

Quantifying Structural Aesthetic Features and Personality Trait Preferences in *Kai Shu* Calligraphy

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Abstract

Chinese calligraphy offers fruitful visual structure not found in abstract/ figurative paintings or photographic images. It makes it well-suited for studying how personality shapes aesthetic preference, yet few works have explored this link. This paper introduces the first computational framework that models the link between viewer personality and *Kai Shu* calligraphic preference. It collects a dataset of *Kai Shu* calligraphy images, user preference scores, and Big Five personality traits. It extracts 160 structural feature descriptors from eight categories, such as stroke curvature, layout, and whitespace. Regression and attribution methods reveal five patterns, such as visual structure predicts perceived style, and that traits like Openness and Neuroticism influence preference patterns. High-Openness users prefer balanced, clean layouts. Low-Neuroticism users favor lighter, irregular forms. Some personality–feature pairs follow inverted-U trends, where moderate structural complexity leads to higher preference. These results connect cognitive traits with visual structure and support interpretable, personality aware modeling of aesthetic response. Our findings support personalized style discovery and open up new directions for interest-driven aesthetic education and digital preservation. Code available at <https://github.com/tianchengliu18/kai2trait>.

CCS Concepts

• **Applied computing** → **Fine arts**; • **Computing methodologies** → **Uncertainty quantification**; *Modeling methodologies*.

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Keywords

Feature modeling, Explainable aesthetic computing, Visual complexity analysis, Chinese calligraphy

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1 Introduction

Chinese calligraphy, a vital form of intangible cultural heritage, embodies deep aesthetic and cultural values but remains challenging to evaluate due to its geometric complexity and subjectivity. The aesthetics of calligraphy depend on the interplay of lines, angles, and shapes [19, 26], influenced by the artist’s style and viewer’s personality traits, making it difficult to quantify and access broadly.

While previous research highlights the influence of personality traits on aesthetic preferences in abstract art, photography, and social media images [10, 13, 20, 36], Chinese calligraphy remains underexplored due to its unique combination of semantic content and visual form, posing challenges for traditional analysis methods. A key challenge is developing interpretable methods to systematically represent and analyze calligraphy’s visual features and link them to personality traits.

This paper investigates how personality traits influence aesthetic preferences in Chinese calligraphy using a structural modeling approach focused on geometry-related factors. We conduct a formative study with six experts, identifying eight key structural features aligned with traditional theories of Chinese calligraphy. We design computational rules to extract geometric patterns and integrate them into measurable indicators. A user study then explores the relationship between calligraphic features and users’ psychological profiles, offering insights into how individuals engage with visual forms rooted in cultural heritage.

Our findings reveal that specific structural features predict perceived style, traits like Openness and Neuroticism shape preferences for balance, tension, and complexity, and some personality–feature pairs follow inverted-U trends, where moderate complexity leads to higher preference. This research contributes by 1) proposing a geometry-based, theory-aligned representation of aesthetic features in calligraphy, 2) modeling the interaction between personality and visual structure, and 3) releasing a dataset linking calligraphic structure with personality-driven preferences. Furthermore, our interpretable image-to-feature-to-personality approach offers a generalizable framework. It can extend to other structured visual domains (e.g., painting, typography), with potential for broader cross-domain aesthetic modeling applications.

2 Related Works

2.1 Aesthetic Preference and Personality Traits

Preference is not noise in perceptual modeling; research shows subjective aesthetic judgments stem from systematic individual differences (e.g., cognitive or perceptual traits) [32]. Personality traits influence aesthetic preferences across diverse art forms, with different reactions to photography [36], social media images [20], and movies [13]. In abstract art (e.g. Kandinsky’s color–shape links [10]), preferences are often culturally universal and independent of personality or affect.

Multi-modal learning highlight personality’s role in shaping perception. Multi-modal attention networks infer personality traits from gaze, speech, and facial expressions [28], and bypass traditional questionnaires via end-to-end models [25]. Unlike these studies, we focus on how personality traits influence subjective aesthetic preferences for visual content like calligraphy.

Creative fields show personality differences across roles, suggesting that individual traits shape the creation and perception of creative artifacts[24]. Approaches like CLIP-based multi-modal fusion predict user traits from images and text[9], and research on food as art reveals how personalized recommendations depend on aesthetic factors[5, 21]. We extend these perspectives to calligraphic structure—a rarely explored domain.

2.2 Quantification of Aesthetics in Art

Birkhoff’s early work $M = f(O/C)$, links aesthetics to order-complexity ratio[2]. Later works apply the complexity-entropy or hierarchical methods on millions of artworks, revealing linear relationships and trends in color usage and texture variation across historical periods[14, 15, 23]. Recent works fuse global and local descriptors[16, 35], and translates theoretical rules (e.g., golden section) into computational models[6–8]. Personalized aesthetic assessment methods[36, 37] focus on fine-grained user preferences.

