Sexual Selection Preferences in Anthropomorphized Imagery of Interpretative Graphics in Quantitative Visualization

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Abstract

When choosing what we find visually attractive, men and women tend to focus on different features, even for simple shapes. This study investigates gender differences in visual feature preferences during the anthropomorphization of graphics in the context of sexual selection. We constructed a feature set consisting of 48 geometric attributes to explore how these elements affect sexual selection preferences across genders. In Study 1, we quantitatively visualized these features using genetic algorithms, GANs, and manual design. Study 2 assessed gender preferences through an online survey of 288 participants, revealing the most significant features and differences in male and female preferences.Finally, in Study 3, we applied these findings to real-world art (Chinese calligraphy) to verify the explanatory power of the features. Our results provide new insights into the role of visual features in sexual selection and have practical applications in art, product design, and user experience optimization.

Keywords: artificial intelligence; psychology; art and cognition; attractiveness; human-computer interaction.

Introduction

In partner selection, physical appearance is an important influencing factor, covering characteristics such as skin color, height, and body shape. Studies have shown that there are significant differences in selection preferences between different genders (Buss & Barnes, 1986). This preference is not only reflected in the individual's partner selection, but also transferred to the selection of other objects or images in an abstract way, prompting people to identify human characteristics in non-human objects (Epley et al., 2007). For example, in a fun test organized by this article, a group of ordinary people faced four suits of playing cards, imagined them as corresponding opposite-sex characters and chose the most attractive one. The results showed that there were significant differences in preferences between men and women (Figure 1). It can be seen that for different visual forms, people can associate them with human images and make intuitive judgments about their sexual attractiveness.

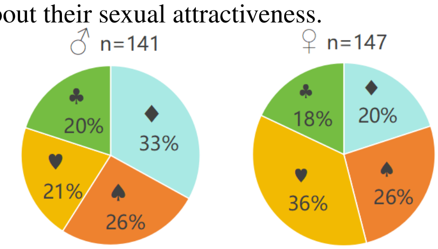

Figure 1: Sexual selection preferences of the four suits of playing cards.

This aesthetic and emotional association method of attributing human characteristics to non-human objects is called anthropomorphism (Wan & Chen, 2021). Anthropomorphic sexual selection preferences also affect people's daily decisions. For example, when women tend to choose the opposite sex with a large frame and a sense of security, they tend to prefer off-road vehicles, while men who like petite and delicate images prefer streamlined sports cars; in terms of mobile phone appearance selection, consumers who prefer business-type opposite sex usually prefer mobile phones with right-angle frame designs, while people who like sports and sunny opposite sex tend to choose mobile phones with rounded corner designs. As a result, many product designs use anthropomorphic techniques to attract consumers of different genders, thereby stimulating their purchasing preferences (Huang et al., 2020). Anthropomorphic sexual selection preferences will also extend to artistic creation and aesthetic activities. Artists usually incorporate gendered image characteristics into their works to stimulate emotional resonance among audiences of different genders (Nieman & Bucholz, 2023).

When making anthropomorphic associations, what kind of graphic features do people use to make judgments? What are the differences in the features that men and women pay attention to? There have been many related studies, but no clear answer can be given. In previous studies on the differences in aesthetic preferences among different groups, more studies focused on the impact of personality differences. For example, Gelli et al. emphasized the role of personality traits in artistic preferences (Gelli et al., 2017); Chamorro-Premuzic studied the dominant role of personality in artistic preferences and found that people with open personalities tend to appreciate creative art forms (Chamorro-Premuzic et al., 2009). Ercegovac and his team further proposed that visual art preferences reflect individual personality traits, especially emotional stability and extroversion (Ercegovac et al., 2015). In addition, cultural background also affects sexual selection preferences. Laland studied how cultural transmission affects the formation of sexual selection preferences (Laland, 1994), and Nakajima and Aoki explored the interaction between cultural transmission and gender preferences by expanding the cultural evolution model of sexual selection (Nakajima & Aoki, 2002). Karandashev et al. found that differences in sensory preferences are closely related to the de-

In D. Barner, N.R. Bramley, A. Ruggeri and C.M. Walker (Eds.), *Proceedings of the 47th Annual Conference of the Cognitive Science Society*

gree of social modernization and cultural background (Karandashev et al., 2020). A few studies also show differences in aesthetic judgments between men and women and try to explain: Leelayudthyothin's research shows that women prefer smooth and harmonious artistic designs, while men prefer designs with tension and sharp edges (Leelayudthyothin, 2024). The application of magnetoencephalography technology also reveals differences in brain activity between men and women when making aesthetic decisions (Cela-Conde et al., 2009). However, although existing studies have revealed the potential impact of gender differences on aesthetic preferences, quantitative research and verification on the basis of preferences of different genders in anthropomorphic choices and differences between the two sexes are still insufficient. To fill this gap, this study aims to reveal the intrinsic relationship between anthropomorphic imagery and sexual selection preference. By quantitatively analyzing the association between graphic features and selection preference, this study explores the feature dependence and differences of different genders in anthropomorphic selection.

