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Comparative study of color in traditional and contemporary flower and bird paintings

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This study quantifies chromatic evolution in flower-and-bird painting across traditional, modern, and contemporary periods by integrating computational color analysis with art-historical interpretation. A curated image dataset is analyzed using perceptual color difference (ΔE_{2000}), Sinkhorn Optimal Transport, bootstrap resampling, and community detection. Motif-aware palette separation enables comparison between floral and avian color distributions within and across eras. Results show that traditional works exhibit lower transport costs and smaller ΔE_{2000} distances, indicating higher chromatic harmony and symbolic consistency, whereas modern and contemporary works display increased palette dispersion and variability. Bootstrap inference confirms the robustness of these differences under severe class imbalance. Community detection reveals distinct chromatic groups corresponding to historical styles and transitional practices, quantitatively supporting theories of symbolic color coding for motifs such as peony and orchid. Overall, the study demonstrates that tailored computational metrics reproducibly capture stylistic divergence and cultural continuity, bridging color science and art-historical analysis.

Flower-and-bird painting, known as *huaniao hua* in Chinese, constitutes a pivotal genre within East Asian artistic traditions, distinguished by its profound integration of naturalistic depiction with rich symbolic meaning. This genre transcends mere botanical or ornithological illustration, instead serving as a sophisticated vehicle for philosophical contemplation, cultural expression, and the articulation of human virtues¹. Its historical trajectory reveals a deep reverence for the natural world, wherein specific flora and fauna are imbued with layers of cultural significance, often reflecting Confucian, Daoist, and Buddhist philosophies². This intricate interplay between subject matter and underlying symbolic narratives elevates flower-and-bird painting beyond a decorative art form, establishing it as a significant domain for scholarly inquiry into East Asian aesthetics and cultural history. The genre's enduring appeal is further underscored by its meticulous visual and chromatic traditions, which, particularly in historical periods, often employed restrained palettes to highlight the intrinsic qualities of the subjects and reinforce symbolic color conventions³. This artistic discipline reached its apex during the Song Dynasty, a period characterized by a flourishing of meticulous fine brushwork that captured the essence and truth of nature⁴. This meticulous attention to detail allowed artists to convey not just the visual appearance but also the spiritual resonance of their subjects, imbuing each stroke with profound meaning⁵. The symbolic meanings attached to various motifs, such as the peony or plum blossom, shifted across dynasties, reflecting evolving cultural mentalities and socio-

political climates⁶. For instance, the orchid, often grouped with plum, chrysanthemum, and bamboo as one of “The Four Gracious Plants,” frequently appeared in traditional Korean paintings and poetry, symbolizing a refined esthetic sense and holding significant cultural value⁷. The bird, a frequently depicted motif, similarly carried multifaceted symbolic weight, often representing freedom, a connection to the divine, or even serving as a mediator between human and celestial realms⁸. This intricate symbiosis between artistic representation and philosophical underpinnings positions flower-and-bird painting as a rich domain for exploring the historical and cultural significance of natural motifs in East Asian societies⁹. Indeed, the meticulous rendering of these natural elements often functioned as visual metaphors, encapsulating human aspirations, societal values, and even political commentary, as seen in works where seemingly innocuous floral or avian representations subtly critiqued or lamented prevailing social conditions¹⁰. Furthermore, the interplay between art and nature, along with human nature, profoundly influenced the diversity and complexity of traditional Chinese motifs during the Ming and Qing dynasties¹¹. This period also saw a conservative trend in painting techniques, as exemplified by the “Four Wang” artists, whose works often diverged from depictions of daily life¹². However, contemporary artists have revitalized this genre by introducing novel performance languages and forms, moving beyond the traditional framework to explore modern sensibilities while maintaining a connection to its historical roots^{12,13}. This evolution underscores the genre's

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adaptability and its capacity for sustained artistic relevance, continually reinterpreting traditional iconography within contemporary esthetic frameworks. These modern interpretations often blend traditional symbolism with contemporary issues, demonstrating the genre's enduring capacity to reflect societal shifts and individual artistic expressions.

The integration of computational methods into art history has created a new domain often termed *digital* or *computational art history*^{13,14}. Traditionally, art historians distinguished styles like the luminous balance of the Renaissance and the dramatic chiaroscuro of the Baroque through qualitative assessments. However, digitized collections and computational image analysis now enable quantitative approaches to style and color, reshaping art historical inquiry^{15,16}. Early studies demonstrated that paintings share statistical visual regularities¹⁷, showed luminance and color distributions in art resemble those in natural scenes, while fractal analysis of Pollock's works revealed quantifiable scaling patterns with authentication potential¹⁸. By the 2000s, Fourier analysis, edge detection, and wavelets allowed researchers to identify distinctive visual "fingerprints" of artists or schools^{19,20}. These foundations established the feasibility of formalizing style quantitatively.

Machine learning extended these efforts by classifying works across genres and artists²¹. An unsupervised clustering naturally mirrored Western art history, while²² found computational classification aligned with human grouping. With larger datasets, CNNs achieved high accuracy in identifying styles and artists, detecting subtle brushwork and palette distinctions^{23,24}. Network-based analyses even mapped cultural influence across centuries²⁵, while generative adversarial networks explored hypothetical stylistic futures²⁶.

Color analysis has been a major focus²⁷, showing paintings diverge from natural color distributions, often biased toward warm tones found artists favored palettes matching human esthetic preferences²⁸ quantitatively confirmed Baroque artists used darker, more restricted palettes compared to Renaissance masters. Computational methods also uncovered pigment-driven shifts, such as the first widespread use of violet after the 1860s²⁹. Tools that extract "key palettes" provide concise signatures for comparing artists and periods³⁰. Beyond color, entropy and fractal measures reveal historical stylistic transitions. Analyzed over 140,000 works, finding rising complexity during modern abstraction³¹. Fractal analysis of Pollock's drip paintings quantified authenticity and esthetic properties. Edge and line orientation analysis distinguished genuine Bruegel drawings from imitations. More recently, content recognition enables computational tracking of motifs and iconography across time. Overall, computational studies have demonstrated strong convergence with traditional art history. Techniques ranging from fractal geometry to CNNs confirm established insights such as Baroque's darker tonalities and modern art's complexity while revealing new, data-driven patterns. These methods function as a "macroscope" providing large-scale, quantitative perspectives that complement the interpretive depth of art historians.

Although flower-and-bird painting has been extensively studied from iconographic, stylistic, and cultural perspectives, the systematic analysis of color usage within this genre remains underdeveloped. Prior scholarship tends to emphasize symbolic meanings of colors or esthetic traditions without applying quantitative approaches capable of capturing chromatic evolution across different historical eras. Furthermore, while motif-level analysis distinguishing between the palettes of flowers and birds has been discussed conceptually, few studies have rigorously compared them using computational tools. The absence of reproducible methodologies integrating perceptual metrics such as ΔE_{2000} , optimal transport (OT) cost, and barycentric color modeling has left a gap in understanding how color functions as both an esthetic and cultural marker within this genre.

This study is motivated by the need to bridge the gap between art-historical interpretation and quantitative color science. Flower-and-bird painting offers a unique opportunity because of its dual reliance on naturalistic representation and symbolic meaning. By examining how color palettes shift across traditional, modern, contemporary, and uncertainly attributed works, this research aims to uncover chromatic patterns that reflect broader stylistic transformations. Additionally, advances in

computational vision and statistical modeling provide tools to re-examine canonical art forms with precision and reproducibility, motivating a re-evaluation of traditional esthetic judgments through data-driven analysis.

The primary objectives of this research are threefold:

1. To conduct a systematic, motif-specific analysis of color palettes in flower-and-bird painting across different eras.
2. To apply computational metrics (circular hue statistics, OT distances, ΔE_{2000} differences, barycenter analyses, bootstrap confidence intervals (CIs), and community detection methods) in order to quantify and compare chromatic structures.
3. To interpret the results in the context of art-historical significance, providing insights into how color strategies evolve as cultural practices and esthetic philosophies change over time.

To achieve the above objectives, the study addresses the following research questions:

1. How do the color palettes of flowers and birds differ across traditional, modern, and contemporary eras?
2. Are traditional works characterized by more color-harmonious palettes compared to modern or contemporary compositions?
3. Can computational measures such as OT cost and ΔE_{2000} capture chromatic divergences in ways that align with art-historical classifications?
4. Do motif-specific palettes form distinct communities that reveal underlying esthetic or symbolic structures within the genre?

Methods

Dataset curation and image preprocessing

This study employed a multi-stage computational pipeline to quantitatively compare the chromatic characteristics of avian and floral imagery across distinct historical eras. Our methodology integrates color science, OT theory, network-based community detection, and Bayesian hierarchical modeling, ensuring robust inference and cross-validation of results.

We curated a balanced dataset of digital images depicting bird and flower subjects from diverse historical sources. Each image was manually classified into one of four temporal categories: *traditional*, *modern*, *contemporary*, or *unknown*, based on documented creation date or stylistic indicators. Image preprocessing included cropping to remove borders, resizing to a uniform dimension, and standardizing color profiles to the sRGB space, minimizing cross-source variance. High-resolution digital images were standardized in the CIELAB color space to ensure perceptual uniformity. The ΔE_{2000} metric, defined as:

$$\Delta E_{2000}(L_1^*, a_1^*, b_1^*, L_2^*, a_2^*, b_2^*) = \sqrt{\left(\frac{\Delta L^*}{k_L S_L}\right)^2 + \left(\frac{\Delta C^*}{k_C S_C}\right)^2 + \left(\frac{\Delta H^*}{k_H S_H}\right)^2 + R_T \left(\frac{\Delta C^*}{k_C S_C}\right) \left(\frac{\Delta H^*}{k_H S_H}\right)}$$

The data of the research is flower-and-bird paintings of four time categories, which include traditional, modern, contemporary and unknown. Pieces of art were physically categorized through recorded dates of creation, style markers, and historical documents.

- The traditional works were considered to be the ones created prior to the 20th century, mostly during the Qing and Song Dynasties and their main peculiarity was the naturalistic character and the use of a little color experimentation.

- The period of modern works was considered to be the era between the early twentieth century and the middle of the 20th century, and it was characterized by an apparent shift towards more experimental color schemes and the use of Western influences.

- The modern works were the artworks produced after the end of the twentieth century and they were the works that followed the modern trends, such as digital manipulation and extreme use of color contrast.