Similarly, large language models are adapted for image-based aesthetic tasks, such as training AesExpert on an 88K-comment dataset[11] or using preference alignment for quality evaluation[38].

2.3 Technology in Chinese Calligraphy

Chinese calligraphy blends semantic meaning with visual form, differing from purely abstract or representational art. Computational approaches focus on stroke geometry, layout, and structural analysis[19, 26], but struggle to align these metrics with traditional

aesthetic principles. Some use generative methods to synthesize or classify styles[17, 18, 33], while others quantify factors like symmetry and center of gravity[27, 34]. Behavioral data, such as eye movement, is used to study preferences in calligraphy styles[31], though specific style differences are often overlooked. Research also explores the emotional dimensions of calligraphy in VR education or digital generation[4, 39], emphasizing affect in artistic appreciation[30].

3 Designing Structural Aesthetics Factors for Kai Shu

To design structural aesthetics features for *Kai Shu*, we first conducted expert interviews and then selected the most visually distinctive and interpretable features for further analysis.

3.1 Formative Study

The study aims to identify features most interpretable from binarized *Kai Shu* images by consulting Chinese calligraphy experts.

3.1.1 Recruitment. We recruit six Chinese Calligraphy experts (2 females and 4 males, aged 29-63) via snowball sampling. All have 20+ years of calligraphy practice experience. P1, P2, P4 and P5 are members of the China Calligraphers Association¹. P2, P3, and P6 are active calligraphy educators. Each specializes in different calligraphy genres. We denote participants as “P#” throughout.

3.1.2 Procedure. We conduct semi-structured interviews with experts P1, P2, and P5 in person, and P3, P4, and P6 via Zoom, each lasting about one hour. The interviews included three parts: 1) introduction of study, 2) sharing opinion on visual features in binarized *Kai Shu* images, and 3) ranking their importance. Audio is recorded during the interviews, and only the researchers had access to the data. All experts participated voluntarily without compensation.

3.1.3 Data analysis. We transcribe the audio recordings and conduct open coding and thematic analysis[3]. Three researchers independently code the data using Miro², then discuss and align their codes into a shared version. Themes and sub-themes are recursively formed through affinity diagramming until agreement is reached.

3.1.4 Results of formative study. We finally identify two themes from expert interviews. The first theme includes categories for designing structural aesthetics, where varying use of these features results in different compositions and preferences. These categories reflect the core principles experts use to analyze calligraphic structures. Specifically, they cover aspects of **Central tension**, **Whitespace Structure**, **Visual Symmetry**, **Spatial Distribution**, **Stroke Density**, **Stroke Directionality**, and **Stroke Thickness**. Each category is accompanied by a plain-language interpretation for general audiences. A summary of these categories and their interpretations can be found in the **Interpretation** column in Table 1.

The second theme is the identification of high-level *style vocabulary* as in table 2. Experts are invited to freely describe the expressive impressions of characters in terms of perceived style. Through

¹<https://www.cca1981.org.cn/>

²An online collaborative platform for coding, brainstorming, and design

Table 1: Summary of structural aesthetic features in *Kai Shu* calligraphy. Each row corresponds to a high-level feature category identified through expert interviews. The Interpretation column explains the aesthetic meaning in accessible language, helping readers without a calligraphy background understand each feature’s visual impact. The Technical Description column describes how we computationally model or quantify the feature using image processing and mathematical analysis. The Example Features column lists part of feature examples extracted per category, which are used in downstream modeling.

Category	Interpretation	Technical Description	Descriptor Set
Central Tension	How tightly strokes are grouped around the center, compact or loose.	Measured using radial decay profiles from the character’s centroid, distribution entropy, and offset statistics.	Centroid offset, radial decay slope, radial entropy
Whitespace Structure	How the blank areas let the strokes “breathe” and balance the layout.	Detect connected components & region labeling; complexity via fractal dimension and distribution entropy.	Hole count, whitespace ratio, inverted fractal dimension
Visual Symmetry	Whether character looks balanced across horizontal, vertical, or diagonal.	Calculated via pixel-wise comparisons across symmetry axes and multiscale filter responses.	Axis symmetry score, rotational symmetry, Gabor symmetry
Spatial Distribution	How evenly or unevenly strokes are spread out in the bounding box.	Extracted using clustering of stroke centroids and measures of entropy and statistical dispersion.	Spatial entropy, Gini index, KDE peaks, cluster entropy
Stroke Curvature	How much the strokes bend or flow with arc-like movement.	Curvature is computed along the skeleton trajectory, using entropy of angle change and bending energy.	Curvature entropy, bending energy
Stroke Density	Whether some parts of the character feel heavier or more filled.	Density maps calculated on multiscale grids and polar gradients; captures visual weight distribution.	Grid density, center-to-margin gradient, multiscale fill
Stroke Directionality	Whether strokes move in varied directions or follow consistent angles.	Directional variation assessed via angular histograms, entropy of direction, and KL divergence.	Angular entropy, KL divergence, direction variance
Stroke Thickness	The width of strokes—whether they are thick, thin, or vary within a stroke.	Analyzed along skeleton paths using segmental width profiles, frequency patterns, and peak detection.	Mean width, FFT of thickness profile, segment peak count

