goals of textile design for interior spaces. The central research question of this paper is: Can a quantitative methodology for analyzing and translating the color characteristics of Impressionist paintings lead to the creation of digital textile designs that are perceived by consumers as more aesthetically pleasing and harmonious than those created through more generalized or subjective approaches? This study aims to develop and validate such a methodology, providing a systematic framework that integrates art history, color science, digital technology, and consumer perception to create a more robust and reliable bridge between the painter's canvas and the textile designer's loom.

LITERATURE REVIEW

Color Science in Textile Engineering

The objective measurement of color is a cornerstone of modern textile engineering, crucial for quality control, color matching, and dye formulation. The Commission Internationale de l'Éclairage (CIE) established standardized color spaces to enable the numerical representation of color as perceived by the human eye. Among these, the CIE Lab* color space is paramount. It defines color using three coordinates: representing lightness (from 0 for pure black to 100 for pure white), representing the red-green axis, and representing the yellow-blue axis. This system is designed to be perceptually uniform, meaning that a numerical change of a given magnitude in the coordinates corresponds to a similar magnitude of perceived color change, making it an ideal tool for analyzing and comparing color palettes in a way that aligns with human visual experience [10,11]. In the textile industry, spectrophotometers and colorimeters are used to measure these values, ensuring consistency across production batches. The application of CIE Lab* is not limited to quality control; it provides a powerful analytical framework for designers to deconstruct existing color schemes and develop new, harmonious palettes based on objective data [12].

The Role of Artistic Inspiration in Textile Design

The synergy between fine art and textile design is a well-documented and enduring relationship. Designers frequently draw inspiration from various art movements to inform their collections, translating artistic motifs, compositions, and color schemes into patterns for apparel and interiors [13]. For example, the geometric abstraction of the Bauhaus movement heavily influenced modernist textile design, while the ornate and flowing lines of Art Nouveau found expression in decorative fabrics [14]. This process, however, often involves a subjective selection of elements from the source artwork. The designer might isolate a specific color combination or simplify a complex motif. While this approach is a valid creative method, it lacks a systematic basis for why certain colors are chosen over others, or how the proportional balance and visual texture of the original artwork's palette are maintained. Recent studies have begun to explore more structured approaches, using computer-aided design (CAD) to extract patterns from art, but often focus on shape and form rather than a deep, quantitative analysis of the color itself [15,16].

The Unique Color Language of Impressionism

The Impressionist movement of the late 19th century marked a radical departure from the traditions of academic painting, particularly in its treatment of color and light. Artists like Claude Monet, Pierre-Auguste Renoir, and Edgar Degas moved out of the studio and into nature (*en plein air*) to capture the fleeting moments of daylight. This led to several key innovations in color usage. Firstly, they largely abandoned the use of black and pre-mixed grays for shadows, instead rendering them with complementary colors to create a sense of vibrancy and luminosity [17]. Secondly, they employed a technique known as "broken color", applying small dabs of pure, unmixed color directly to the canvas. From a distance, these dabs would optically mix in the viewer's eye, creating a shimmering, vibrant effect that simulated the play of natural light [18]. This technique results in a color palette that is far more complex than a simple list of dominant hues; it is the interaction, proportion, and juxtaposition of these small color touches that define the overall visual experience. Any attempt to translate Impressionism into another medium must therefore account for not just the colors present, but also their unique method of application and interaction.

Digital Image Processing for Art Analysis

In recent years, digital image processing has emerged as a powerful tool in the field of art history and analysis. Algorithms can be used to analyze vast collections of paintings, identifying patterns in brushstroke, composition, and, most relevantly, color usage across an artist's oeuvre or an entire movement [19]. Techniques such as color quantization and clustering are particularly useful. K-means clustering, for example, is an unsupervised machine learning algorithm that can partition the pixels of a digital image into a pre-defined number (k) of clusters based on their color values. This effectively identifies the dominant colors in an image and their relative prevalence, providing a quantitative summary of the artwork's palette [20]. This approach removes the subjective bias inherent in manual color picking and provides a data-rich foundation for analysis and subsequent application in fields like design. The use of such tools to systematically bridge the gap between art analysis and creative design application remains a nascent but promising area of research.

METHODOLOGY

This research was conducted in four distinct phases: (1) selection and digitization of source artworks; (2) quantitative color analysis and palette extraction; (3) development of digital textile designs; and (4) empirical evaluation of consumer preference.