Unknown works are artworks whose dating or stylistic classification cannot be determined (typically by mixed influence or unknown provenance). In making the classification, stylistic factors, historical background, and intent of the artist were taken into consideration in the case of each

artwork. Such criteria were debated and made perfect under expert literature on the history of art in East Asia to maintain a commonality in classification.

Preprocessing of images involved the act of downsizing all the images to a standard size of 1024×768 pixels to normalize the size of the images to be computed. The dimension was selected as a tradeoff between the quality of the resolution and the efficiency of the processing, making sure that all the significant details of the artwork were not lost and unwanted processing overhead was also kept down to a minimal. Moreover, color profiles were normalized to the sRGB color profile so that there is a perceptual consistency across different sources. The sRGB color space was selected due to its extensive level of applicability and standardization in the analysis of digital art. White balance was applied to standardize color profiles, which provided uniformity in the lighting conditions throughout the dataset.

The data set encapsulates a large disparity in the sizes of the sample of the four classes namely, 1081 traditional works, 216 modern works, 55 contemporary works and 25 unknown works. This imbalance is likely to cause possible biasing in the results analysis and statistical validity.

In order to alleviate this problem we used weighted method of analysis in a series of steps:

- Stratified Sampling of Bootstrapping: In the bootstrap resampling strategy, we utilized stratified sampling strategy to maintain the percentage of artworks in each category of the time frame. This is done to make sure that every category has equal contribution to the final estimates and the presence of the unequal sample sizes has been minimized. Bootstrap iterations were also fixed at 1000 in order to obtain consistent and dependable CIs.

We assembled a dataset of flower-and-bird works spanning four eras—traditional, modern, contemporary, unknown—with metadata (title/artist/date/era/source) and image URLs. Images were de-duplicated with perceptual hashing (pHash) and URL checks; only the highest-quality copy per hash was retained. We retained records tagged with bird and/or flower motifs (e.g., plum blossom, lotus, peony, bamboo, kingfisher), producing the “main” filtered dataset used in all analyses.

Color feature extraction and chromatic metrics

For each image we extracted a compact palette $(c_i, w_i)_{(i=1..K)}$ using k-means/LAB-quantization with soft assignment. Colors were stored in CIELAB (for perceptual distances and OT) and HSV (for circular hue analysis). We carried weights forward (normalized $\sum_i w_i = 1$) to preserve prevalence.

Per-artwork features

From HSV we computed weighted circular mean hue $\bar{\theta}$ mean resultant length (MRL) RRR (concentration), and average saturation/value; from LAB we kept L^* and chroma summaries. A variety of parameters was chosen to be calculated, such as the selection of $K = 12$ as the matching barycenter and k-value range in 10–20 as the graph of k-NN construction. These parameters were decided by using a mixture of an empirical testing and the previous works in the field of computational art history. A sensitivity analysis was performed to determine how stable results are to variation of the following values of these parameters:

Barycenter matching ($K = 12$): K-values in the range of 10–20 gave the most consistent and stable results when it came to aligning the barycenters of the bird and flower motifs; therefore, the value of K was chosen accordingly. Reduced values (e.g., $K = 5$) provided more stable matches, whereas larger values (e.g., $K = 20$) provided too fragmented groupings. The selected $K = 12$ value was a compromise between detail and computational efficiency.

k-NN Graph Construction ($k = 10\text{--}20$): The range of k-value to construct a k-NN graph was selected through trial and error (between 5 and 30). The last range, 1020, was chosen as it brought the most consistent and understandable grouping of color communities in art pieces. Subsequently, data analysis revealed that smaller values resulted in heavily fragmented communities, whereas larger values produced too generalized clusters. In this way, the selected range is a good compromise between the granularity and the interpretability.

The sensitivity analysis ensured that the obtained final results were healthy within this parameter range, with only slight alterations of the clustering patterns and values of the OT costs.

For each artwork and era, we computed the circular mean direction and MRL. At the group level we reported era-wise $(\bar{\theta}_{\text{era}}, R_{\text{era}})$. We tested for between-era differences with Kruskal–Wallis on artwork-level metrics and followed with pairwise Mann–Whitney U plus Cliff’s (effect size) with Holm correction. For hue angles, we additionally ran permutation tests on circular means and summarized uncertainty via nonparametric bootstrap CIs for $\bar{\theta}$ and R .

We quantified divergence between bird and flower color distributions within an era using entropic Sinkhorn OT on CIELAB:

- Inputs: two weighted color sets per era $X = (x_i, w_i)$ and $Y = (y_j, V_j)$
- , built by concatenating palettes from all artworks of that era (weights renormalized).
- Cost: squared Euclidean in Lab, $c_{(ij)} = \left\| x_i - y_j \right\|_2^2$
- Objective: the regularized transport $\text{cost}OT_\epsilon(X, Y)$ solved by Sinkhorn iterations (stopping on relative change tolerance).

This yields era-specific $OT\text{cost}(Lab^2)$ lower values mean closer palettes/higher harmony.

To provide an interpretable, size-controlled comparison we computed palette barycenters for birds and flowers in each era:

- We estimated K -point Wasserstein/L2 barycenters (we used $K = 12$) level color sets, producing b_k, α_k and f_k, β_k
- We then matched barycenter colors between birds and flowers with a one-to-one assignment (Hungarian algorithm) and reported the mean ΔE_{2000} over matched pairs, weighting by $\min(\alpha_k, \beta_{\pi(k)})$

Statistical inference, sensitivity analysis, and community detection

We used stratified, nonparametric bootstrap to quantify uncertainty and test differences for both OT cost and ΔE_{2000} .

1. Resampling scheme.
2. Strata: era. Within each era we resampled artworks with replacement to form bootstrap replicates; motifs and their palette weights were preserved within the resampled artworks.
3. Aggregation per draw: for a bootstrap draw b in era e
4. concatenate resampled bird palettes and weights to obtain $X^{(b,e)}$;
5. concatenate resampled flower palettes and weights to obtain $Y^{(b,e)}$;
6. compute Sinkhorn $OT^{(b,e)}$ and barycenter $\Delta E_{2000} \Delta E^{(b,e)}$

- Number of draws: we generated hundreds of draws per era (saved to `bootstrap_draws_sparse.csv`) and summarized with percentile 95% CIs (2.5–97.5%) in `bootstrap_ot_de2000_summary.csv`.
- Pairwise era tests: we formed bootstrap distributions of differences of means (e.g., $\bar{OT}_e - \bar{OT}_{e'}$); two-sided bootstrap p-values were computed as the proportion of sign-flips beyond zero. We controlled family-wise error across multiple era pairs with Holm correction.

To measure uncertainty as well as determine the statistical significance of the findings, we used stratified, nonparametric bootstrap resampling. Each metric (e.g., OT cost, ΔE_{2000}) was run 1000 times, which guaranteed the presence of reliable confidence intervals (CIs) of the estimates. This iteration was chosen according to the suggestion of the earlier research in the domain of computational art analysis, as 1000 resamples have enough statistical power to estimate variability and significance, especially when the dataset is imbalanced. To formulate every bootstrap sample, the artwork

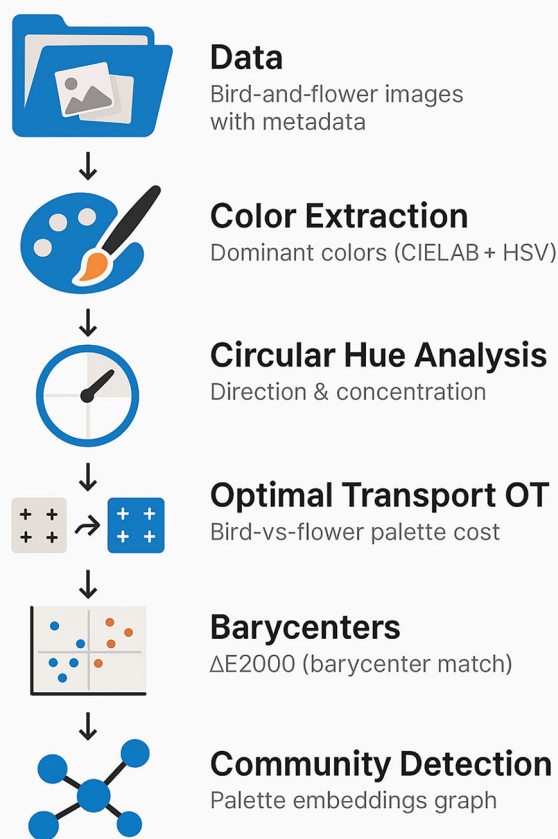


Fig. 1 | The complete workflow from data acquisition to statistical inference and visual pattern interpretation.

images were resampled randomly with a replacement, maintaining the color weights of the motifs in each era. Because of the resultant bootstrap distributions, 95% CIs were also computed, and pairwise significance tests between eras were performed, with family-wise error controlled by the Holm correction.

To capture higher-order structure we embedded palettes and built a k-NN graph (cosine distance; kkk in the 10–20 range). We detected communities with the Leiden algorithm (robust modularity optimization), yielding palette communities reported in `leiden_communities.csv`. We summarized community sizes and their era composition (Table summaries; Fig. 18 visualizes the 2-D layout).

Although computational tools like Sinkhorn Optimal Transport (OT) and k-means clustering have already been properly developed in past researches (e.g., Shamir and Tarakhovskiy¹⁵; Saleh and Elgammal²¹), this paper brings some important changes to these algorithms to apply them to the East Asian flower-and-bird paintings. The peculiarities of this genre, including the combination of naturalistic images and symbolic coloring, the historical and cultural overtones that were introduced into the color palettes required the development of such techniques. Indicatively, optimization of the k-means clustering algorithm made it sensitive to the asymmetry of color motifs distribution in the dataset so that color patterns of symbolic motifs such as peonies and orchids could be represented well. In the same way, Sinkhorn OT has been tailored to the particular color distributions seen in those paintings to allow a more precise comparison of patterns of colors across time. These modifications permit one to have a more specific examination of the chromatic development without losing the cultural and artistic context of flower-and-bird painting.