inductive coding, we synthesize a list of 14 distinct style labels, reflecting visual qualities such as stroke energy, layout tension, and compositional rhythm. These categories formed the basis of the style annotation task in our later user study (Section 4.2).

Table 2: Style vocabulary derived from expert interviews, grouped into contrastive pairs.

Style A	Style B
Firm strength	Lightweight grace
Compact arrangement	Open spacing
Neat precision	Dynamic irregularity
Restrained strokes	Expansive lines
Poised tension	Release of energy
Balanced composition	Asymmetric tilt
Heavy solidity	Soft flow
Others	—

The third theme includes four features not retained due to binarization limits: 1) ***Xuan paper texture*** (ink spread); 2) ***paper color*** (mood perception); 3) ***ink shade variation*** (brush control); and 4) the ***flying white*** technique (rare in *Kai Shu*). These were excluded but noted for future work.

3.2 Geometric Feature Descriptors

We extract 184 geometric feature descriptors designed to capture salient and aesthetic structural patterns. We filter them through: 1) low-variance removal based on the coefficient of variation ($CV = \sigma/\mu$, threshold < 0.01), 2) and dropping statistically uninformative features. This left 160 interpretable features mapped to eight aesthetic dimensions.

We organize the descriptors into seven categories as in Descriptors Set column in table1, each designed to quantify a set of specific geometrical features in *Kai Shu* calligraphy.

3.2.1 Central Tension. It reflects how compact or open the composition appears under the nine-square grid conceptual framework. We compute both 1) global (*centroid offset* between stroke mass and canvas center) and, 2) local descriptors (*radial statistics* including mean, variance, entropy, and decay slope) to capture this push–pull balance. 3) Combined metrics such as *radial decay slope*, *peak density location*, and *distribution entropy* quantify how stroke clustering around the center.

3.2.2 Whitespace Structure. It shapes visual rhythm and breathing space - how open or tight a character feels. 1) We extract geometric, spatial, and topological features, including the *number* and *size* of enclosed holes, *global whitespace ratio*, and a 3×3 *grid-based distribution*. 2) Background fragmentation is measured through *connectivity analysis*, distinguishing between messy and stable layouts. 3) *Fractal dimension* captures multiscale complexity, reflecting how ordered or chaotic the whitespace appears.

3.2.3 Visual Symmetry. Symmetry reflects structural harmony. 1) We measure pixel-wise differences across four axes—horizontal, vertical, diagonal, and rotational—between original and mirrored/rotated versions. 2) To detect local patterns, we apply multiscale Gabor filters across orientations and compare responses with their mirrored counterparts. All symmetry scores are aggregated into a composite multiscale index.

3.2.4 Spatial Distribution. Spatial distribution influences visual balance and layout spread. 1) We compute *entropy*, *Gini index*, and *quadrant density* based on stroke centroid dispersion across a grid. 2) Local clustering is modeled via KDE to extract *peaks*, *variance*, and *entropy*. 3) K-means clustering is applied to centroid coordinates, with *silhouette score* and *cluster entropy* used to assess group structure. The optimal cluster count is selected using the elbow method.