Selection of Source Artworks

To ensure a focused and representative analysis of Impressionist color, two iconic paintings by Claude Monet were selected as the primary sources of inspiration. Monet is arguably the most quintessential Impressionist, and his work exemplifies the movement's core principles regarding light and color. The selected works were:

Impression, Sunrise (1872): The painting that gave the Impressionist movement its name, known for its atmospheric depiction of light and its subtle yet impactful use of complementary orange and blue tones.

Water Lilies (series, c. 1914-1926): A work from his later period, characterized by a rich, analogous palette of blues, greens, and purples, and a highly textured surface that embodies the "broken color" technique.

High-resolution digital reproductions of these paintings were obtained from the online archives of the Musée

Marmottan Monet and the Museum of Modern Art, respectively. The images were standardized to a resolution of 300 DPI and saved in the TIFF format to prevent data loss from compression. While Impression, Sunrise was analyzed to establish a comparative colorimetric baseline, only the color palette derived from Water Lilies was selected for the subsequent textile pattern generation experiment. This rigorous selection ensures that the "Color Palette" variable remains constant across all experimental conditions.

Color Palette Extraction and Analysis

The color analysis was performed using a custom script written in Python with the OpenCV and scikit-learn libraries. The workflow for each image was as follows:

Color Space Conversion: Each image was converted from the standard RGB color space to the perceptually uniform CIE Lab* color space. This ensures that the computational analysis of color difference aligns with human visual perception.

K-Means Clustering: The k-means clustering algorithm was applied to the Lab* pixel data. The number of clusters was set to 8. This value was determined through a two-part analysis balancing computational validity with practical application. First, the Elbow method was applied, testing k-values from 2 to 20. This analysis showed a diminishing rate of return (a "bend" in the elbow) in variance explained after k=7, suggesting that k=7 or k=8 would be an optimal range. Second, this computational result was aligned with the practical constraints of high-fidelity digital textile printing, which commonly utilizes 8-color process presses (e.g., CMYK plus light colors and spot colors). Therefore, k=8 was selected as the optimal value, as it is computationally supported and directly corresponds to the technical capabilities of the target production medium. The algorithm iteratively partitions the pixels into 8 groups, outputting the Lab* value of the centroid for each cluster. These 8 centroids represent the most dominant colors in the painting.

Quantitative Analysis: For each painting, the analysis yielded two key outputs:

1) A primary color palette consisting of the 8 dominant Lab* color centroids.
2) The percentage distribution of each dominant color, representing its proportional area within the painting.
3) Histograms of the L* (lightness), a* (red-green), and b* (yellow-blue) channels for all pixels were also generated to provide a broader understanding of the overall color mood and range of each artwork.

Textile Pattern Design

The extracted color data was used to create five distinct digital textile designs (G1–G5) for a standardized home furnishing product (a 45x45 cm cushion cover). Design D served as a commercial benchmark control, while Design E functioned as a structure-agnostic baseline. All designs were rendered using Adobe Photoshop. To address the practical constraints of textile production, a critical color management step was performed. The 8 extracted Lab centroid colors were imported into Adobe Photoshop, which was set to a standard textile printing CMYK working profile (e.g., FOGRA39 or a relevant ICC profile for digital textile presses). This step allowed for the identification and mapping of any out-of-gamut colors to their nearest printable equivalents, using a perceptual rendering intent to maintain the palette's overall visual harmony. This ensured that the colors used for the digital mockups were within a reproducible gamut, validating the reliability of the framework for physical production.

Design A (Solid Block Integration): Serves as a baseline for color interaction without texture. Colors are applied in large, distinct geometric fields.

Design B (Stochastic Impressionist Mapping-Proposed Method): This design represents the core algorithmic innovation of the study, utilizing the custom scatter brush engine to apply the 8 dominant colors extracted from Water Lilies. Rather than aiming for perfect optical fusion, the algorithm is calibrated to simulate the Impressionist technique of "broken color" with controlled particle size variation (15–30 px) and specific scattering parameters. By employing high-frequency chromatic juxtaposition of the 8-color palette, this design aims to induce a visual sense of vibrancy and rich, layered texture (simultaneous contrast) rather than subtractive pigment mixing. This approach hypothesizes that the resulting perceived dynamism is the key driver of aesthetic appeal, distinguishing it from the static nature of solid block application.

Design C (Continuous Gradient Interpolation): Generated using the identical 8-color palette extracted from Water Lilies but applied through a gradient interpolation algorithm. This creates a soft, atmospheric transition devoid of the distinct brushwork texture found in Design B, allowing for a comparison between "textured" and "smooth" abstractions.