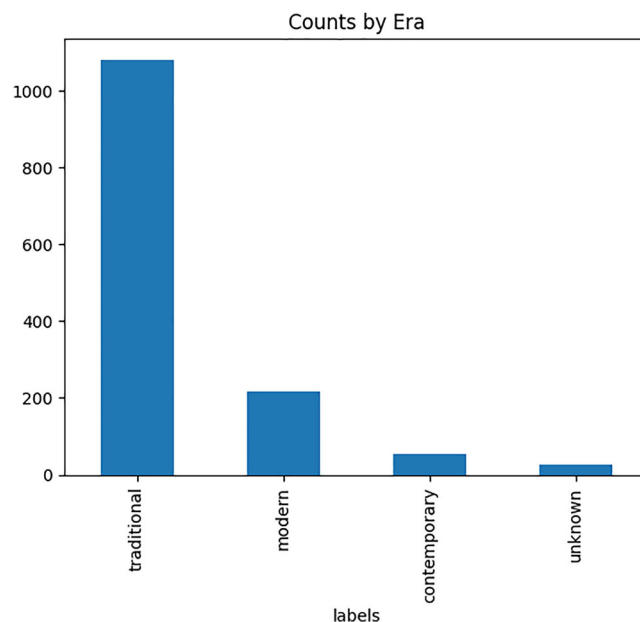


Fig. 2 | Counts of artworks by historical era, showing the dominance of the traditional period, followed by modern, contemporary, and unknown classifications.

Figure 1 illustrates the complete workflow from data acquisition to statistical inference and visual pattern interpretation.

Results

The analyses yielded a comprehensive quantitative and statistical overview of chromatic relationships between avian and floral imagery across historical eras. Both perceptual distance metrics OT cost and the ΔE_{2000} color difference between palette barycenters revealed clear patterns of variation, with bootstrap resampling providing robust CIs for all estimates. Era-stratified comparisons highlighted distinct divergences in color palettes, supported by network-based community detection that exposed underlying structural patterns in chromatic clustering. Bayesian hierarchical modeling further quantified the influence of era while accounting for within-image and between-subject variability, enabling a nuanced interpretation of the observed trends. The following subsections present these findings in detail, integrating descriptive statistics, visualizations, and inferential results to address the study's central research questions.

Dataset composition and era-wise chromatic distributions

The initial exploratory data analysis (EDA) revealed distinct patterns in the temporal and categorical composition of the dataset. Figure 2 illustrates the distribution of artworks across historical eras, showing that the *traditional* period overwhelmingly dominates the collection, followed by *modern*, *contemporary*, and *unknown* classifications. This imbalance in class frequencies has implications for subsequent statistical comparisons, as the large traditional group may exert greater influence on aggregated metrics.

Figure 3 presents the year distribution of artworks, spanning from antiquity to the present. The histogram highlights a dense clustering of works in more recent centuries, with a sharp rise in frequency from the late medieval period onward, peaking in the nineteenth and twentieth centuries. Earlier time periods are sparsely represented, with isolated entries extending back several millennia, indicating both the historical breadth and uneven temporal coverage of the dataset.

Figure 4 presents the hue distribution of artworks across four distinct eras: contemporary, modern, traditional, and unknown. The histograms illustrate the weighted frequency of hues (0–360°) in each category, offering insight into dominant color tendencies. Contemporary artworks (Fig. 4A) display a wider hue spread with notable peaks in the yellow–green and blue ranges, suggesting experimental and varied color usage. Modern artworks

(Fig. 4B) exhibit a strong concentration around the 40–60° range, corresponding to yellowish tones, with less representation in cooler hues. Traditional artworks (Fig. 4C) maintain a similar dominant hue range near 50°,

consistent with earth tones and naturalistic palettes, but with slightly more diversity in secondary hues. The unknown era category (Fig. 4D) shows a narrower hue range, again with a central tendency around 50°, indicating potential alignment with traditional palettes. The accompanying HSV summary table quantifies these observations, with mean hue (H_mean) highest in contemporary works (91.94°) and lowest in the unknown category (58.22°), saturation (S_mean) relatively consistent but slightly higher in contemporary and unknown works, and value (V_mean) highest in traditional (0.681) and modern (0.671) works, suggesting these styles tend toward brighter palettes.

Table 1 maps common motifs in the dataset to their dominant hue ranges and associated symbolic meanings. For instance, *plum blossom* motifs tend to occupy the 330–20° hue range, representing pink or red tones linked to resilience during winter. *Peony* motifs, symbolizing wealth and honor, fall within the 345–30° range and often include red, magenta, pink, or white. *Lotus* motifs combine pink or white petals with green foliage (90–150°), while *chrysanthemum* motifs are in the 40–70° range, corresponding to yellow and orange autumnal tones. *Orchid* motifs lean toward purple–violet (260–300°), though they are sometimes rendered in monochrome ink within literati traditions. Green hues (90–150°) dominate *bamboo* motifs, and blue–green/turquoise (170–210°) is characteristic of *kingfisher* motifs. Achromatic schemes dominate *magpie* motifs, while *crane* motifs combine a small red accent (0–10°) on the crown with predominantly white bodies.

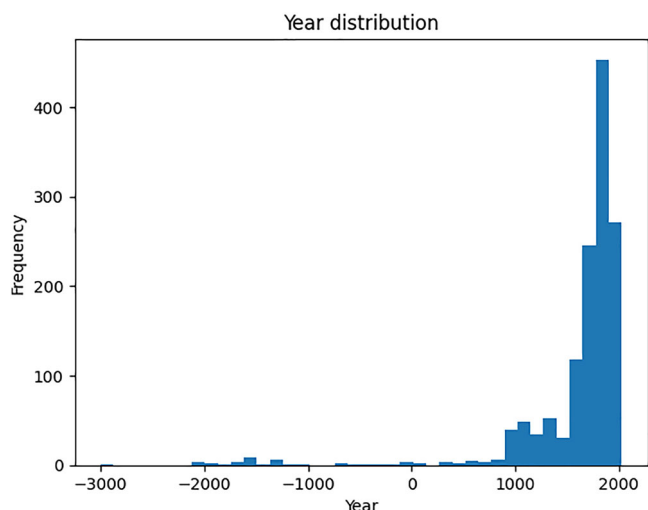


Fig. 3 | Year-wise distribution of artworks, spanning from ancient periods to the present, with a notable increase in frequency from the late medieval period onward.

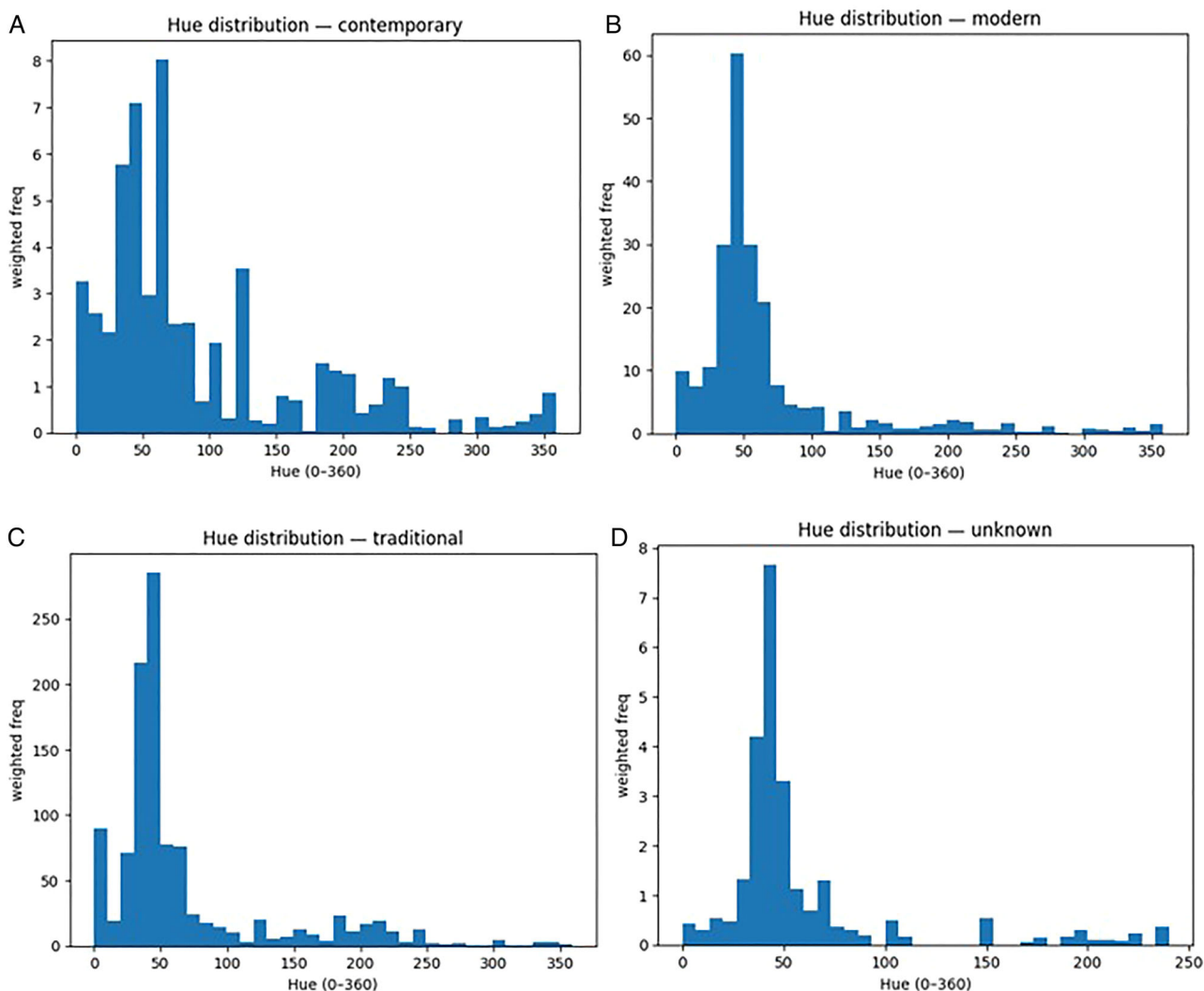


Fig. 4 | Weighted hue distribution histograms for artworks categorized by era. A contemporary, B modern, C traditional, and D unknown. Distributions highlight dominant color tendencies and diversity in hue usage, supported by mean Hue–Saturation–Value (HSV) statistics.