The core question of this study is: When making anthropomorphic sexual selection judgments on visual forms, what objective features do men and women rely on respectively? What are the significant differences between these features? To this end, the main work of the study is as follows: First, design and construct graphic features with precise mathematical descriptions and visualization (Study 1); then, extract and quantify the key graphic features that affect sexual selection preferences in anthropomorphic images, and present the correlation between these features and sexual selection preferences through visualization (Study 2); finally, use the above feature system to explain the sexual selection preferences of men and women for actual works of art and verify its effectiveness (Study 3).

The value of this study is reflected in three aspects: (1) A model interpretation method combining visualization and quantification in cognitive modeling is proposed. This method can not only provide a clearer and more intuitive result display for this research field, but can also be applied to the interpretability research of abstract features. (2) For the first time, the preference differences between men and women in the selection of anthropomorphic images are systematically measured, and a quantitative, visual and detailed explanation is given. (3) The interpretable model obtained in the study has a variety of application potentials. For example, in artistic creation design and product design, by revealing the preference differences between different genders in anthropomorphic selection, designers can more accurately mobilize the elements of gender preferences, thereby optimizing product form and improving market competitiveness; in the field of AI-assisted design and user experience optimization, it helps to develop personalized and emotional recommendation systems to enhance user interaction and experience; it can also be applied to the field of computer vision, especially in sentiment analysis, face recognition and automated design, to promote the development of visual intelligence technology.

Study 1: Constructing Interpretable Graphical Feature Sets for Quantitative Visualization

The purpose of this study is to construct a set of self-explanatory graphical features that meet two interpretability requirements: one is precise mathematical description, and the other is intuitive visualization.

Deep learning is not achieved by the above-mentioned preferred method of selection. Deep learning has outstanding visual modeling capabilities, but its "black box" nature makes its interpretability a problem. In the field of aesthetic modeling, it is generally believed that the aesthetic process is to extract "features" from visual objects and make judgments based on these features (Brachmann & Redies, 2017; Morgenstern et al., 2021). Deep learning automatically learns features from data through deep neural networks, and has demonstrated powerful capabilities in visual modeling in recent years. Classic visual models can extract high-dimensional feature vectors, such as VGG (Simonyan & Zisserman, 2014), which extracts image features from low-level to high-level through deep convolutional networks, and finally maps them to high-dimensional feature spaces for tasks such as classification. ResNet (He et al., 2016) extracts more complex high-dimensional features through residual learning, while ViT (Dosovitskiy et al., 2020) uses Transformer to capture long-range information and fine-grained features to generate high-dimensional feature vectors, which performs well in many computer vision tasks. Wu et al. proposed an adaptive patch comparison method to further enhance the model accuracy (Wu et al., 2025). However, the features obtained by deep learning often do not have precise mathematical definitions and lack intuitive visual explanations.

In order to achieve the interpretability requirements of both mathematical description and intuitive visualization, the idea of this study is as follows: First, the precisely defined features in existing studies are gathered, and new features are introduced on this basis to expand the feature space and construct a feature set with precise mathematical description; then, three methods are used to design the visual explanation of the feature set: genetic algorithm, generative adversarial network (GAN), and artificial graphic design with computational auxiliary prompting function, and the optimal visual explanation is generated through a competition mechanism.

Constructing a set of graphical features with precise mathematical description

This step aims to construct a universal feature set with precise mathematical definitions for monochrome graphics. We exclude factors such as color, light and shadow, focus on morphological features, integrate relevant research in multiple fields, and bring together a variety of graphic features, mainly covering geometry (Vijendran et al., 2024)(Morgenstern et al., 2021), morphology (Soille, 1999), computational aesthetics (Bo et al., 2018), visual aesthetics (Brachmann &

Redies, 2017)(Guo et al., 2018) and texture features (Thumfart et al., 2008), and have made adaptive improvements and extensions to them, and finally defined 48 computable visual features. These features can be divided into four categories: (1) Morphological features (F1-F16): describe the overall geometric shape of the graphics; (2) Structural features (F17-F27c): focus on the internal structure and spatial distribution of the graphics, revealing its internal composition and layout rules; (3) Texture features (F28-F30): Quantify the texture quality of the graphics; (4) Contour features (F31-F34) analyze the contour lines of the graphics and capture the detailed characteristics and complexity of its boundaries.