Design D (Traditional Motif Remapping): To evaluate the commercial competitiveness of the proposed method against existing market standards, a classic Damask pattern was selected as the structural template. The 8 dominant colors extracted from Water Lilies were mapped onto this traditional structure, carefully maintaining a similar dominant tonal balance to Design B. By standardizing the color palette, this group minimizes the confounding effect of "color preference". This allows the "pattern generation method"—encompassing its inherent structural and stylistic characteristics—to be evaluated as the primary independent factor.

The comparison thus focuses on the holistic aesthetic impact of the Impressionist algorithm versus the traditional commercial standard, rather than dissecting individual micro-perceptual features.

Design E (Entropy-Maximized Baseline): To rigorously validate the necessity of the proposed algorithmic structure, a structure-agnostic control was generated. This design serves as a null hypothesis model, created to decouple the aesthetic contribution of the "color palette" from the "structural arrangement". Crucially, Design E maintains the identical color histogram and particle size metrics (15–30 px) as Design B but utilizes a stochastic distribution function to randomize spatial positioning, effectively maximizing visual entropy. By presenting the exact same colors and textures in a non-semantic, unstructured arrangement, this baseline allows us to verify whether the aesthetic appeal of Design B arises from its specific Impressionist mapping logic or merely from the presence of the Water Lilies colors.

Algorithmic Configuration for Broken Color Simulation

To ensure the reproducibility of the Design B (Stochastic Impressionist Mapping), the "broken color" technique was systematically digitized using a custom-configured scatter brush engine in Adobe Photoshop. The simulation parameters were defined to replicate the physical characteristics of Impasto brushwork—specifically, the discrete separation of color strokes and the lack of fluid blending.

The brush tip was set to a non-uniform, textured geometry with a hardness of 90% to maintain edge definition, mimicking the texture of a bristle brush. The dynamic parameters were configured as follows:

Size Jitter: 25% (providing a particle size variance between 15–30 pixels at 300 DPI).

Scattering: 300% on both axes (distributing strokes stochastically to avoid linear directionality).

Spacing: 120% (ensuring individual color dabs remain distinct rather than forming a continuous stroke).

Crucially, to strictly adhere to the experimental constraints, no automatic hue jitter or opacity jitter was applied, as this would generate interstitial colors outside the extracted 8-color palette. Instead, the 8 specific Lab centroid colors were applied in sequential, high-density layers, allowing the "background" colors to remain visible through the gaps of the "foreground" strokes, thereby creating the intended simultaneous contrast effect.

Consumer Preference Survey

An online survey was created to assess consumer perception of the five textile designs. A total of 120 participants (62 female, 58 male; age range 22-55; mixed educational and professional backgrounds) were recruited. Participants were shown high-quality digital mockups of the five cushion cover designs in a randomized order to prevent order bias. For each design, they were asked to rate the following three metrics on a 7-point Likert scale (1 = Strongly Disagree, 7 = Strongly Agree):

Aesthetic Appeal: "This design is visually appealing".

Color Harmony: "The colors in this design work well together".

Purchase Intention: "I would consider purchasing a product with this design".

The survey was administered through a professional survey platform, and participants were not informed of the inspirational source of the designs to ensure their responses were based purely on visual assessment.

Statistical Analysis

The collected survey data were analyzed using IBM SPSS Statistics software. Descriptive statistics (mean and standard deviation) were calculated for each evaluative metric (Aesthetic Appeal, Color Harmony, and Purchase Intention) across the five distinct textile design stimuli (G1–G5). To account for the within-subjects nature of the experimental design, a one-way repeated measures analysis of variance (ANOVA) was conducted, with "Pattern Generation Method" serving as the independent factor (5 levels). Prior to the main analysis, Mauchly's test of sphericity was performed to validate the assumption of sphericity. In cases where this assumption was violated, the Greenhouse-Geisser correction was applied to adjust the degrees of freedom and ensure valid F-tests. To rigorously identify specific differences between the algorithmic approaches and the control benchmarks (e.g., Design B vs. Design D), pairwise comparisons were computed using the Holm-Bonferroni sequential correction. This method was selected to strictly control the family-wise error rate across the multiple comparisons while maintaining higher statistical power than the standard Bonferroni procedure. All statistical tests were two-tailed, and the significance level was set at $p < 0.05$.