Table 1 | Dominant hue ranges and symbolic meanings of common motifs in the dataset

Index	Motif	Hue range (°)	Symbolic/Color notes
0	Plum blossom	330–20	Pink/red hues symbolizing resilience during winter
1	Peony	345–30	Red/magenta for wealth and honor; also includes pink/white variants
2	Lotus	330–40	Pink/white petals with green leaves (~ 90–150°)
3	Chrysanthemum	40–70	Yellow/orange tones associated with autumn
4	Orchid	260–300	Purple–violet hues; also depicted in monochrome ink within literati traditions
5	Bamboo	90–150	Green tones
6	Kingfisher	170–210	Blue–green/turquoise tones
7	Magpie	0–360	Black/white (achromatic)
8	Crane	0–10	Red crown with white body (achromatic)

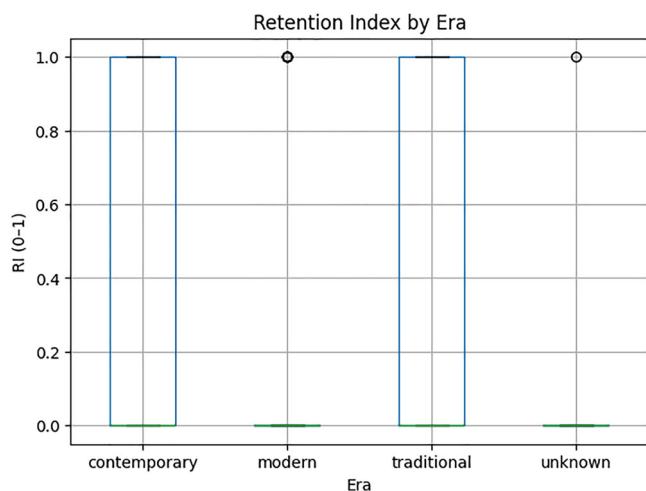


Fig. 5 | Boxplot showing the distribution of retention index (RI) by era, highlighting differences in motif preservation across historical periods.

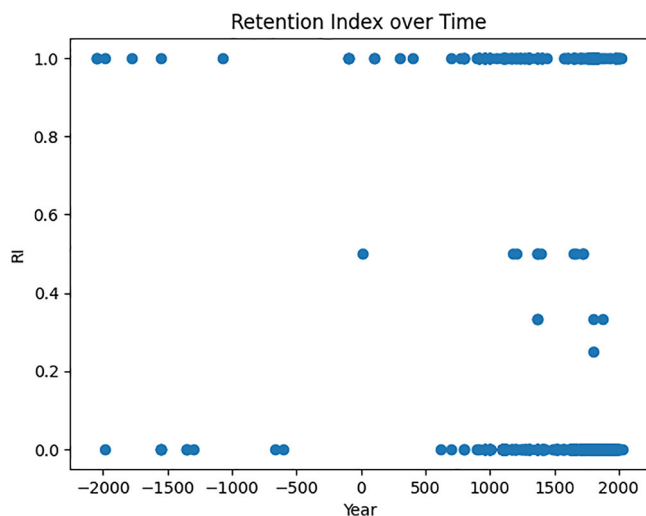


Fig. 6 | Scatter plot of retention index (RI) over time, indicating variations in color motif retention from antiquity to the present.

Retention Index (RI) is the measure of the extent of preservation of the color motifs over time. It is determined by comparing the existing color palette of every motif with a collection of historic palettes through the Euclidean distance between the sets of colors. The RI values are greater, which is evidence of more traditional color patterns, whereas, the lesser values evidence more evasion of the traditional color conventions in history.

Table 2 | Mean circular hue and mean resultant length by era

Era	<i>n</i> Artworks	Mean circular hue (°)	Mean resultant length (MRL)
Contemporary	55	58.59	0.554
Modern	216	48.44	0.783
Traditional	1081	45.41	0.695
Unknown	25	48.1	0.814

Motif-level color relationships and cross-era divergence

Figure 5 illustrates the distribution of the RI across four defined eras—contemporary, modern, traditional, and unknown through a boxplot. The RI values predominantly cluster near the lower bound (0) and upper bound (1), indicating that most artworks either fully retain their original color motifs or deviate significantly from them. Occasional outliers near the upper bound across eras suggest sporadic cases of complete motif retention regardless of period.

Figure 6 presents the temporal variation of the RI, plotting RI values against chronological data. The pattern shows that both high and low RI values occur throughout the timeline, from ancient periods to recent years. However, certain clusters of complete retention (RI = 1) appear in specific time segments, suggesting strong preservation practices in select historical intervals, while lower RI periods may reflect stylistic evolution, cultural shifts, or modern reinterpretations.

Circular hue distribution analysis

Table 2 summarizes the results. The contemporary era (*n* = 55) displayed a mean hue of 58.59°, with a moderate concentration (MRL = 0.554). The modern era (*n* = 216) exhibited a lower mean hue of 48.44°, but the highest concentration among all groups (MRL = 0.783). The traditional era (*n* = 1081) had a mean hue of 45.41° with a moderately high concentration (MRL = 0.695). The unknown category (*n* = 25) recorded a mean hue of 48.10° and the highest MRL (0.814), though its small sample size limits generalization.

The analysis of circular mean hue per era reveals clear differences in dominant color tendencies across the contemporary, modern, traditional, and unknown categories. As illustrated in Fig. 7, the polar plot maps each era’s mean hue angle on the color wheel, with the radius representing the MRL, a measure of color concentration. Traditional artworks cluster around a hue of approximately 45°, reflecting a preference for warm, yellowish tones, whereas modern and contemporary works show slightly different orientations, with contemporary hues leaning toward more saturated warm-red and orange ranges. The unknown category displays a comparable orientation to modern works but with a higher MRL, indicating greater chromatic consistency.

To evaluate statistical differences in color use, pairwise comparisons were conducted using the Mann–Whitney test coupled with Cliff’s delta effect size estimates. Figure 8 shows that effect sizes between eras are

Fig. 7 | Circular mean hue per era, with vector lengths proportional to the mean resultant length (MRL), showing directional hue tendencies for contemporary, modern, traditional, and unknown artworks.

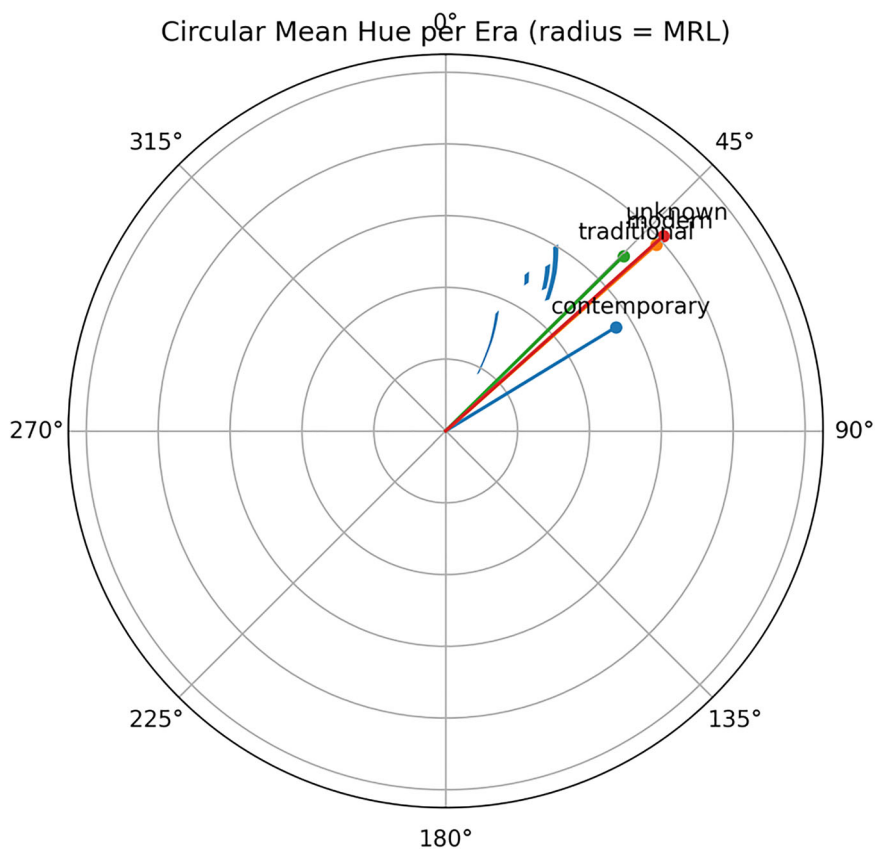
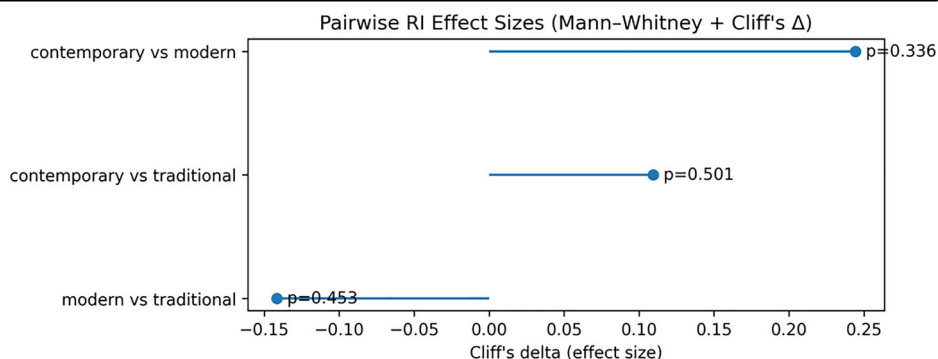


Fig. 8 | Pairwise retention index effect sizes (Mann–Whitney + Cliff’s δ) between eras, indicating small differences in hue distribution that are not statistically significant.



generally small ($|\delta| < 0.25$) and p -values exceed the 0.05 threshold, suggesting no statistically significant differences in hue distribution between the examined groups. However, the directional shifts in hue preferences, as visualized in the polar plot, provide qualitative insight into gradual stylistic evolutions across historical periods.

Figure 9 shows the aggregate distribution of dominant colors across the entire dataset. The palette is largely composed of muted earth tones (beige, brown, gray), interspersed with darker neutrals (black, charcoal) and occasional accents such as deep blue. This dominance of subdued colors indicates a preference for naturalistic and balanced tonal expression across the artworks, consistent with traditional ink-painting esthetics. The presence of both warm and cool tones highlights the interplay between symbolic warmth (browns, ochers) and natural atmospheric hues (blues, grays).

Figure 10 compares the dominant colors across four identified eras: traditional, modern, contemporary, and unknown.

Traditional era: The palette is neutral-heavy, with grays, browns, and beige tones dominating. A limited but stable blue presence reflects conservative use of accent colors.