Graphic feature visualization design based on optimization algorithm and competition mechanism

This step aims to achieve intuitive visualization of the 48 defined features. In previous studies, methods for feature visualization interpretation include Feature Visualization (Erhan et al., 2009), which optimizes the input image to maximize the activation of specific neurons, thereby revealing the sensitivity of the network to specific visual features; Deconvolution (Zeiler & Fergus, 2014), which locates the area in the input image that contributes most to the prediction by back-propagating gradients, helping to understand the layer-by-layer feature extraction and decision-making process of the neural network; and Class Activation Mapping (CAM) (Zhou et al., 2016), which uses the feature map of the convolutional layer to generate a heat map to intuitively identify the area that contributes most to the classification task. This paper adopts another unique idea: **for a feature in the feature set, if a set of gradient graphics can be designed, their values on the specified feature form a "gradient", and the numerical differences on all other features are small enough, then this set of graphic gradients can be regarded as an intuitive visualization of the feature.**

In order to generate a gradient graph set, our basic idea is to combine the graph generation model with manual design, use the above indicators to evaluate the quality of the generated graph, and select the best one as the result. We combined three methods to visualize the generated feature change images, as follows:

$$A_i = \frac{\sigma(f_{i1}, f_{i2}, f_{i3}, f_{i4}, f_{i5})}{\max\limits_{1 \le j \le 48, j \ne i} \left[\sigma(f_{j1}, f_{j2}, f_{j3}, f_{j4}, f_{j5})\right] + 1}$$

In the formula, f_{i1},f_{i2},f_{i3},f_{i4},f_{i5} are five values obtained by calculating feature i for the five patterns, and $\sigma(f_{i1}, f_{i2}, f_{i3}, f_{i4}, f_{i5})$ is the standard deviation of these five values. The fitness function quantifies the effectiveness of each group of images by calculating the feature prominence. The goal is to minimize the interference of other features while ensuring the difference of the target features, so as to ensure that the visualization effect is both intuitive and interpretable.

We combined three methods to visualize the generated feature change images, as follows:

Genetic algorithm: Optimizes image features by simulating natural selection, and its initial population generates 1,000 images through "center diffusion" to ensure population diversity. Subsequently, the pixel data of each group of 5 images is flattened into a gene sequence, the feature significance is evaluated by the fitness function, and the feature performance is optimized through genetic operations such as crossover, mutation, and selection.

Generative adversarial network: GAN generates images through adversarial learning between the generator and the discriminator. The discriminator evaluates the feature significance based on the fitness function of the genetic algorithm, and the generator optimizes the image generation based on the discriminator feedback.

Drawing tool combined with feature calculation: We developed a drawing program that supports manual drawing and calculates 48 feature values and their fitness in real time. This allows us to precisely control the prominence of the target feature while maintaining the stability of other features when adjusting graphic details (such as shape and size).

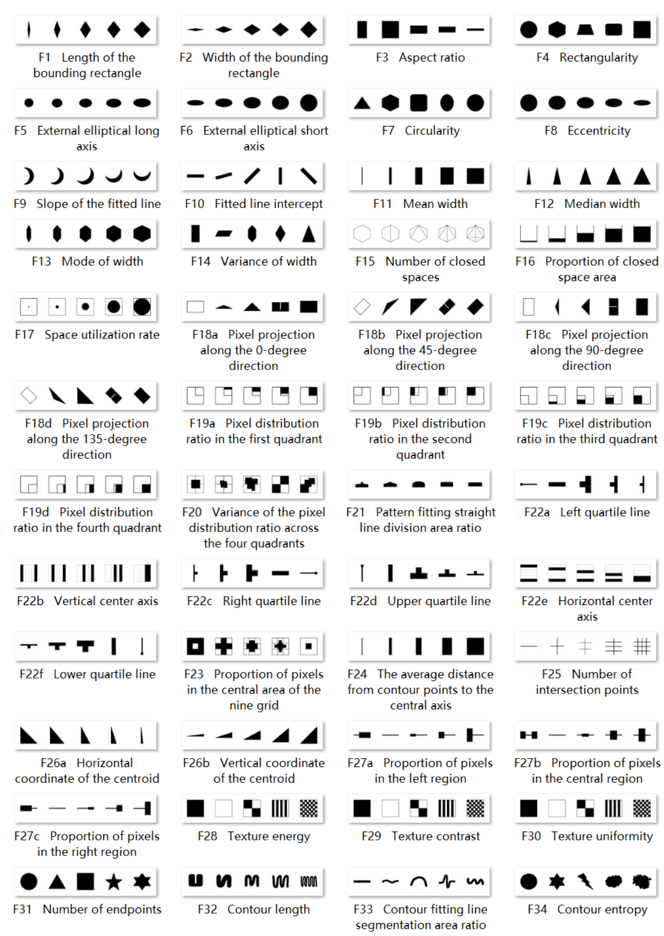

Figure 2: Visualization of 48 features.Each feature image contains 5 patterns, which are arranged in ascending order according to the feature values of the patterns to form a feature change sequence.