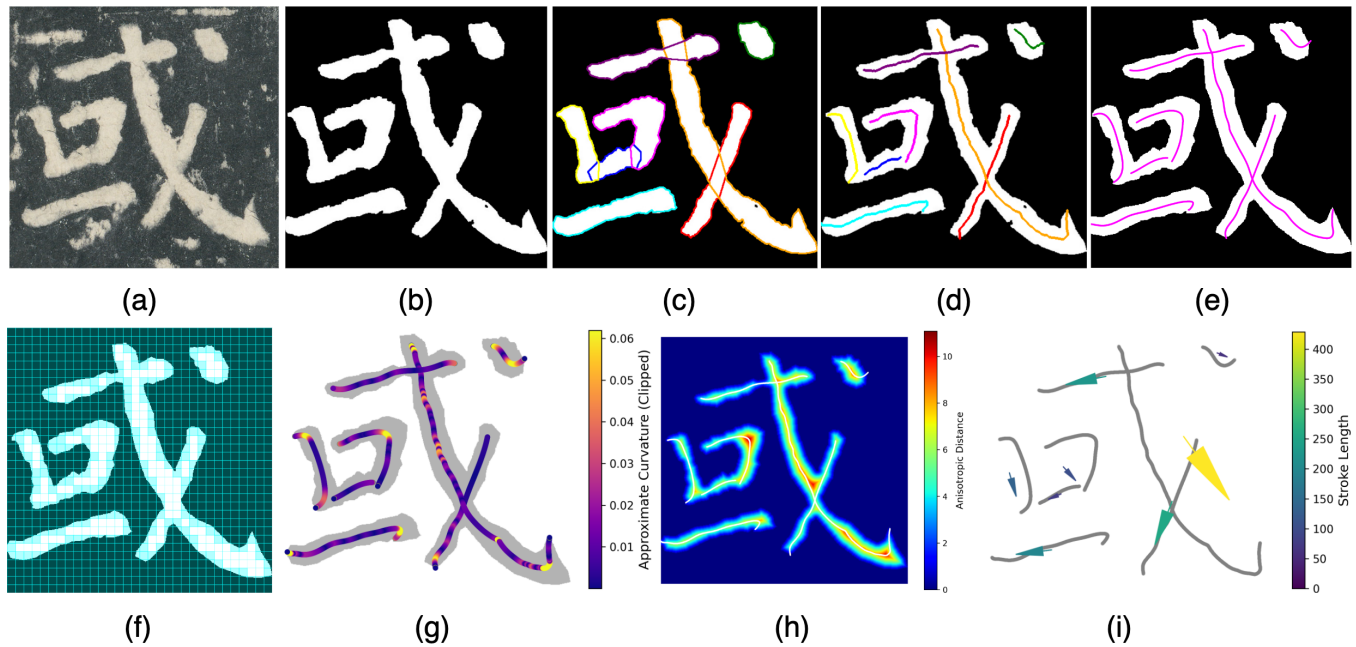


Figure 1: Visualization of selected stages from the geometric feature descriptors extraction pipeline, demonstrated on a single calligraphy example. (a)Original calligraphy image; (b)binarized and denoised image; (c)stroke segmentation using a semi-automatic tool based on the Segment Anything Model (SAM); (d)initial skeleton extracted from stroke mask; (e)optimized and smoothed skeleton; (f)box-counting representation of whitespace for fractal analysis; (g)curvature of skeleton points, color-coded for local shape variation; (h)stroke thickness estimated from local radius around skeleton; (i)stroke direction and length encoded as vector arrows and color.

3.2.5 Stroke Curvature. Curvature conveys smoothness and dynamic energy. 1) We estimate *pointwise curvature* from skeleton derivatives, 2) summarize global variability using *curvature entropy*, and 3) compute *bending energy* by integrating squared curvature across strokes to assess motion tension, which reflects how much effort or tension is used to make curved movements.

3.2.6 Stroke Density. Density reflects visual heaviness. We compute global and grid-based density maps, center-to-margin gradients, and analyze how stroke mass changes through multiscale dilation. Fractal dimension captures nested complexity, while lacunarity quantifies gap size and dispersion, distinguishing dense from irregular structures.

3.2.7 Stroke Directionality. It shows the flow and rhythm of the strokes' trajectories. 1) We compute *angle histograms*, *entropy*, *mean*, *variance*, and *angular changes*. These show how stroke directions vary and how smooth they are. 2) We compute *KL divergence* from a uniform distribution. This tells us whether the directions are balanced or biased. 3) We extract *stroke length statistics*—*mean*, *variance*, *entropy*, *Gini coefficient*. These capture how consistent or irregular the stroke lengths are.

3.2.8 Stroke Thickness. It reflects brush pressure and control. 1) We estimate stroke width at each skeleton point using *anisotropic distance transform* guided by local orientation. This better captures real stroke shape, especially in curves. We use the fast marching

method to solve the *Eikonal equation*. This gives accurate and efficient width estimation. 2) We analyze the thickness profile with *Fourier transform*. This shows how thickness changes over frequency. 3) We compute *segmental statistics* like *mean*, *variance*, and *peak count*. These describe local fluctuations and brush control.

4 Methodology

This study proposes a data-driven, interpretable framework to understand how personality traits shape aesthetic preferences in *Kai Shu* calligraphy. By combining image-derived geometric feature descriptors with user evaluations and personality profiles, we conduct multi-level statistical modeling and attribution analysis.

4.1 Dataset Construction

Our *Kai Shu* dataset consists of 67,776 binarized images of 2,500 commonly used Chinese characters³, collected from public repositories and calligraphy forums⁴. Each character has multiple stylistic variations. Preprocessing includes denoising, contrast enhancement, and resizing to 512×512 pixels.