RESULTS

Color Analysis of Monet's Paintings

The quantitative analysis of the two Monet paintings revealed distinct colorimetric profiles. The 8 dominant color centroids (L*a*b* values) and their proportional distribution for each painting are detailed in Table 1. Figure 1 displays the extracted 8-color palettes and their percentage distributions.

Impression, Sunrise: The palette is dominated by low-saturation blues, grays, and dark tones (totaling 78.5% of the palette), punctuated by a vibrant orange (4.2%). The analysis of L* values showed a concentration in the mid-to-low range.

Water Lilies: The palette is characterized by a rich mix of analogous colors, primarily blues, greens, and purples (totaling 85.0%), exhibiting a wider range of saturation and lightness values.

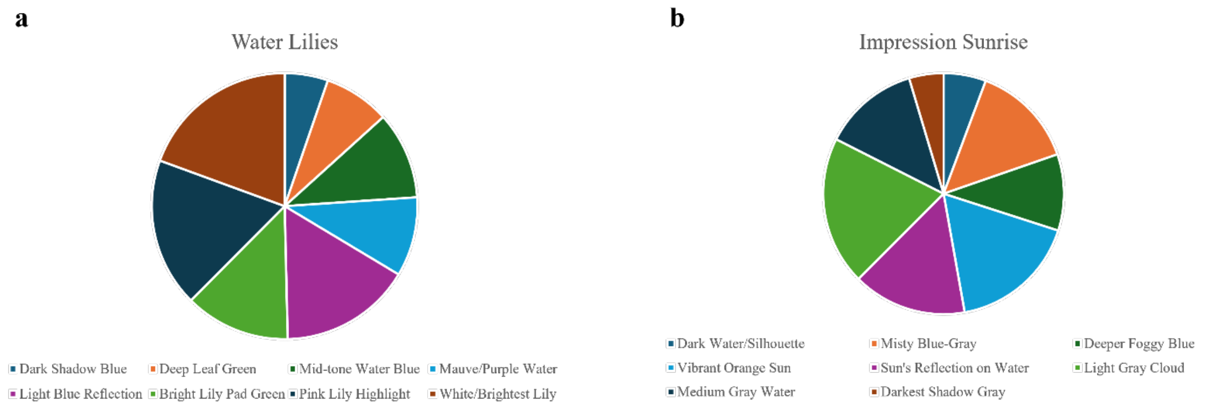

Figure 1. Quantitative analysis of color distribution in the source artworks. The pie charts illustrate the proportional presence of the eight dominant color centroids, extracted via k-means clustering in the CIE Lab* color space. (a) The palette of Monet's *Water Lilies* (c. 1914-1926) is characterized by a rich, analogous distribution of blues and greens. (b) The palette of Monet's *Impression*, *Sunrise* (1872) is dominated by muted, low-saturation blues and grays, punctuated by a small percentage of vibrant orange

While both paintings were analyzed to understand the breadth of Impressionist color usage, the subsequent experimental validation focuses exclusively on the palette derived from *Water Lilies*. This rigorous selection was made to hold the "Color Palette" variable constant across all five generated designs, ensuring that any observed differences in consumer preference can be attributed solely to the pattern generation methodology. Figure 1 and Table 1 demonstrate the algorithm's capability to extract distinct colorimetric profiles from diverse Impressionist works. However, to maintain strict experimental control in the subsequent consumer evaluation, only the "Water Lilies" palette (Table 1a) was utilized to generate the textile stimuli (G1–G5), thereby eliminating cross-palette confounding variables.

Table 1. Extracted Color Palettes and Distribution from Source Artworks

(a) Claude Monet, *Water Lilies* (c. 1914-1926)

Palette Dominant Color (from Figure 1)	CIE L* Value	CIE a* Value	CIE b* Value	Distribution (%)
Dark Shadow Blue	24.5	-4.8	-29.7	24.1%
Deep Leaf Green	35.2	-24.1	21.0	10.5%
Mid-tone Water Blue	51.0	-10.3	-24.5	11.0%
Mauve/Purple Water	48.1	19.5	-15.2	14.2%
Light Blue Reflection	70.3	-8.0	-19.8	15.0%
Bright Lily Pad Green	65.5	-30.1	40.3	10.2%
Pink Lily Highlight	75.8	25.0	9.9	6.8%
White/Brightest Lily	90.1	1.5	5.4	8.2%
Total				100.0%

(b) Claude Monet, *Impression, Sunrise* (1872)