We selected the best generation strategy for each feature through a competition mechanism, and finally generated 48 sets of feature images (Figure 2). Each set of 5 images formed a significantly different gradient on its designated feature, while the variation on the other 47 features was small enough to visualize the intuitive morphological changes that its designated feature could produce.

Study 2: Experiment on Evaluating Sexual Selection Preference of Graphic Features

This stage aims to evaluate the sexual selection preferences of men and women for 48 interpretable features and select the features that have the most significant impact on the preferences of men and women. To this end, this paper designed an online questionnaire to recruit subjects from the general public to evaluate the sexual selection preferences of the gradient visualization graphs of the 48 features.

Method

Questionnaire design We randomly divided the 48 feature gradient images from Study 1 into three groups of 16 images each. Each subject randomly selected a group for evaluation, and the evaluation questions (Figure 3) were presented in a random order.

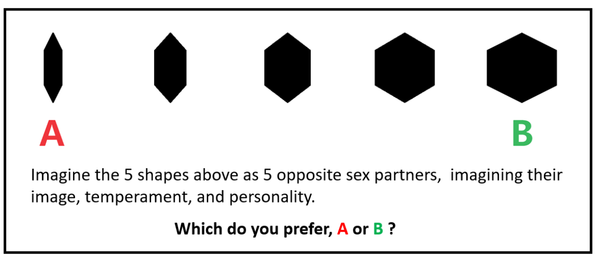

Figure 3: Example of interactive questionnaire questions.

Participants A total of 288 participants (141 female, 147 male) were recruited online, aged 19-34 (Mean = 24, SD = 1.76), and all participants signed informed consent. Demographic variables such as cultural background and age were not controlled, but may impact preferences. Future research should consider these confounding factors. All participants received compensation for completing the questionnaire.

Data Analysis

We calculated the voting probability as the score value of each feature based on the number of votes cast by different genders on the same feature image. The gender difference in the voting score of each image was analyzed using a t-test, and the parameter p was estimated using a binomial distribution model. The 95% confidence interval of p was calculated, and the threshold was set to 0.8 based on the study of Cohen (2013) to extract features with significant gender differences. It should be noted that the choice of 0.8 is not a standard, but is based on previous studies to ensure that gender preferences have high significance. Values below 0.2 are considered as opposite choices (dislike) and are still considered significant. Therefore, we inverted them, that is, converted them to 1 minus the value (for example, 0.1 is converted to 0.9). These screened features can be regarded as features that have a significant impact on gender in the selection of anthropomorphic images.

Results

By observing the t-test results, it was found that most of the characteristics were not significantly different between men and women ($p > 0.05$), and some characteristics were slightly different, such as F27b ($p = 0.28$) and F34 ($p = 0.33$), showing a high consistency between different genders. Although some characteristics were different between men and women, the significance was low, such as F22e ($p = 0.049$) and F23 ($p = 0.053$). However, the difference between men and women in F6 ($p = 0.005$) and F8 ($p = 0.006$) was more significant, indicating that there were significant differences in gender preferences for these characteristics.

We extracted features in the confidence interval based on the set threshold. These features showed significant differences in preferences between different genders, indicating that these features have a strong discriminatory power for the selection preferences of anthropomorphic images. Specifically, these features showed a clear preference trend in male and female subjects, reflecting the differences in visual feature perception and aesthetic choices between different genders. Tables 1 and 2 show the meaning or calculation methods of the features and the confidence intervals of these features.

Table 1: Meaning or calculation method of the selected features.

Feature	Meaning or calculation method
F2	The width of the pattern's bounding rectangle.
F3	The aspect ratio of the pattern's circumscribed rectangle.
F6	The length of the minor axis of the ellipse circumscribing the pattern.
F8	Eccentricity of the pattern's outer ellipse.
F18b	Pixel projection amount of the pattern at 45 degrees.
F22b	The position of the vertical line that divides the pattern pixels horizontally into two equal parts.
F24	The average distance from the points on the outline of the pattern to the central axis of the pattern.
F26b	The vertical coordinate of the center of gravity of the pattern.
F27b	Divide the pattern horizontally into 3 parts, and the pixel ratio of the middle area.
F32	The length of the pattern outline, which is the sum of the number of pixels on the outline.
F33	The pattern contour fitting straight line divides the pattern into two partsthe ratio of the area of the smaller part to the larger part.
F34	The contour entropy of a graphic is used to measure the complexity of the image contour. First, the graphic contour is extracted and the grayscale distribution is statistically analyzed, and then the contour entropy is calculated using the entropy formula.