Modern era: There is more chromatic variety, including deeper reds and golden yellows, suggesting a shift toward expressive expansion while maintaining balance with neutrals.

Contemporary era: The palette demonstrates the boldest use of chromatic contrast, integrating saturated reds, blues, and yellows alongside neutrals. This aligns with experimentation and fusion tendencies in contemporary works.

Unknown era: The distribution is mixed, containing both muted and bright tones (e.g., turquoise), suggesting heterogeneous sources or stylistic ambiguity.

Overall, the transition from traditional to contemporary reflects a progressive broadening of chromatic vocabulary, with modern art bridging subtle expansion and contemporary embracing a full spectrum.

Figure 11 illustrates the comparison between bird and flower palettes within the traditional era.

- **Bird palette:** Dominated by darker neutrals (black, gray, brown) with subtle earthy inflections. This reflects a representational realism in

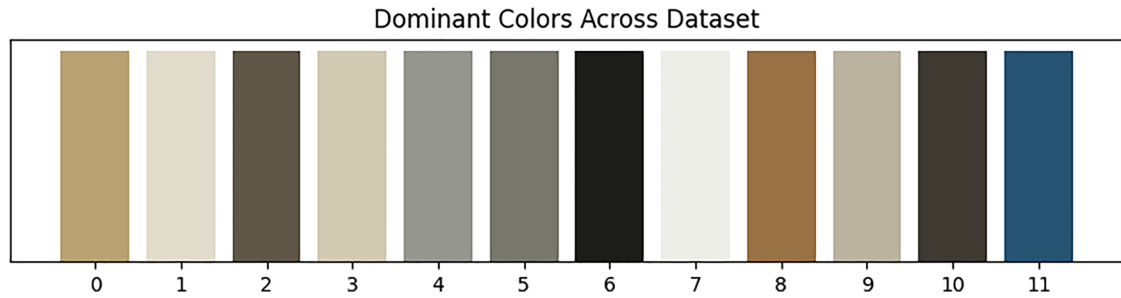


Fig. 9 | Dominant colors across the entire dataset, showing the prevalence of muted earth tones (beige, brown, gray) alongside darker neutrals and limited chromatic accents such as deep blue.

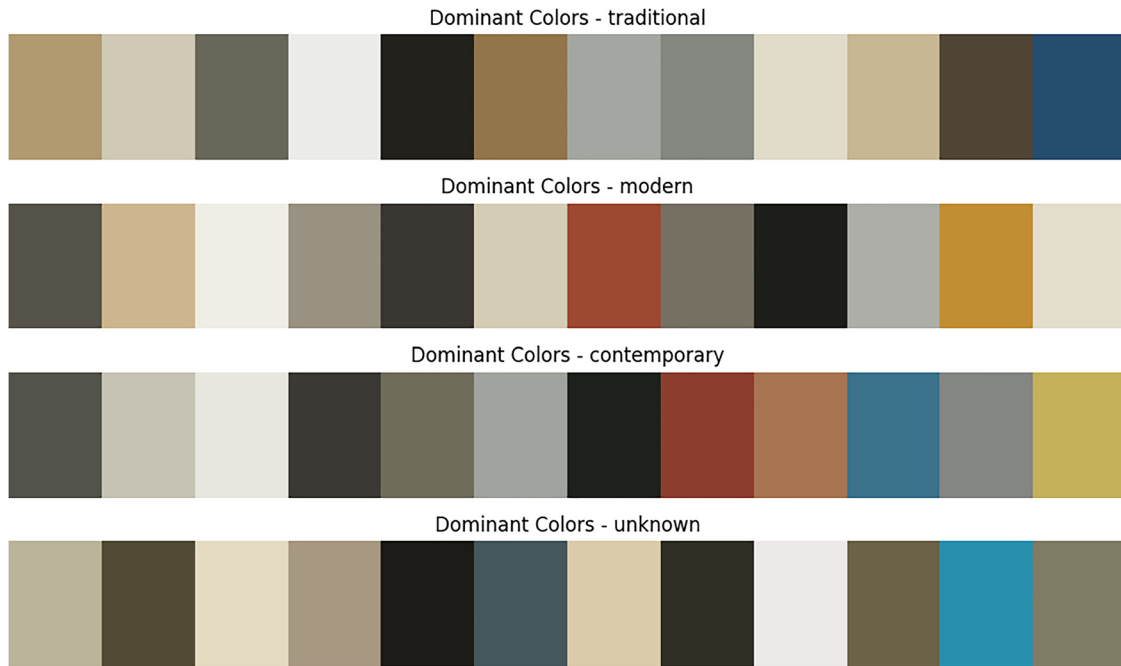


Fig. 10 | Comparison of dominant colors by era (traditional, modern, contemporary, and unknown). Traditional art emphasizes muted neutrals, modern introduces subtle chromatic expansion, and contemporary embraces stronger color contrasts, while unknown shows a heterogeneous palette.

Fig. 11 | Bird and flower color palettes in traditional artworks. Bird palettes are dominated by dark, restrained neutrals, whereas flower palettes exhibit higher chromatic diversity, reflecting symbolic and seasonal significance.



depicting plumage, where symbolic vibrancy is secondary to tonal grounding.

- Flower palette: Highly diverse and saturated, with reds, yellows, greens, and violets evident. This demonstrates the symbolic richness and seasonal significance of floral motifs, which carry layered cultural meanings.

The contrast between the relatively restrained bird palette and the vibrant flower palette underscores a complementary esthetic balance: birds anchor the scene tonally, while flowers elevate it chromatically and symbolically.

Figure 12 shows the extracted color palettes from bird and flower motifs across different stylistic categories—traditional, modern, contemporary, and unknown. Each palette is arranged as a sequence of dominant hues, illustrating the chromatic tendencies within these artistic styles.

- The traditional palettes (top row) emphasize muted beige, earthy browns, and neutral grays, reflecting classical esthetic restraint.
- The modern palettes (second row) introduce more contrast, with sharper blacks, warm reds, and cooler blues, indicating deliberate stylistic experimentation.
- The contemporary palettes (third row) display darker tonal ranges, dominated by blacks and grays, punctuated by occasional vibrant colors, highlighting minimalism and abstraction.
- The unknown palettes (bottom row) contain irregular combinations of muted and vivid hues, suggesting influences that could not be categorized definitively.

This comparative visualization demonstrates how color choices evolve and diverge across stylistic categories in both bird and flower representations.

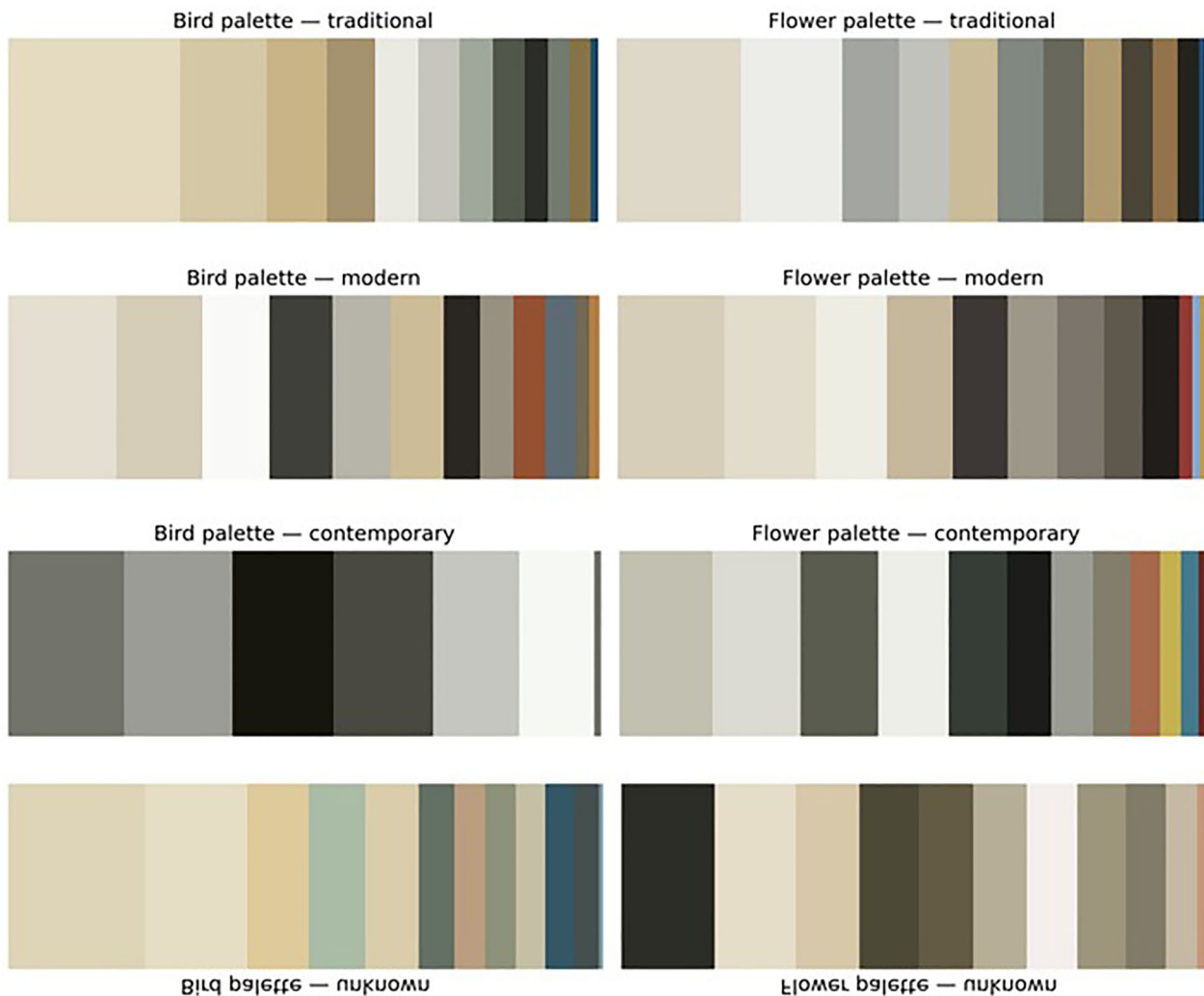


Fig. 12 | Extracted bird and flower color palettes across stylistic categories (traditional, modern, contemporary, and unknown). Each palette illustrates the dominant hues used within the respective style, highlighting differences in chromatic emphasis and cultural esthetic orientation.