From these, a subset of 388 stylistically distinct images across 42 unique characters (min 4, median 10, max 10 images per character; mean = 9.2, SD = 1.4, skew = -2.26) is selected via expert screening. We initially extracted 184 geometric descriptors

³<https://github.com/quanh/chinese-char-dict>

⁴<https://www.9610.com/>; <https://www.shufazidian.com/>

per image. Through a two-stage filtering process—removing constant, trivially correlated, and collinear or statistically insignificant features—we retained 160 interpretable features covering all eight aesthetic dimensions.

4.2 User Study Design

We conduct an online user study (Participants $N = 258$), each participant completes a validated Big Five personality inventory and performs three tasks for all 388 images: (1) continuous aesthetic rating (0–100) via a slider for fine-grained preference expression; (2) style label annotation using a fixed list derived from expert interviews and literature; (3) within-character style ranking task—participants rank multiple stylistic renderings of the same character.

Trait Binning and Distribution. To analyze how personality traits influence preferences, we binned each Big Five trait into Low, Medium, and High levels using 25th and 75th percentiles. This approach accommodates non-normal distributions observed in the trait scores. Table 3 summarizes descriptive statistics and normality test results (Shapiro–Wilk).

Table 3: Descriptive statistics of Big Five personality traits (N = 258).

Trait	Mean	SD	Skew	Kurtosis	Shapiro-W p
Neuroticism	36.83	5.02	-0.23	0.26	2.3×10^{-17}
Extraversion	37.38	5.29	-0.27	-0.12	5.6×10^{-19}
Openness	36.73	4.99	0.47	1.23	2.7×10^{-29}
Agreeableness	35.56	5.21	0.28	-0.22	6.6×10^{-19}
Conscientiousness	37.48	5.03	0.26	0.54	3.3×10^{-23}

4.3 Statistical Modeling

We build a multi-level statistical modeling framework to understand how personality traits shape aesthetic preferences for *Kai Shu* calligraphy. The process begins by preprocessing user-generated ratings to remove individual biases. We then screen aesthetic features based on their interaction with personality traits. From the selected features, we extract interpretable latent factors using dimensionality reduction. Finally, we model how these factors interact with personality profiles using both linear and non-linear regressions. Each step aims to balance statistical rigor with interpretability, revealing how personal traits influence visual perception.

4.3.1 Data Debiasing User-assigned ratings and rankings are subject to personal scale and range effects, making direct comparison unreliable. To mitigate such subjectivity, we apply user-wise z -score normalization separately to raw scores and rankings (Equation 1):

$$z_u^{\text{score}} = \frac{s_u - \mu_u^{(s)}}{\sigma_u^{(s)}}, \quad z_u^{\text{rank}} = \frac{r_u - \mu_u^{(r)}}{\sigma_u^{(r)}} \quad (1)$$

where s_u and r_u denote the raw score and ranking for user u , and μ , σ are the corresponding user-specific means and standard deviations. Since lower ranks imply stronger preference, the normalized ranking is inverted. We then compute a composite preference score:

$$\text{Preference}_u = \frac{1}{2} (z_u^{\text{score}} - z_u^{\text{rank}}) \quad (2)$$

The composite debiased preference score (Equation 2) serves as the dependent variable for all downstream models.

4.3.2 Personality–Style Preference Modeling We use Generalized Estimating Equation (GEE) to study how personality traits influence style preferences. This method accounts for repeated ratings from the same user and provides stable estimates for both main effects and interactions. Each calligraphy image contains one or more style tags, such as *Balanced composition* or *Dynamic irregularity*. These tags are encoded into binary columns using one-hot encoding. Big Five personality traits categorize Low, Medium, and High levels based on quantile thresholds. For each personality–style pair, the following model is fitted:

$$\text{Preference Score}_{ij} \sim C(\text{Personality Level}) \times \text{Style}_j \quad (3)$$

We group data by user ID to handle repeated measures. GEE suits our data because the scores do not strictly follow a normal distribution and user responses are correlated. We set a significance threshold of $p < 0.05$ for the main effect of personality. Only styles with significant main effects are retained for further analysis, based on the GEE specification in Equation 3.

4.3.3 Structural Feature Attribution to Calligraphic Style

We adopt a two-model approach: Logistic Regression, and Random Forest to identify which geometric feature descriptors contribute to the perception of different calligraphic styles. 1) A logistic regression model captures linear associations between features and style presence, using coefficients to show whether a feature increases or decreases the probability of that style. 2) A random forest classifier models nonlinear relationships and provides feature importance scores that reflect overall contribution without regard to direction.

4.3.4 Analyzing Structural Complexity and Preference We study how structural complexity relates to user preference. The analysis includes feature selection, dimensionality reduction, and regression modeling.