Table 2: Significant features and 95% confidence intervals for males and females. Features marked with "-" indicate inverted features, i.e. significant "dislike".The bold fonts are common characteristics of both men and women.

Male			Female		
Feature	Lower CI	Upper CI	Feature	Lower CI	Upper CI
F34 -	0.871	0.998	F8 -	0.860	0.980
F26b	0.867	0.990	**F3**	0.854	0.976
F33 -	0.834	0.963	**F34 -**	0.835	0.968
F27b -	0.860	0.958	**F26b**	0.841	0.966
F6 -	0.807	0.950	F32 -	0.841	0.955
F18b	0.807	0.921	F22b	0.818	0.948
F3	0.811	0.904	F2	0.801	0.925
F24 -	0.801	0.899	**F27b -**	0.810	0.901

Discussion

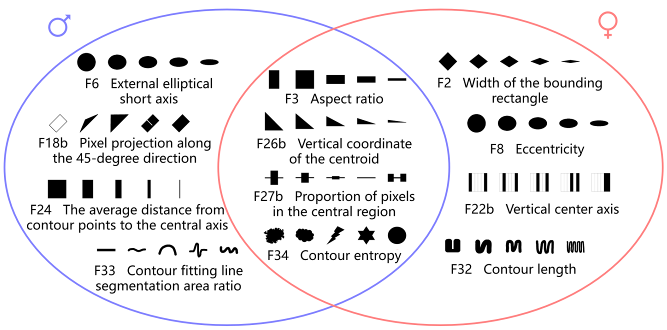

Figure 4: The preferred characteristics of men and women in the selection of anthropomorphic images. The left side shows male characteristics, the right side shows female characteristics, and the middle part shows the common characteristics of men and women. The preference for each characteristic gradient picture increases from left to right.

Figure 4 shows the features that men and women rely on and the features that they pay attention to in their choice of anthropomorphic images. It can be seen that the features that both sexes pay attention to are mainly concentrated on indicators that describe the overall shape of the figure, such as F3 (aspect ratio), F26b (center of gravity vertical coordinate), and F27b (middle area ratio). These features can be quickly judged through intuitive observation. In addition, features such as F34 (contour entropy) that reflect the complexity and irregularity of the figure are also of great concern, because contour entropy intuitively reflects the visual characteristics of the appearance of the figure and fits the natural tendency of human aesthetics (Nadal et al., 2010). However, there are also significant differences in the features that men and women pay attention to. For example, men tend to prefer rational and structured aesthetics (F6, F18b, F24, F33), especially the feature of F33 (contour fitting line segmentation area ratio). This type of image often makes people anthropomorphize into the opposite sex with prominent body curves.Previous studies have shown that this dynamic is an important factor for men when choosing a partner of the opposite sex (Singh, 1993), while women generally consider this less.Women tend to choose elements that can evoke emotional resonance and express softness and harmony (F2, F8, F22b, F32). The dynamic sense reflected by F8 (eccentricity) is that when women choose anthropomorphic images, they map their pursuit of their own form into the aesthetic judgment of the opposite sex (Baker & Wertheim, 2003), thereby arousing emotional resonance. The vertical central axis (F22b) can be regarded as the "center" or "core" of emotions and relationships. In many cultures, the stability of family, relationships and emotions is often regarded as a social ideal (Eagly & Wood, 1999), and women are more inclined to reflect this psychological need and emotional projection through pattern selection.

Study 3: Evaluation and Interpretation of Sexual Preference for the Single Calligraphy Stroke "yi"

This study aims to further verify whether the feature set that men and women pay attention to in Study 2 can explain the differences in male and female preferences in actual works of art. The ability of Chinese calligraphy to express rich anthropomorphic images with a single stroke is widely recognized in literature and practice(Lin & H, 2023)(Chen-Chun & E, 2017). In particular, the single stroke is concise in form and intuitive in meaning, making it suitable as experimental material (Pan et al., 2020). Therefore, this study invited several calligraphy experts to independently screen and select 432 "yi" calligraphy samples with diverse forms and wide distribution from a large-scale calligraphy dataset through joint voting. The subjects voted on these samples for sexual selection preferences through an anthropomorphic imagination task, and quantitatively measured the 48-dimensional visual features of the samples. Finally, by observing the association between sexual selection preferences and visual features, we focused on testing whether the preference results were consistent with the key features found in the previous experiments.