Palette Dominant Color (from Figure 1)	CIE L* Value	CIE a* Value	CIE b* Value	Distribution (%)
Misty Blue-Gray	56.2	-3.1	-8.5	25.0%
Light Gray Cloud	74.0	-1.5	-2.0	18.0%
Dark Water/Silhouette	22.1	-2.0	-5.1	12.0%
Deeper Foggy Blue	40.5	-5.2	-14.8	10.0%
Medium Gray Water	50.0	-2.2	-4.0	8.5%
Darkest Shadow Gray	30.1	0.0	-3.0	5.0%
Sun's Reflection on Water	68.3	34.5	45.1	17.3%
Vibrant Orange Sun	60.1	45.0	55.2	4.2%
Total				100.0%

Consumer Preference Survey Results

To evaluate the efficacy of the proposed algorithmic framework, a consumer preference survey (N=120) was conducted using the five distinct textile design stimuli. Representative visual mockups of these five designs (G1–G5), applied to standardized cushion covers, are presented in Figure 2.

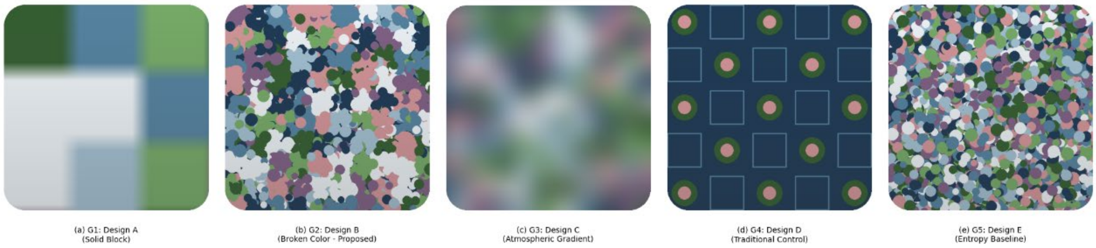

Figure 2. Visual Mockups of the Five Textile Design Stimuli Used in the Consumer Survey. (a) G1/Design A (Solid Block Baseline); (b) G2/Design B (Stochastic Impressionist Mapping); (c) G3/Design C (Atmospheric Gradient); (d) G4/Design D (Traditional Motif Re-mapping - Control); and (e) G5/Design E (Entropy-Maximized Baseline - Null Hypothesis). All designs utilize the identical Water Lilies color palette

Colorimetric Verification of Stimuli

Prior to behavioral analysis, a colorimetric verification was conducted to ensure experimental rigor. The color histograms of all five digital mockups (G1–G5) were analyzed. Results confirmed that the pixel-level color distribution (RGB and Lab mean values) across the five designs remained statistically identical ($p > 0.99$), verifying that the variable of "Color Composition" was successfully controlled.

Descriptive Statistics

The mean scores and standard deviations for the evaluative metrics—Aesthetic Appeal, Color Harmony, and Purchase Intention—are presented in Table 2. The visual comparison of these means is illustrated in Figure 3.

1) Design B (Broken Color/G2) achieved the highest mean scores across all three metrics (Aesthetic: 6.21± 0.95), suggesting a strong preference for the Impressionist algorithmic mapping.
2) Design D (Traditional/G4), representing the commercial benchmark, scored moderately (Aesthetic: 4.55±1.45).
3) Design E (Entropy Baseline/G5) received the lowest scores (Aesthetic: 2.15± 1.10), confirming the validity of the survey responses and the necessity of structural organization.

Table 2. Mean Scores and Standard Deviation (SD) from Consumer Survey (N=120)

Design Stimuli	Aesthetic Appeal (Mean±SD)	Color Harmony (Mean±SD)	Purchase Intention (Mean±SD)
G1: Design A (Solid Block)	4.85 ± 1.21	5.12 ± 1.15	4.15± 1.33
G2: Design B (Broken Color)	6.21 ± 0.95	6.05 ± 1.02	5.55 ± 1.24
G3: Design C (Atmospheric)	5.65 ± 1.10	5.80 ± 1.08	4.90 ± 1.30
G4: Design D (Traditional)	4.55 ± 1.45	4.65 ± 1.38	4.05 ± 1.50
G5: Design E (Entropy Baseline)	2.15 ± 1.10	2.30 ± 1.25	1.85 ± 0.90