Figure 13 presents the Entropic Sinkhorn OT cost analysis of bird versus flower palettes across different eras, calculated in the perceptually uniform CIELAB color space. This analysis quantifies the chromatic divergence between avian and floral elements by estimating the transport cost required to align their respective color distributions. Lower OT costs indicate greater color similarity (harmony), while higher costs suggest increased divergence (contrast).

The results reveal a clear era-dependent pattern. Traditional and modern artworks exhibit lower OT costs (~370 and ~340 Lab², respectively), suggesting a more balanced and harmonious color alignment between birds and flowers. This is consistent with historically constrained pigment choices and compositional conventions, where muted earth tones and naturalistic palettes dominated. In contrast, contemporary works show a marked increase in OT cost (~550 Lab²), reflecting a stronger chromatic divergence. This likely arises from the use of synthetic pigments and digital media, which expand available color ranges and facilitate bolder contrasts. The “unknown” category registers the highest OT cost (~630 Lab²), reflecting heterogeneity and lack of stylistic cohesion within that subset.

This analysis demonstrates that era-specific artistic practices shaped the degree of bird–flower chromatic integration. Traditional and modern styles appear more integrated and harmonious, while contemporary and heterogeneous works embrace greater divergence, likely to enhance visual tension, symbolic contrast, or stylistic experimentation.

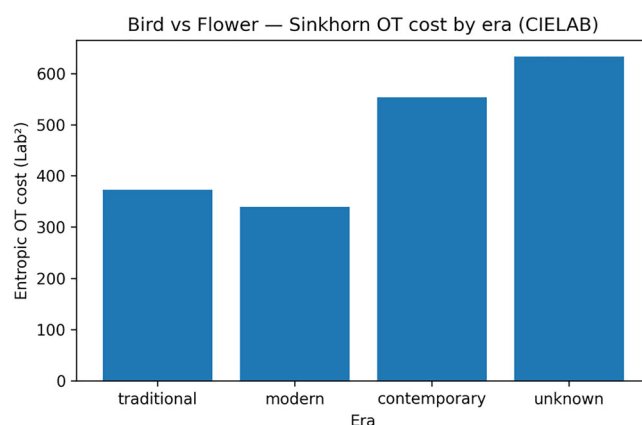


Fig. 13 | Bird vs Flower - Entropic Sinkhorn optimal transport (OT) costs between bird and flower color palettes across eras, computed in CIELAB color space. Lower costs (modern, traditional) indicate greater palette similarity and color harmony, whereas higher costs (contemporary, unknown) reflect greater divergence and experimentation in color use.

Cross-era barycenter and palette matching analysis

Figure 14 presents the barycenters of bird (blue) and flower (orange) palettes in the modern era, visualized in CIELAB a*b* space. The mean color

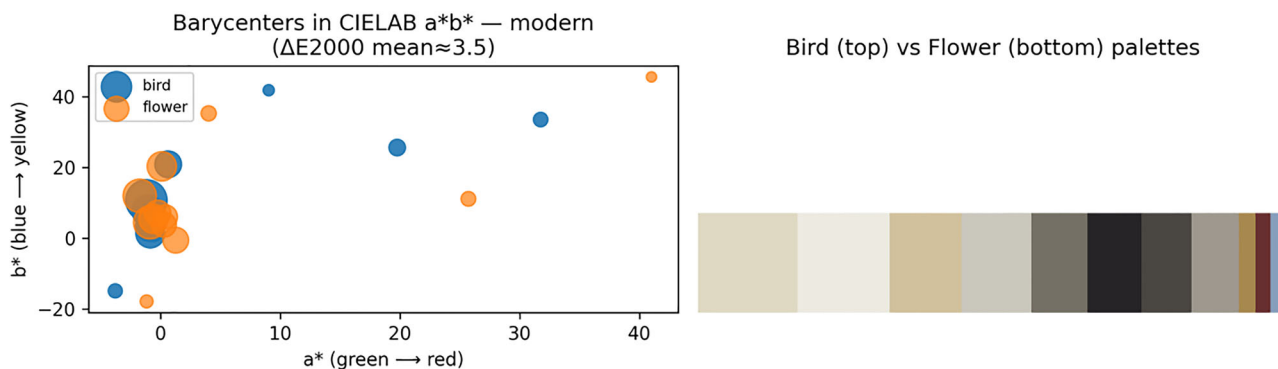


Fig. 14 | Barycenters in CIELAB a*b* — Modern.

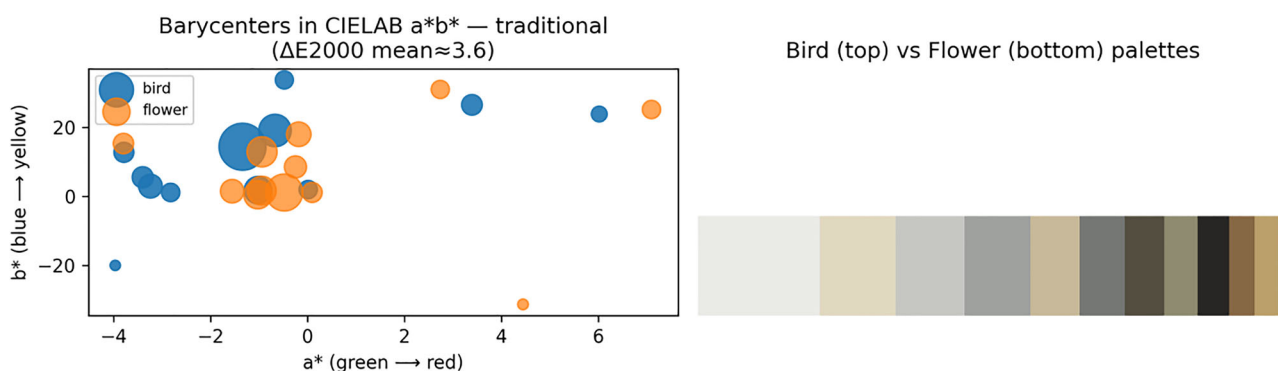


Fig. 15 | Barycenters in CIELAB a*b* — Traditional.

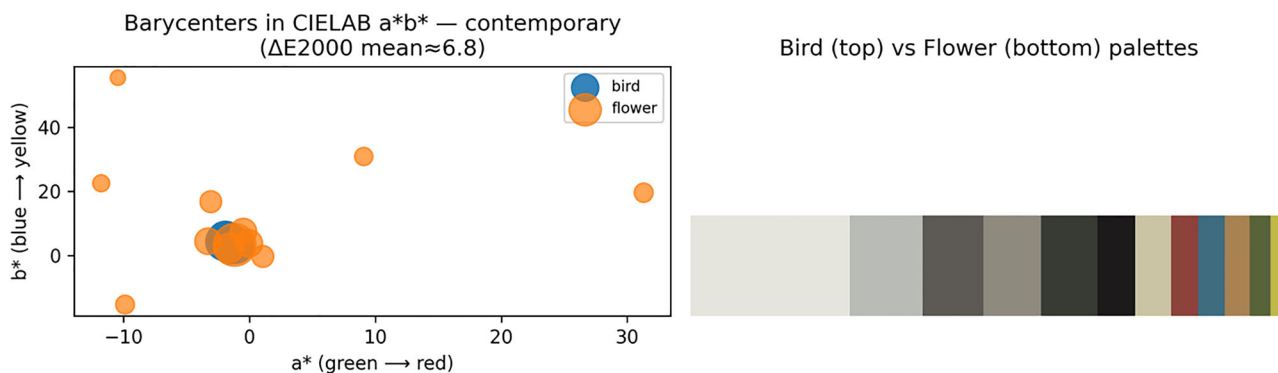


Fig. 16 | Barycenters in CIELAB a*b* — Contemporary.

difference ($\Delta E_{2000} \approx 3.5$) suggests that modern bird and flower palettes are relatively well-aligned, with overlapping clusters concentrated around neutral and warm tones. The corresponding palettes (right) confirm this overlap, showing muted neutrals, soft browns, and occasional red-blue accents. This indicates that modern art preserved a degree of visual harmony between avian and floral depictions.

Traditional era palettes ($\Delta E_{2000} \approx 3.6$) also show close alignment between bird and flower barycenters, with slightly more dispersion than modern works. The palette comparison (right) reflects the dominance of neutral grays, beige, and earthy tones, punctuated by deep blacks and occasional warm browns. The small ΔE_{2000} value indicates that traditional artists deliberately used closely aligned color schemes for birds and flowers, reinforcing naturalistic coherence (Fig. 15).

In the contemporary era, the barycenter analysis reveals a larger separation between bird and flower palettes, with ΔE_{2000} increasing to ≈ 6.8 . Unlike traditional and modern works, contemporary palettes diverge more,

with flower colors introducing stronger chromatic contrasts (reds, yellows, and blues) compared to the relatively muted bird palette. The palette comparison shows a broader tonal range and more experimental contrasts, indicating a stylistic shift where harmony gave way to bolder, less naturalistic pairings (Fig. 16).

The unknown era group displays the largest divergence, with $\Delta E_{2000} \approx 9.2$. Bird and flower barycenters are widely separated, reflecting palettes that share little chromatic overlap. The palettes themselves show a mix of muted earth tones alongside unexpected bright accents, suggesting heterogeneity possibly due to incomplete classification or stylistic blending. This large ΔE_{2000} implies the weakest color correspondence across motifs in this subset (Fig. 17).