We start by grouping features into four types of complexity, guided by domain knowledge and previous research in visual design. 1) Stroke curvature complexity includes curvature entropy, bending energy, and stroke peak variation. 2) Stroke directionality complexity covers angle variance, directional entropy, and stroke length dispersion. 3) Layout complexity measures entropy and spread of spatial and cluster distributions. 4) Whitespace complexity captures how whitespace is distributed, connected, and structured. Each group reflects a distinct type of visual complexity.

For each group, we standardize the features and apply Principal Component Analysis (PCA). We use the first principal component (PCA1) as a summary score of complexity. This reduces feature redundancy and gives one interpretable value per group. To model

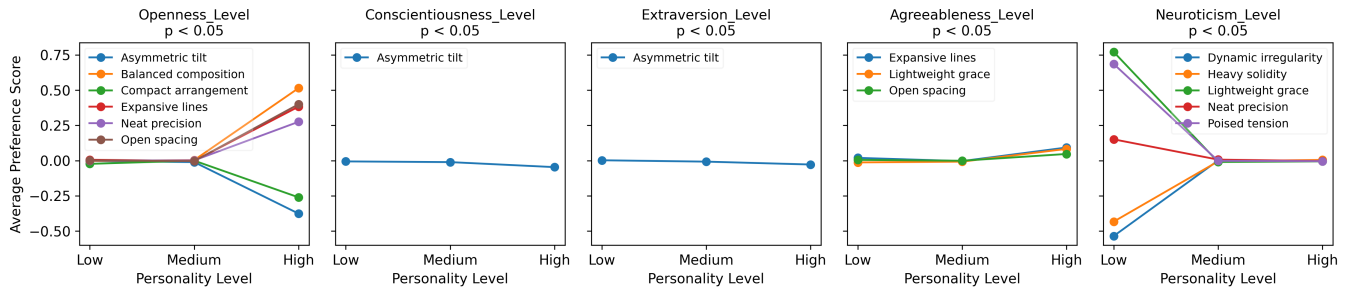


Figure 2: Trends in average aesthetic preference scores across personality levels for styles with significant main effects ($p < 0.05$). Each subplot corresponds to one of the Big Five personality traits (Openness, Conscientiousness, Extraversion, Agreeableness, Neuroticism), with three levels: Low, Medium, and High. Lines represent calligraphy styles that showed statistically significant main effects in Generalized Estimating Equation (GEE) models. For Openness, high-level participants consistently preferred structured and open styles (e.g., Balanced Composition, Neat Precision). Neuroticism shows a notable trend where low-level individuals favored expressive and irregular styles (e.g., Dynamic Irregularity, Heavy Solidity). Other traits exhibited minimal score variation and fewer significant style preferences.

preference, we fit second-order polynomial regressions as shown in Equation 4:

$$\text{Preference} \sim \beta_0 + \beta_1 \cdot \text{Complexity} + \beta_2 \cdot \text{Complexity}^2 \quad (4)$$

Here, *Complexity* refers to the PCA1 score. We use Ordinary Least Squares (OLS) to estimate the model and check if preference follows an inverted-U pattern.

We then stratify users by Big Five personality traits. For each trait, we divide users into Low, Medium, and High levels using quantile thresholds. We fit separate regression models in each group to see how personality changes the preference–complexity curve.

5 Results

This section presents three key findings: (1) We analyze how personality traits relate to calligraphy style preferences. (2) We examine which structural features contribute most to the perception of Balanced Composition. (3) We model how different types of structural complexity influence preference, and how this relationship changes across personality levels. Together, these results reveal how both viewer traits and visual structure shape aesthetic responses to calligraphy.

5.1 Personality-Level Main Effects on Calligraphy Style Preference

We examine how style preferences vary across Low, Medium, and High levels of each Big Five trait, using only styles with significant main effects ($p < 0.05$). The figure 2 shows the results.

Openness shows the clearest trend. High-openness participants prefer styles such as Balanced Composition, Expansive Lines, Open Spacing, and Neat Precision. They dislike dense or tilted styles like Compact Arrangement and Asymmetric Tilt. This suggests high level openness aligns with with balance, openness, and neat layout.

Conscientiousness, Extraversion, and Agreeableness show weak or inconsistent effects. A few styles reach significance, but preferences stay flat across trait levels. These personality traits do not strongly shape visual preference style among levels.

Neuroticism shows contrast at the low end. Emotionally stable participants prefer light, and tensioned styles, like Lightweight grace, Poised tension, and Neat precision. They relatively dislike Heavy solidity and Dynamic irregularity. High-neuroticism participants show no clear positive preference, though Poised Tension and Neat Precision appear slightly favored.

Overall, Openness and Neuroticism influence style preference most. High-openness individuals favor structure and openness. Emotionally stable individuals prefer dynamic, irregular styles. Other traits show minimal effect.