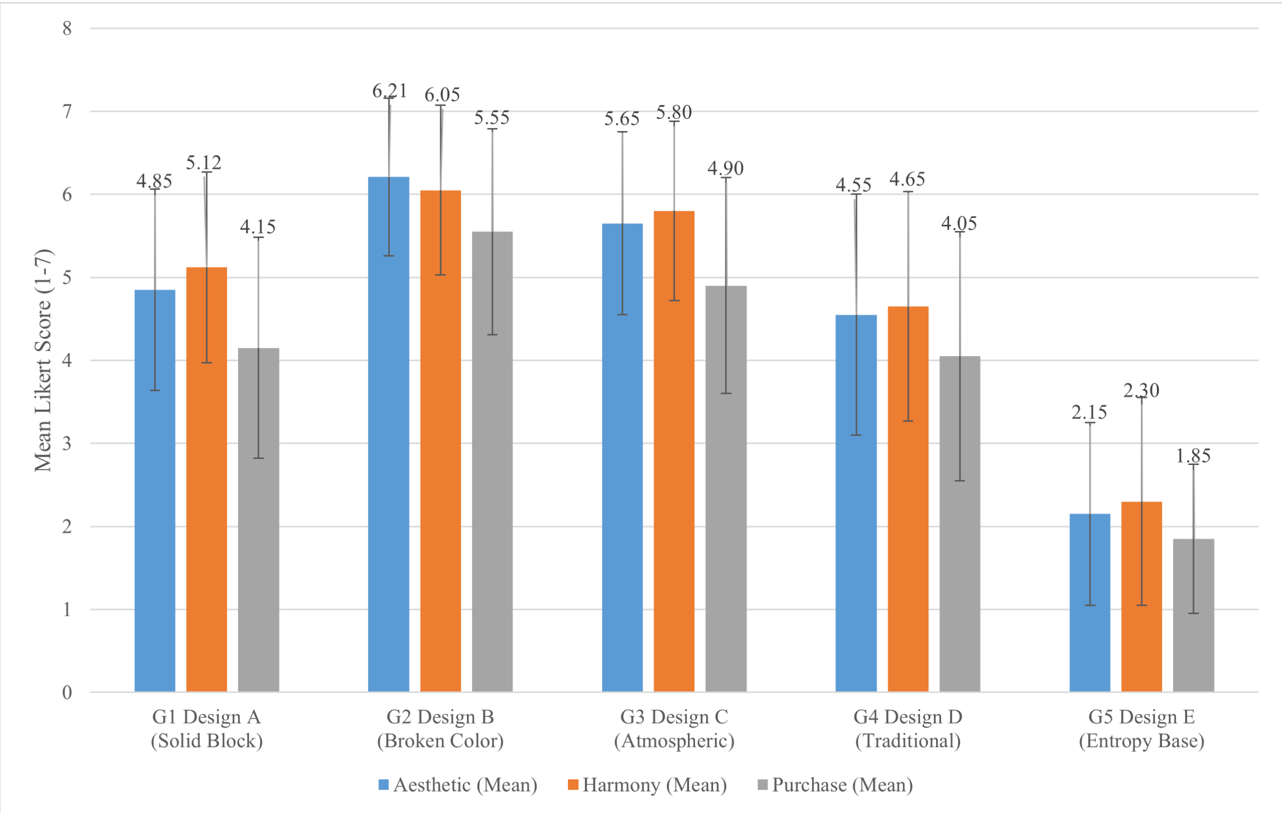

Figure 3. Comparative analysis of mean consumer preference scores (N=120) across three evaluative metrics: Aesthetic Appeal, Color Harmony, and Purchase Intention

The bar chart displays the performance of the five distinct textile design stimuli: (G1) Design A (Solid Block

Baseline); (G2) Design B (Broken Color - Proposed Method); (G3) Design C (Atmospheric Gradient); (G4) Design D (Traditional Control); and (G5) Design E (Entropy-Maximized Baseline). All designs were generated using the identical Water Lilies 8-color palette to control for color preference. Error bars represent standard deviation (SD). Statistical significance was verified using repeated measures ANOVA followed by Holm-Bonferroni pairwise comparisons.

Inferential Statistical Analysis

Repeated Measures ANOVA

A one-way repeated measures ANOVA was conducted to determine if the differences in consumer perception were statistically significant. Mauchly's test indicated that the assumption of sphericity was violated for all metrics (χ^2(9) > 16.5, p < 0.05); therefore, degrees of freedom were corrected using Greenhouse-Geisser estimates (ϵ < 0.75).