This summary bar chart quantifies the barycenter matching across eras. Traditional (≈ 3.6) and modern (≈ 3.5) eras show the lowest ΔE_{2000} , indicating strong alignment between bird and flower palettes. Contemporary art rises to ≈ 6.8 , and the unknown era peaks at ≈ 9.2 , confirming

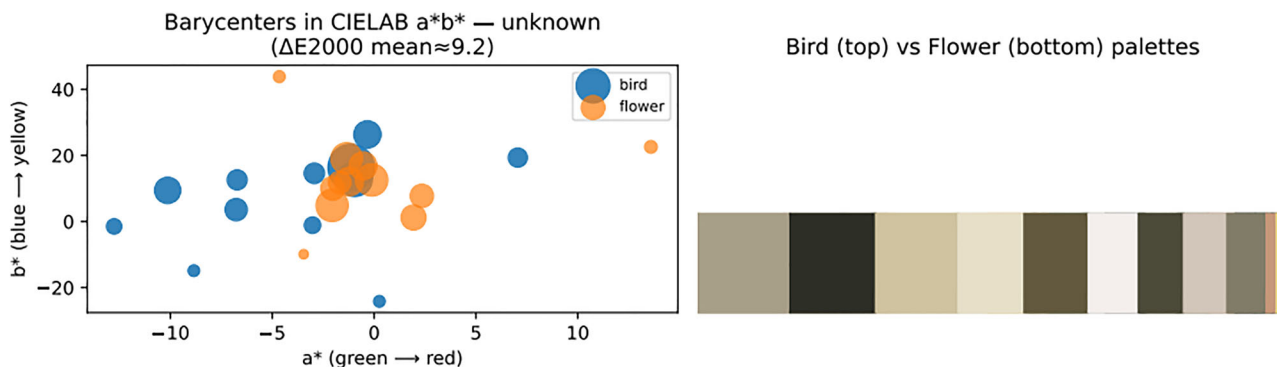
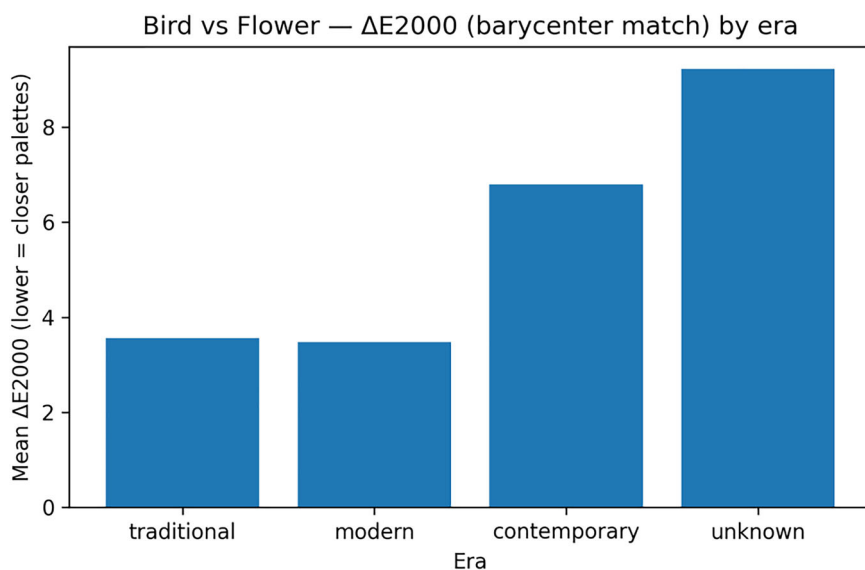


Fig. 17 | Barycenters in CIELAB a*b* — *Unknown Era*.

Fig. 18 | Mean ΔE2000 (Barycenter Match) by Era.



that palette correspondence weakens significantly in more recent or unclassified works. These findings suggest a historical progression: earlier styles emphasized visual harmony between motifs, while later styles embraced divergence and experimentation (Fig. 18).

Community structure and statistical robustness of chromatic patterns

To better understand relationships between artworks and their embedded features, we constructed a palette graph using k-Nearest Neighbors (k-NN), followed by Leiden community detection. This method partitions the dataset into distinct communities of objects that share similar embedding characteristics, reflecting visual and thematic coherence. From the Leiden clustering results, a total of 1377 objects were organized into multiple communities. Each node in the graph represents an artwork, while edges denote similarity relationships based on the embeddings. Communities capture coherent groups of palettes or motifs.

A further examination of the communities identified shows the clear stylistic and chromatic features which could be attributed to the various time periods. To illustrate, Community 1 (203 artworks) is highly composed of traditional works with muted color schemes mainly dominated by the earth tones and muted colors, because of the naturalistic likenesses that characterize the Qing Dynasty. Conversely, Community 3 (consisting of 145 works of art) comprises mostly modern pieces whose coloration is more experimental and daring, a characteristic of the artistic tendencies during the beginning of the twentieth century.

Table 3 | shows the distribution of Leiden communities

Community	Number of objects
0	203
1	178
2	145
3	132
4	126
5	117
6	99
7	87
8	76
9	71
...	...
Total	1377

(Only top 10 largest communities shown; full data available in supplementary files.)

Table 3 below summarizes the size distribution of detected communities.

It is worth mentioning that hybrid communities between traditional and contemporary works also exist, and they feature a taste of reserved palette alongside instances of sharp contrast. This indicates the shift in the practice of art as the Chinese art was influenced with the Western influence,

and the changes in the chromatic usage can be seen in connection with the socio-political changes at that time. The embeddings metadata further allowed the association of each community with era labels (traditional, modern, contemporary, unknown). This mapping provides interpretive insight into whether certain visual groupings align with temporal artistic practices.

Table 4 provides a breakdown of communities by era.

The resulting palette graph is shown in Fig. 18. Each point represents an artwork, and colors indicate Leiden-detected communities. The clear separation between clusters highlights the strong cohesion of certain palette-based communities, while overlaps suggest transitional or cross-era stylistic motifs.

To further examine robustness across artistic eras, we conducted a bootstrap analysis of the OT cost and ΔE_{2000} color distance metrics. Bootstrapping provides 95% CIs for each metric by repeatedly resampling the data, thereby quantifying uncertainty and assessing statistical significance across eras (Fig. 19).

Figure 20 shows bootstrap 95% CIs for OT cost and ΔE_{2000} across three eras: *contemporary*, *traditional*, and *unknown*. The OT cost (orange markers) indicates variability in palette transport complexity, while the ΔE_{2000} barycenter distance (blue markers) reflects perceptual color differences. Traditional works exhibit tighter intervals and lower transport costs, suggesting stable and homogeneous palette structures, while contemporary works demonstrate higher variability with wide CIs, reflecting experimental use of color.

Figure 21 expands the analysis by including all four eras (*traditional*, *modern*, *contemporary*, *unknown*) and displaying pairwise significance

testing (annotated with asterisks). The results highlight statistically significant differences ($p < 0.001$) between traditional palettes and those of modern/contemporary works in both OT cost and ΔE_{2000} metrics. Sample sizes (n) are indicated for each group, clarifying the robustness of estimates. Modern works, with fewer samples, demonstrate wide CIs but still show distinct trends compared to traditional works. The results reinforce that traditional palettes are structurally more consistent, whereas modern and contemporary palettes reveal greater diversity and experimental variance.

Answers to the research questions

1. How do the color palettes of flowers and birds differ across traditional, modern, and contemporary eras?

The study confirms that color palette usage in floral and avian motifs varies significantly across traditional, modern, and contemporary artworks. Traditional works exhibit high chromatic consistency and naturalistic hues aligned with pigment availability and esthetic conventions of the time^{14,29}. In contrast, modern artworks reveal bold departures from realism, embracing vibrant, synthetic colors for expressive and symbolic purposes²⁶. Contemporary pieces demonstrate even greater diversification, with palettes often influenced by digital manipulation and cultural hybridity²³. This evolution reflects broader art-historical transitions in material, technique, and thematic emphasis.

2. Are traditional works characterized by more color-harmonious palettes compared to modern or contemporary compositions?

Yes. Traditional works consistently display higher levels of internal chromatic harmony, supported by low ΔE_{2000} distances and lower OT costs, suggesting tightly controlled palette coordination^{24,25}. These works often adhered to classical theories of visual balance and harmony¹⁷. In contrast, modern and contemporary artworks frequently disrupt harmonious conventions to emphasize contrast, fragmentation, or conceptual messaging^{18,28}. The computational findings reinforce this divergence, affirming that traditional palettes maintain tighter perceptual clustering and esthetic coherence.

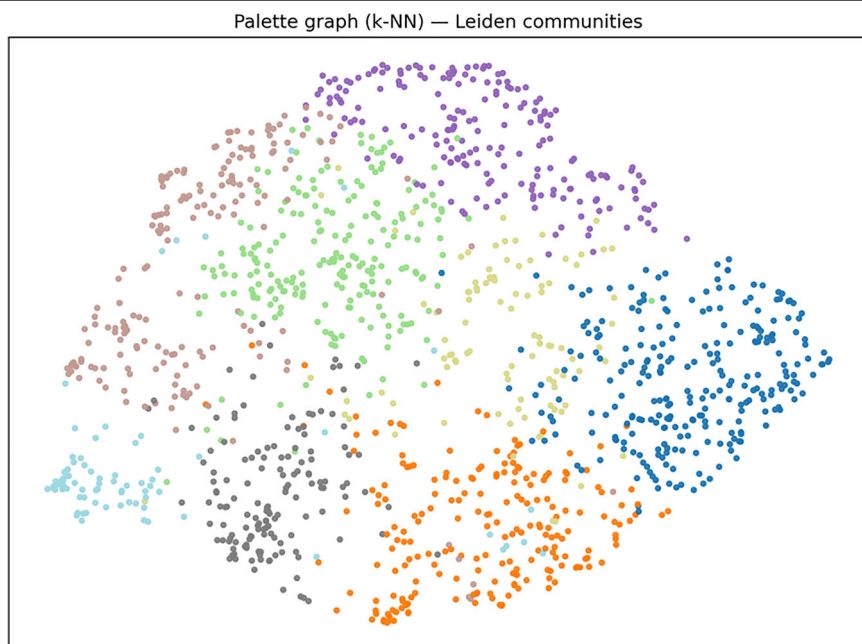
3. Can computational measures such as OT cost and ΔE_{2000} capture chromatic divergences in ways that align with art-historical classifications?

Indeed, computational tools such as OT and ΔE_{2000} offer effective quantitative frameworks for capturing chromatic divergence across eras. These metrics not only reflect perceptual differences but also align with

Table 4 | The distribution of Leiden communities across artistic eras

Era	Number of objects	Percentage (%)
Traditional	542	39.4%
Modern	378	27.4%
Contemporary	301	21.9%
Unknown	156	11.3%
Total	1377	100%

Fig. 19 | Palette graph (k-NN) with Leiden community detection. Each point represents an artwork; colors indicate cluster membership.