5.2 Structural Feature Attribution for *Balanced Composition* Style

To understand what shapes the perception of Balanced Composition, we train two models: a logistic regression and a random forest classifier. Both predict whether a sample belongs to the Balanced Composition style based on 184 structural features described in Section 3.2. While our framework applies equally to other expert-defined styles, we focus on this representative case for clarity and brevity. All features are standardized before modeling. We normalize feature importance scores and visualize the results in Figure 3.

The logistic model shows which features increase or decrease the likelihood of this style. Positive contributors include max thickness segment 1 mean, which captures mid-stroke thickness, density region densities mean, which reflects stroke density across regions, and stroke overall max mean, which measures global peak thickness. These features point to bold, dense, and stable strokes as key visual elements. Negative contributors include stroke overall mean and radial distribution std, which indicate that overly thin or spatially uneven layouts reduce the sense of balance.

The random forest model captures nonlinear patterns and highlights both micro and macro structure. Important features include



Figure 3: Feature attribution results for the Balanced composition style. Left: normalized logistic regression coefficients; right: normalized feature importance from Random Forest. Features are sorted by absolute importance within each model. Labels indicate the top contributing features, grouped into visual categories such as stroke thickness, curvature, and spatial distribution.

stroke bending energy min and stroke curvature entropy std, which reflect local stroke complexity, as well as spatial distribution cluster density and symmetry horizontal symmetry, which reflect global layout consistency.

Some features show high importance in both models. These include lengths length ratio, indicating balance in stroke length, std thickness segment 1 std, capturing variation in mid-stroke thickness, stroke E low std, reflecting energy stability, and radial distribution std, related to spatial balance.

The two models focus on different aspects, but they converge on three key factors. Stroke thickness and density define visual weight. Stroke regularity reflects brush control. Spatial structure ensures evenness and symmetry. Balanced Composition arises from the combination of these elements: controlled strokes, consistent spacing, and a stable layout.

5.3 Relationship Between Structural Complexity and Preference

This analysis examines how structural complexity shapes visual preference, modeling preference scores using four complexity

types: Stroke Curvature, Stroke Directionality, Layout, and White-space. Regression curves are fitted at both the population and personality levels (Figure 4).

Across all users, no strong inverted-U pattern emerges. Layout Complexity shows a positive trend, with users preferring more spatially intricate compositions. Whitespace Complexity shows a slight U-shape, with preferences declining when whitespace is too minimal or too crowded.

Personality traits reveal clearer patterns. High Openness users prefer complex layouts, while Low-Openness users show flat trends. Conscientiousness has little effect. Extraversion shows weak U-shapes, particularly in Whitespace and Directionality. High Agreeableness users slightly prefer more complex layouts. Neuroticism exhibits the strongest interaction, with Low Neuroticism users preferring moderate Stroke Directionality (U-shaped) and High Neuroticism users favoring more complex Whitespace, possibly due to a higher tolerance for visual noise.

In sum, we conclude five main patterns: 1) Structural features like stroke curvature, central tension, and stroke density predict calligraphic style, linking visual form to style labels. 2) Balanced Composition, favored by High-Openness participants, is defined by mid-stroke thickness, horizontal symmetry, and radial evenness. 3) Personality traits affect style preferences, with High Openness users favoring balanced styles and Low-Neuroticism users preferring lighter, tensioned forms. 4) High Openness users respond to layout and symmetry, while Low Neuroticism users focus on stroke weight and irregularity. 5) Some personality–feature pairs show an inverted-U curve, with moderate complexity preferred, particularly in Openness and Extraversion, supporting empirical aesthetics theories.

6 Discussion

6.1 How Personality Traits Shape Sensitivity to Visual Structure

Our results show that personality traits shape responses to visual structure, with Openness and Neuroticism exerting the strongest influence. These findings align with research showing that personality shapes aesthetic preferences in photography, film, and digital images [13, 20, 36], but extend this evidence to Chinese calligraphy—a culturally rich domain where visual structure and semantic form are tightly coupled. In contrast, Kandinsky-inspired studies of abstract art report that color–shape preferences are largely universal and independent of personality [10], highlighting the unique perceptual-cognitive demands of calligraphy. This pattern supports the view that personality traits influence both overall preference and the structural cues that attract attention. By using interpretable features rather than black-box models or generic labels [19, 33], we link traits such as Openness or Neuroticism directly to visual elements—symmetry, curvature, or density—that define aesthetic experience in calligraphy.