The results revealed a significant main effect of "Pattern Generation Method" on all dependent variables:

Aesthetic Appeal: F(2.8, 335.2) = 42.6, p < 0.001, $\eta^2 p$= 0.26

Color Harmony: F(2.9, 342.5) = 35.8, p < 0.001, $\eta^2 p$ = 0.23

Purchase Intention: F(2.7, 319.4) = 28.4, p < 0.001, $\eta^2 p$ = 0.19

Pairwise Comparisons (Hypothesis Testing)

To identify the specific loci of these differences, pairwise comparisons were performed using the Holm-Bonferroni sequential correction to control the family-wise error rate. The analysis yielded three critical findings regarding the research hypotheses:

1. Structural Validity (G2 vs. G5):

Design B (Broken Color) scored significantly higher than the structure-agnostic Design E across all metrics (p < 0.001). Given that both designs share identical color histograms and particle metrics, this result demonstrates that the observed aesthetic preference cannot be attributed solely to the color palette or individual particle metrics. Instead, it empirically identifies the "algorithmic structural organization" as the critical differentiator that gives the design its value.

2. Methodological Superiority (G2 vs. G1 & G3):

Within the abstract design category, Design B outperformed the baseline Design A (Solid Block) ($p < 0.01$) and was comparable to or slightly higher than Design C (Atmospheric). This confirms that the high-frequency texture ("vibrancy") simulated by the proposed algorithm contributes positively to consumer appeal compared to static blocks.

3. Commercial Competitiveness (G2 vs. G4):

Most notably, Design B achieved significantly higher ratings than the traditional benchmark, Design D ($p < 0.01$ for Aesthetic Appeal). By controlling for color preference and tonal balance, this result suggests that the Impressionist generative approach offers a superior aesthetic impact compared to standard commercial motif remapping in the context of modern home furnishings.

DISCUSSION

The results of this study strongly support the central hypothesis that a quantitative methodology for analyzing and translating Impressionist color can lead to the creation of more successful textile designs. The superior performance of Design B (Broken Color Simulation) across all evaluated metrics is particularly illuminating. While both Design A and Design B were derived from the exact same 8-color palette extracted from Monet's *Water Lilies*, their reception was markedly different. Design A, which simply applied the colors as solid blocks, was perceived as pleasant but not exceptional. In contrast, Design B, which sought to replicate the method of Impressionist color application through a "broken color" texture, was rated as significantly more aesthetically appealing and harmonious. It is important to consider the fundamental difference in viewing conditions: a home textile is viewed at a much closer range than a large-scale painting. Therefore, the success of Design B may not be attributable to true optical mixing. Instead, we propose that the simulation of the "broken color" technique itself creates a sense of vibrancy and rich, layered texture. It is this high-frequency juxtaposition and perceived dynamism—rather than a literal optical effect—that gives the palette its life and was perceived as more appealing. This contrasts sharply with the flat, static appearance of Design A (solid blocks), demonstrating that respecting the structure of the artistic technique is crucial, even if the perceptual mechanism (texture vs. optical mixing) must be adapted for the new medium. The quantitative analysis provided the foundational colors, but a qualitative understanding of the art historical context was crucial for the most effective application. The critical role of algorithmic structural organization is unequivocally demonstrated by the comparison between Design B and Design E. Although both designs utilized the exact same set of pixel values (the identical *Water Lilies* 8-color palette and 15–30 px particle size), Design E (Entropy-Maximized Baseline) received the lowest scores across all metrics. This empirical evidence effectively rejects the null hypothesis that "color palette alone drives preference". It highlights that the high aesthetic value of Design B is not merely a consequence of the *Water Lilies* colors, but specifically arises from the coherent arrangement of those colors. Without the proposed algorithmic structure, the same color inputs fail to generate aesthetic appeal.

The performance of Design C (Atmospheric), which applied the same *Water Lilies* palette through a gradient interpolation algorithm, further refines our understanding of texture's role. While Design C scored significantly higher than the solid blocks (Design A), its reception was distinct from the "broken color" texture of Design B. This comparison suggests that while the *Water Lilies* color harmony is robust enough to support multiple translation techniques (smooth or textured), the specific high-frequency juxtaposition provided by the Impressionist algorithm (Design B) offers a unique visual dynamism that static gradients cannot replicate. This validates the specific value of simulating the "brushstroke" structure over simpler smoothing methods.