Method

Questionnaire design This phase aims to measure people's evaluation of the anthropomorphic intention of 432 "yi" calligraphy pictures. The experiment was conducted through a questionnaire survey, and the material of the questionnaire was 432 picture samples (Figure 5). In order to avoid the fatigue effect of participants due to too many samples, the random grouping method was used to divide the samples into 16 groups, each with 54 "yi", to ensure that each "yi" appeared in two groups, and each tester randomly selected one group for evaluation.

The questionnaire was designed as follows: from a set of randomly presented "yi" pictures (54 pictures), participants were asked to imagine the "yi" pictures as objects of the opposite sex, and select 10 to 20 pictures they liked, and then select 10 to 20 pictures they disliked, in order to measure the participants' subjective preferences for different samples. Under this setting, the two multiple-choice questions were approximately equivalent to a 3-level scale test (dislike, neutral, like) for a group of samples, but its loading was lower than the scale rating for each sample.

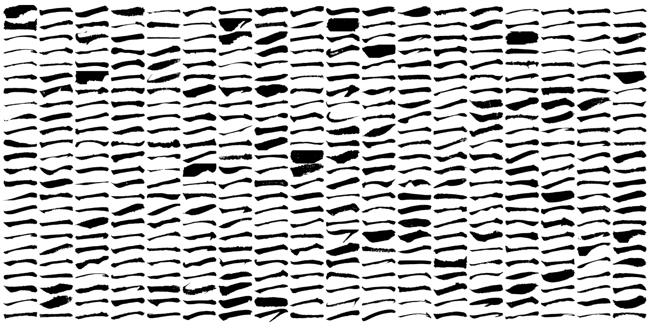

Figure 5: 432 samples of "yi".

Participants A total of 512 participants (247 female, 265 male) were recruited online, aged 19-34 (Mean = 27, SD = 2.4), and all participants signed informed consent. Demographic variables such as cultural background and age were not controlled, but may impact preferences. Future research should consider these confounding factors. All participants received compensation for completing the questionnaire.

Data Visualization

We accumulated the scores of the same pictures given by men and women in the questionnaire data to obtain the likeability score of each picture. Next, we selected the three "yi" pictures with the highest and lowest scores in the votes of men and women as the most and least liked measurement samples. Then, based on the feature system extracted in Study 2, we used the code to calculate the features of these 12 "yi" samples one by one to obtain the feature data of each sample. In order to eliminate the dimensional differences between different feature values, we normalized the value of each feature to the (0, 100) interval (see Figure 6).

Discussion

Figure 6 shows the sample graphs with the highest and lowest votes for males and females in the questionnaire survey on anthropomorphic images in Experiment 3. From the feature data calculated from the samples, the images with high likes usually show higher positive feature values, while the images with low likes have significant negative feature values, which is consistent with the feature system we extracted. The sample of the character "yi" in the figure shows that both males and females tend to prefer the slender anthropomorphic "yi" image, but there are significant gender differences in the preferred features. The "yi" preferred by females shows more slenderness and softness, while males tend to emphasize rigidity and strength. The gender difference is more obvious in the disliked "yi" image. The "yi" image disliked by males usually deviates from the traditional form and has a wider and rough outline; while the "yi" image disliked by females maintains a more typical "yi" structure, but its top is sharper. This strong sense of boundary in the design is the main factor leading to the reduction of female preference.

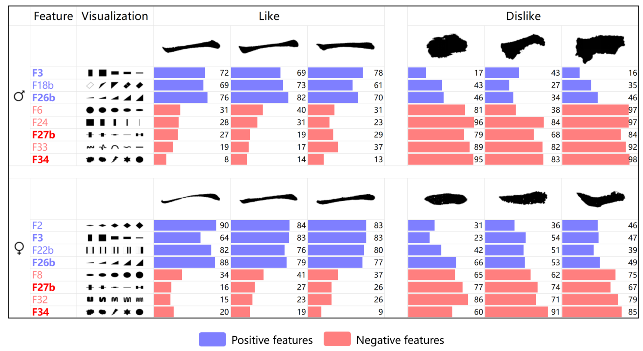

Figure 6: Examples of male and female evaluations of anthropomorphic images and comparison of feature values.features common to both sexes are bolded.

Conclusion

This study quantitatively visualized the sexual selection preferences of graphic anthropomorphic images, revealed the different visual features that men and women rely on in such choices, and explored the gender differences behind them. The results show that men and women pay attention to different graphic feature systems when making anthropomorphic judgments, and this difference reflects the significant differences in aesthetic preferences between the two sexes.