6.2 Nonlinear Preference and the Inverted-U Hypothesis

Some structural features show nonlinear relationships with preference: users often prefer moderate complexity over extremes. This inverted-U pattern appears most clearly for traits such as

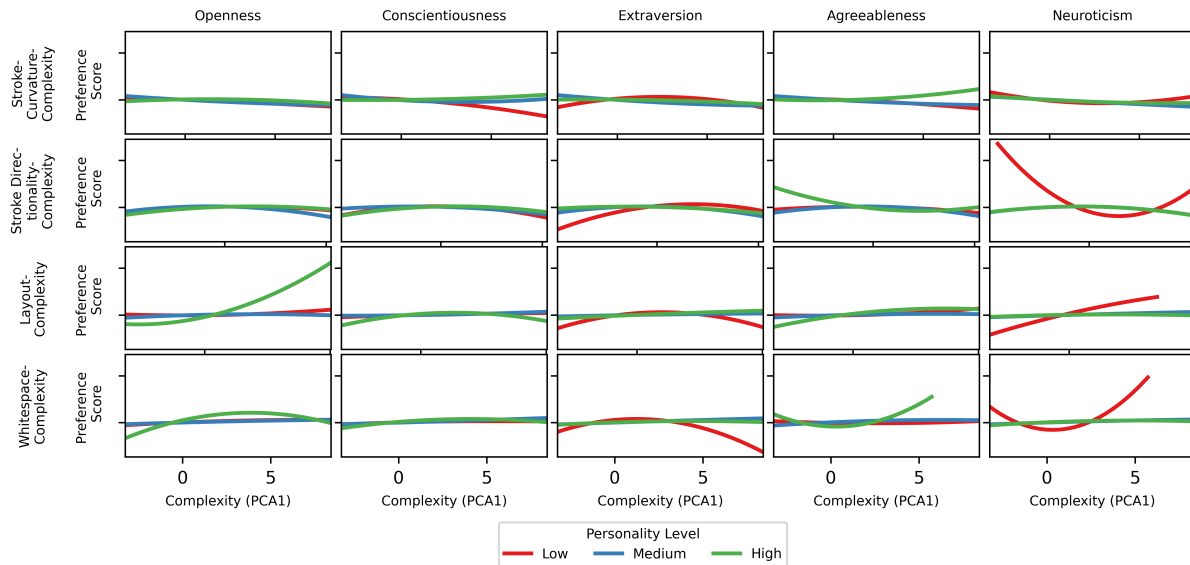


Figure 4: Preference trends across four structural complexity dimensions (rows) and five personality traits (columns). Each subplot shows a set of quadratic regression curve modeling the relationship between complexity (first principal component) and average preference score, separately for Low (red), Medium (blue), and High (green) levels of the corresponding personality trait. Notably, several dimensions—such as Layout Complexity for individuals with high Openness, or Stroke Directionality for low Neuroticism—exhibit an inverted U-shape trend, suggesting an optimal complexity zone for aesthetic preference.

Openness and Extraversion. High-Openness participants display inverted-U curves for central tension, stroke directionality, and layout entropy; they dislike styles that are too simple or too chaotic and prefer moderate variation and structure. This supports classic theories in empirical aesthetics [1, 12, 22, 29] that moderate complexity produces the highest visual interest. Low-Neuroticism participants show U-shaped patterns, especially in stroke curvature and whitespace complexity; while many users avoid irregularity, emotionally stable individuals tolerate or even prefer it in moderate amounts, suggesting a distinct aesthetic strategy. They may process visual variation more calmly or discern structure where others see chaos. Not all trait-feature pairs exhibit this effect; many remain flat or reversed, underscoring that aesthetic preference varies widely. Where inverted-U or U patterns occur, they mark trait-specific responses to visual complexity and its interpretation.

6.3 Implications

These findings motivate computational models of taste and style that incorporate interpretable aesthetic factors. The factors we propose offer a pathway to personality-adaptive generative models of calligraphy, with potential applications in digital arts, education, and therapeutic settings. Our results also demonstrate that explainable features—rather than opaque neural embeddings—can personalize visual content, complementing recent multimodal approaches to aesthetic learning [11, 38].

6.4 Limitations and Future Work

Subjective ratings may be noisy and reflect mood or cultural context. The Big Five captures broad traits but omits finer constructs such as aesthetic sensitivity [10]. Our features exclude expressive elements like ink texture or stroke dynamics, and static images restrict generalization to dynamic formats. Future work could include behavioral signals (e.g., gaze, EEG) to validate engagement [31], expand features to multimodal cues, and integrate affective or cultural identity traits. Cross-cultural studies could reveal universal and trait-specific patterns [5], and generative systems might use these models for emotionally adaptive, personalized creation.

7 Conclusion

We present the first interpretable, data-driven framework showing how personality shapes aesthetic preferences for Chinese calligraphy. Integrating structural features with trait profiles reveals that personality modulates sensitivity to symmetry, central tension, and stroke density, particularly among high-*Openness* and high-*Neuroticism*. We find inverted-U relationships between structure and preference. This bridging of computational aesthetics and personality psychology enables personalized calligraphy and culturally adaptive design.

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