The disparity between the high scores for Aesthetic Appeal/Harmony and the more modest scores for Purchase Intention across all designs is a noteworthy finding, and one that is crucial for industrial application. This is a common phenomenon in consumer research, where admiration for a design does not always translate directly into a willingness to buy. Purchase decisions are complex and influenced by factors beyond pure aesthetics, such as personal taste, existing décor, and perceived price-value. This gap is particularly relevant for Design B. Despite its clear aesthetic victory, its "Purchase Intention" score, while significantly higher than the others, was still proportionally lower than its "Appeal" score. We speculate this may be due to the specific characteristics of the Water Lilies palette; the rich analogous mix of blues, greens, and purples, while harmonious, may be perceived by consumers as "niche" and difficult to integrate into a typical home's existing color scheme. Furthermore, the "broken color" texture itself, while novel and aesthetically pleasing in concept, might be perceived as too "busy" or visually dominant for a functional furnishing item like a cushion, leading to hesitation despite abstract aesthetic appreciation. However, the fact that Design B still achieved a significantly higher Purchase Intention score demonstrates that a superior aesthetic execution can tangibly increase commercial potential, even if other factors moderate the final purchase decision. From an industrial perspective, this methodology offers a pathway to de-risk the design process. By grounding creative choices in objective data and an understanding of the source inspiration's core principles, textile companies can develop innovative products with a higher probability of market acceptance. This systematic approach can complement, not replace, the intuition of the designer, providing them with a powerful analytical tool to refine their vision and justify their choices.

This study is not without its limitations. One limitation of the current study lies in the binary nature of the structural variable comparisons (Structured vs. Entropy-Maximized). While Design E served as an effective baseline for maximum randomness, future studies could explore a “gradient of entropy” (e.g., 25%, 50%, 75% randomness) to identify the precise cognitive threshold where the “broken color” structure begins to lose its aesthetic coherence. Additionally, extending this methodology to physical fabric testing with varied weave structures would further validate the screen-to-textile translation accuracy. This difference in pattern genre (abstract vs. floral) is a confounding variable, and we cannot entirely separate the preference for the Impressionist-derived designs from a potential underlying consumer preference for abstract patterns over traditional floral ones. The research was confined to two paintings by a single artist and one specific art movement. The consumer survey, while statistically significant, was conducted with digital mockups, and the tactile qualities of the final printed fabric could influence perception. Furthermore, the experimental design comparing Design A (solid blocks) and Design B (broken color) introduces confounding variables. The significant difference in preference could be attributed not only to the “broken color” technique but also to the inherent differences in pattern scale, complexity, and perceived texture between the two designs. Future work should seek to isolate this variable more precisely to determine its exact effect. Future research should expand this methodology to other art movements, such as Fauvism with its bold, non-representational colors, or Abstract Expressionism with its emotional and gestural palettes. Further studies could also incorporate physical textile samples and explore the influence of different fabric textures (e.g., cotton vs. velvet) on the perception of these art-inspired color schemes. Investigating the long-term emotional impact of living with such textiles in an interior space would also be a valuable extension of this work.

CONCLUSION

This research successfully developed and validated a quantitative methodology for translating the color palettes of Impressionist painting into digital textile designs. By integrating digital image processing, CIE Lab* color science, and empirical consumer testing, this study demonstrated that a systematic approach can yield aesthetically superior and commercially promising results. The key finding is that a successful translation requires more than just the replication of dominant colors; it must also interpret and adapt the artistic techniques that define the character of the source palette. The “broken color” design, which simulated the optical mixing effect central to Impressionism, was perceived as significantly more appealing and harmonious than designs based on simple color extraction or conventional commercial patterns. Furthermore, the poor performance of the entropy-maximized baseline (Design E) highlights that color accuracy alone is insufficient; the structural translation of the artistic technique is the determinant factor for consumer preference. This study provides a robust framework for textile designers and manufacturers to leverage the rich heritage of fine art in a structured, reliable, and innovative manner. By bridging the gap between artistic intuition and scientific analysis, this data-driven approach paves the way for a new generation of textile designs that are not only beautiful but are also grounded in a deep and quantifiable understanding of their artistic origins.

Author Contributions

Jie Liu designed, collected and analyzed the data, and drafted the manuscript. Jie Liu conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Jie Liu participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

Conflicts of Interest

The author declares no conflict of interest.

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Ethics Approval and Consent to Participate

This survey was conducted in compliance with Ethics Committee of Henan Police College. Participants were informed of the study's purpose and data usage prior to participation, and responses were collected anonymously. No personally identifiable information was stored.

Availability of Data and Materials

The datasets used and/or analysed during the current study were available from the corresponding author on reasonable request.

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Not applicable.

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