This study systematically reveals the differences in preferences between men and women in anthropomorphic choices through quantitative and visual methods for the first time, and clarifies the key features that both sexes rely on in this process. This finding provides empirical support for the manifestation of gender differences in aesthetic preferences, and provides a theoretical basis for its application in art creation, product design, user experience optimization and other fields. Understanding the aesthetic preferences of different genders can help designers accurately mobilize gender elements, enhance product appeal, and promote personalized and emotional design. For example, the design of smart air purifiers can cater to gender preferences: the male style emphasizes structure and rationality, with straight lines, tilts and hard cubic shapes, while the female style focuses on softness and emotional resonance, with quirky and symmetrical layouts, and smooth and warm designs. This study provides a new perspective for understanding the role of gender in anthropomorphic aesthetics and lays the foundation for interdisciplinary research. In the future, we can explore the impact of cultural background, personality differences and other factors on gender selection preferences.

Acknowledgments

We sincerely thank all the participants who participated in this study. We thank the Medical Ethics Committee of Jiangnan University for approving this study protocol (approval number: JNU202409RB0029). All procedures of this study strictly followed the relevant regulations of the Ethics Committee and complied with the ethical requirements of the Declaration of Helsinki. It should be noted that this study did not involve any human biological specimens, and all participants signed informed consent.

References

Aiken, L. S., West, S. G., & Reno, R. R. (1991). *Multiple regression: Testing and interpreting interactions*. sage.

Alexey, D. (2020). An image is worth 16x16 words: Transformers for image recognition at scale. *arXiv preprint arXiv: 2010.11929*.

Baker, C., & Wertheim, E. H. (2003). Body image: A handbook of theory, research, and clinical practice, edited by thomas f. cash and thomas pruzinsky, new york: Guilford press, 2002, 530 pages, $60.00.

Bo, Y., Yu, J., & Zhang, K. (2018). Computational aesthetics and applications. *Visual computing for industry, biomedicine, and art*, *1*, 1–19.

Brachmann, A., & Redies, C. (2017). Computational and experimental approaches to visual aesthetics. *Frontiers in computational neuroscience*, *11*, 102.

Buss, D. M., & Barnes, M. (1986). Preferences in human mate selection. *Journal of personality and social psychology*, *50*(3), 559.

Cela-Conde, C. J., Ayala, F. J., Munar, E., Maestú, F., Nadal, M., Capo, M. A., del Río, D., López-Ibor, J. J., Ortiz, T., Mirasso, C., et al. (2009). Sex-related similarities and differences in the neural correlates of beauty. *Proceedings of the National Academy of Sciences*, *106*(10), 3847–3852.

Chamorro-Premuzic, T., Reimers, S., Hsu, A., & Ahmetoglu, G. (2009). Who art thou? personality predictors of artistic preferences in a large uk sample: The importance of openness. *British Journal of Psychology*, *100*(3), 501–516.

Chen-chun, E. (n.d.). Cultural signification and philosophy embedded in chinese calligraphy: A semiological analysis.

Cohen, J. (2013). *Statistical power analysis for the behavioral sciences*. routledge.

Cressie, N., & Whitford, H. (1986). How to use the two sample t-test. *Biometrical Journal*, *28*(2), 131–148.

DeCoster, J. (2006). Testing group differences using t-tests, anova, and nonparametric measures. *Accessed November*, *30*(2010), 202006–.

Eagly, A. H., & Wood, W. (1999). The origins of sex differences in human behavior: Evolved dispositions versus social roles. *American psychologist*, *54*(6), 408.

Epley, N., Waytz, A., & Cacioppo, J. T. (2007). On seeing human: A three-factor theory of anthropomorphism. *Psychological review*, *114*(4), 864.

Ercegovac, I. R., Dobrota, S., & Kuščević, D. (2015). Relationship between music and visual art preferences and some personality traits. *Empirical Studies of the Arts*, *33*(2), 207–227.

Furnham, A., & Avison, M. (1997). Personality and preference for surreal paintings. *Personality and Individual Differences*, *23*(6), 923–935.

Furnham, A., & Walker, J. (2001). Personality and judgements of abstract, pop art, and representational paintings. *European Journal of personality*, *15*(1), 57–72.

Gelli, F., He, X., Chen, T., & Chua, T.-S. (2017). How personality affects our likes: Towards a better understanding of actionable images. *Proceedings of the 25th ACM international conference on Multimedia*, 1828–1837.

Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., & Bengio, Y. (2014). Generative adversarial nets. *Advances in neural information processing systems*, *27*.

Guo, X., Qian, Y., Li, L., & Asano, A. (2018). Assessment model for perceived visual complexity of painting images. *Knowledge-Based Systems*, *159*, 110–119.