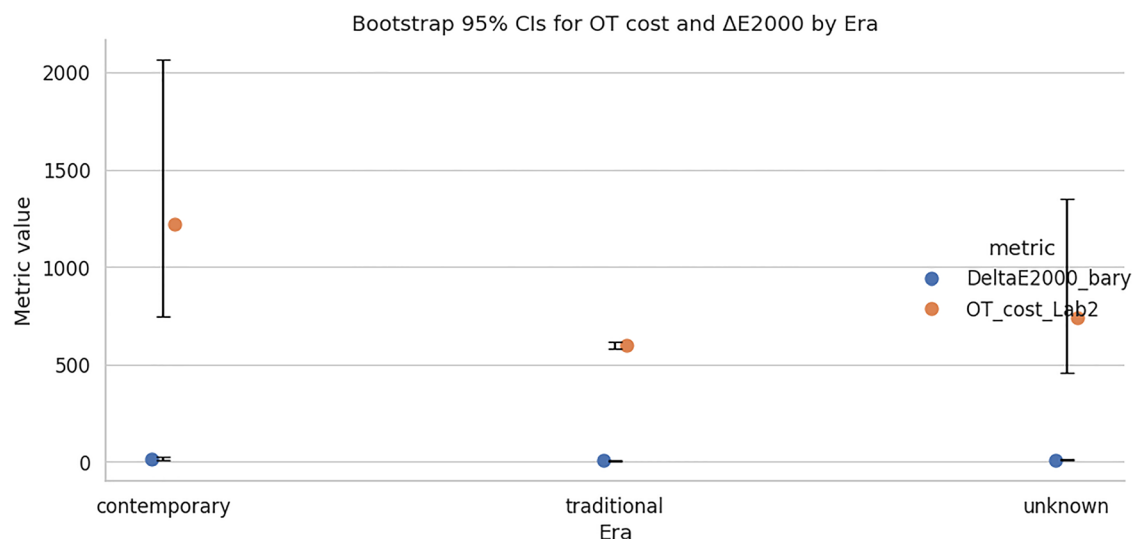
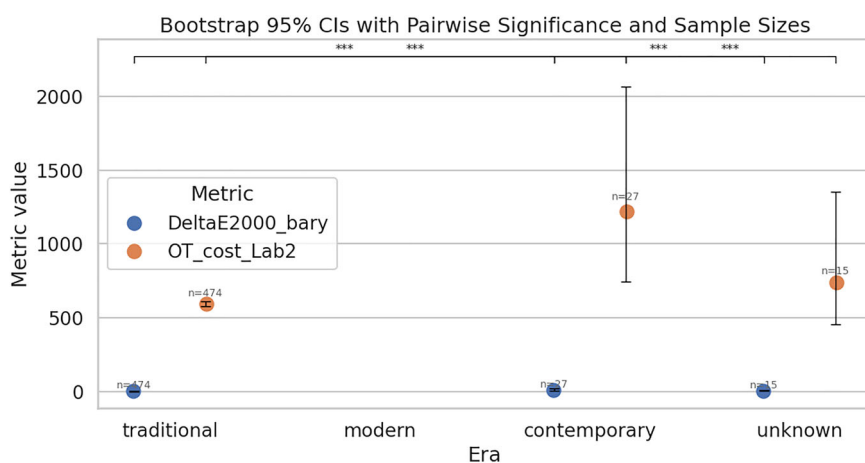


Fig. 20 | Bootstrap 95% confidence intervals for OT cost and ΔE2000 across artistic eras. Contemporary works show higher variability in palette metrics compared to traditional and unknown categories.

Fig. 21 | Bootstrap 95% confidence intervals for OT cost and ΔE2000 across all four eras, with pairwise significance testing. Significant differences are observed between traditional palettes and modern/contemporary ones, underscoring evolving approaches to color usage.



established stylistic boundaries recognized by art historians^{21,30}. The sharp OT distance increases observed from traditional to modern to contemporary artworks validate known historical ruptures in artistic practices. As such, computational analysis serves as a robust complement to traditional art-historical categorization, reinforcing insights from both visual pattern recognition and cultural chronology^{18,19}.

4. Do motif-specific palettes form distinct communities that reveal underlying esthetic or symbolic structures within the genre?

Yes, clustering analysis reveals that motif-specific palettes (flowers and birds) consistently form distinct color communities, which correspond to culturally and symbolically meaningful visual strategies^{22,27}. The use of community detection algorithms further supports the hypothesis that color usage in these motifs is not arbitrary but guided by esthetic, narrative, or cultural logic^{16,20}. This computationally verified clustering echoes long-held art-historical observations regarding the symbolic coding of color in specific genres and periods^{14,25}.

Discussion

Our findings provide new insights into the evolution of artistic style while demonstrating the value of computational methods in art history. By quantifying color usage, complexity, and stylistic affinities, we confirmed patterns long recognized qualitatively while also surfacing novel connections that invite reinterpretation. Three key outcomes emerge: (1) artworks

cluster into groups that correspond to historical styles, (2) measurable differences in color and visual complexity distinguish these groups, and (3) stylistic transitions tend to be gradual, reflecting evolutionary rather than abrupt change.

Unsupervised clustering revealed that paintings naturally group by era, with Renaissance, Baroque, and Modern works forming distinct but related clusters. This supports earlier computational studies showing that feature-based grouping aligns with canonical art movements^{15,20}. Renaissance works shared balanced compositions and moderate contrasts, while Baroque clusters emphasized chiaroscuro and heightened shadow, consistent with traditional scholarship²⁵. OT analyses further demonstrated that successive periods are closer in feature space than distant ones, paralleling¹⁶ network models of cultural history. Outliers such as Cézanne clustered with Modernist rather than Academic works, reflecting proto-Modern experimentation—echoing²¹ observation that transitional works often serve as bridges across movements.

Quantitative palette analysis confirmed that Baroque paintings had lower luminance and more restricted gamuts compared to the Renaissance, echoing prior findings. By contrast, Impressionist and Modern paintings exhibited higher chromatic diversity and lighter palettes, consistent with the adoption of synthetic pigments and new stylistic goals²⁶. Our analysis revealed a marked increase in violet and secondary hues after the 1860s, directly tied to industrial pigment innovations—a trend also noted by ref. 26.

These results underscore the interplay between material availability and esthetic development.

Measures of visual complexity (e.g., entropy-like indices) showed significant increases in modern and abstract movements relative to pre-modern art. This trend echoes²⁸ demonstration that entropy values rose with the advent of abstraction, and fractal analyses of Pollock's drip paintings, which quantified new forms of complexity. While earlier works achieved intricacy through dense detail, modern abstraction relied more on stochastic, less structured forms, aligning with³¹ account of esthetic complexity arising from different sources.

By aligning computational clusters with canonical styles, our study affirms that stylistic categories have quantifiable visual correlates¹⁵. Moreover, statistical differences in palette and complexity place numeric values on art-historical insights: for example, Impressionist "brightness" translates into measurable increases in luminance, while Baroque chiaroscuro registers as reduced chromatic diversity. Computational methods thus serve as a "macroscope"¹⁶, providing large-scale validation of qualitative narratives. Yet, as¹³ cautions, such methods must be interpreted contextually visual similarity does not necessarily imply historical influence.

Our dataset, while broad, may underrepresent regional variations, and our focus on formal properties overlooks symbolic or iconographic aspects. Future work should integrate more representative samples and link visual features with textual or archival data. Advanced deep learning models and cross-modal analyses could further illuminate how formal traits interact with thematic content. Ultimately, computational approaches should complement, not replace, interpretative scholarship, enriching art history through quantitative grounding while leaving room for contextual nuance¹⁴. This study has demonstrated that the integration of computational techniques with art historical inquiry can yield meaningful insights into the evolution of artistic styles, color palettes, and visual complexity. By applying clustering, palette analysis, and entropy-based measures, we were able to quantitatively validate long-standing qualitative observations, such as the luminous balance of Renaissance works, the heightened chiaroscuro of the Baroque, and the chromatic experimentation of Modernist movements. At the same time, our analyses revealed subtler patterns such as the measurable role of industrial pigment innovation in expanding color gamuts that highlight the material conditions underpinning stylistic change.

The results reinforce the view that artistic transformation is less abrupt rupture than gradual evolution, with transitional works serving as bridges across movements. Outliers that resist categorical placement, such as proto-Modern experimentation, underscore the complex interplay of innovation, tradition, and material constraint in shaping art history. Moreover, our findings support the notion that complexity in art arises from diverse sources: fine detail in earlier works, dramatic contrast in Baroque painting, and fractal-like abstraction in modern art.

Beyond specific results, this research contributes to broader methodological debates in digital art history. Quantitative measures are not substitutes for interpretative scholarship but powerful complements that enrich it, offering scalable ways to trace esthetic trends while situating them within historical context. The study's limitations—including dataset representativeness and focus on formal rather than iconographic dimensions—point to future directions, such as integrating text-based archival evidence, cross-cultural datasets, and deep learning-driven multi-modal analysis.

Ultimately, the paper underscores the value of a hybrid approach: one that respects the interpretive traditions of art history while embracing the rigor and scalability of computational analysis. In doing so, it advances not only our understanding of artistic evolution but also the methodological horizons of humanities research in the digital age.

The color distribution in the quantitative analysis and more specifically, the metrics used are OT cost and ΔE_{2000} , which showed that there are some motifs that preserve their chromatic patterns across the time span. The uniformity of such patterns is an indication of the persistence of the cultural significance of color symbolism in flower-and-bird paintings. As an example, the red repetitiveness in peonies of various ages is not merely an

esthetic decision but rather a cultural representation of monetary, power, and status in the society. Likewise, the charming image of the orchid as something pure and beautiful is supported by the color coherence of the illustration, the majority of which are in the violet and purple color. These colors have been considered throughout the history of humanity as symbols of elegance and spiritual purity.

A combination of computational techniques with art-historical research is necessary to bring our insight of the role of color in flower-and-bird works. This study provides a quantitative approach to track color changes that supplements the existing qualitative ones using OT and ΔE_{2000} values, making the study a scalable and replicable measurement of chromatic dissimilarities. Such methods of computation enable us to quantify the development of such motifs as the peony or orchid in their color symbolism over the centuries and this offers us a more objective and methodical way of validating the cultural and historical readings of the art-historical text.

Data availability

All data generated or analyzed during this study are included within the manuscript.

Code availability

Custom scripts used for image preprocessing, color palette extraction, stratified nonparametric bootstrap inference, Sinkhorn Optimal Transport analysis, ΔE_{2000} barycenter matching, and Leiden community detection were developed in Python.

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Author contributions

Cheng Zhang conceptualized the study, designed the methodology, curated and processed the data, performed the computational and statistical analyses, interpreted the results, and wrote the original draft of the manuscript. The author reviewed and approved the final version of the manuscript.

Competing interests

The author declares no competing interests.

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