He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. *Proceedings of the IEEE conference on computer vision and pattern recognition*, 770–778.

Huang, F., Wong, V. C., & Wan, E. W. (2020). The influence of product anthropomorphism on comparative judgment. *Journal of Consumer Research*, *46*(5), 936–955.

Iigaya, K., Yi, S., Wahle, I. A., Tanwisuth, K., & O'Doherty, J. P. (2021). Aesthetic preference for art can be predicted from a mixture of low-and high-level visual features. *Nature Human Behaviour*, *5*(6), 743–755.

Karandashev, V., Zarubko, E., Artemeva, V., Evans, M., Morgan, K. A. D., Neto, F., Feybesse, C., Surmanidze, L., & Purvis, J. (2020). Cross-cultural comparison of sensory preferences in romantic attraction. *Sexuality & Culture*, *24*, 23–53.

Laland, K. N. (1994). Sexual selection with a culturally transmitted mating preference. *Theoretical Population Biology*, *45*(1), 1–15.

Larson, C. L., Aronoff, J., & Steuer, E. L. (2012). Simple geometric shapes are implicitly associated with affective value. *Motivation and Emotion*, *36*, 404–413.

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *nature*, *521*(7553), 436–444.

Leelayudthyothin, M. (2024). Are aesthetic preferences affected by gender and age differences? *Asian Journal of Arts and Culture*, *24*(1), e259070–e259070.

Legendre, P., & Legendre, L. (2012). Ecological resemblance. In *Developments in environmental modelling* (pp. 265–335, Vol. 24). Elsevier.

Lin, H. (2023). Calligraphy to image. *Proceedings of the 16th International Symposium on Visual Information Communication and Interaction*, 1–5.

Lu, Y., Guo, C., Lin, Y., Zhuo, F., & Wang, F. (2020). Computational aesthetics of fine art paintings: The state of the art and outlook. *Acta Automatica Sinica*, *46*(11), 2239–2259.

Marin, M. M., & Leder, H. (2013). Examining complexity across domains: Relating subjective and objective measures of affective environmental scenes, paintings and music. *PloS one*, *8*(8), e72412.

Morgenstern, Y., Hartmann, F., Schmidt, F., Tiedemann, H., Prokott, E., Maiello, G., & Fleming, R. W. (2021). An image-computable model of human visual shape similarity. *PLoS computational biology*, *17*(6), e1008981.

Moss, G., & Gunn, R. (2009). Gender differences in website production and preference aesthetics: Preliminary implications for ict in education and beyond. *Behaviour & Information Technology*, *28*(5), 447–460.

Nadal, M., Munar, E., Marty, G., & Cela-Conde, C. J. (2010). Visual complexity and beauty appreciation: Explaining the divergence of results. *Empirical Studies of the Arts*, *28*(2), 173–191.

Nakajima, A., & Aoki, K. (2002). On richerson and boyd's model of cultural evolution by sexual selection. *Theoretical population biology*, *61*(1), 73–81.

Nie, J., Cui, P., Yan, Y., Huang, L., Li, Z., & Wei, Z. (2014). How your portrait impresses people? inferring personality impressions from portrait contents. *Proceedings of the 22nd ACM international conference on Multimedia*, 905–908.

Nieman, H., & Bucholz, E. G. (2022). Gender and beauty presentation in art: An analysis of gender queer self-portraiture through the lens of judith butler's theory of performativity and aesthetic subjectavism. *Journal of Student Research*, *11*(1).

Pan, Y., Lyu, R., Nie, Q., & Meng, L. (2020). Study on the emotional image of calligraphy strokes based on sentiment analysis. *2020 5th international conference on communication, image and signal processing (CCISP)*, 264–269.

Seber, G. A., & Lee, A. J. (2012). *Linear regression analysis*. John Wiley & Sons.

Seckler, M., Opwis, K., & Tuch, A. N. (2015). Linking objective design factors with subjective aesthetics: An experimental study on how structure and color of websites affect the facets of users' visual aesthetic perception. *Computers in Human Behavior*, *49*, 375–389.

Simonyan, K. (2014). Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*.

Singh, D. (1993). Adaptive significance of female physical attractiveness: Role of waist-to-hip ratio. *Journal of personality and social psychology*, *65*(2), 293.

Sivanandam, S., Deepa, S., Sivanandam, S., & Deepa, S. (2008). Applications of genetic algorithms. *Introduction to Genetic Algorithms*, 317–402.

Skov, M. (2020). Animal preferences: Implications of sexual selection research for empirical aesthetics.

Soille, P. (1999). Morphological image analysis: Principles and applications.

Thumfart, S., Jacobs, R. H., Lughofer, E., Eitzinger, C., Cornelissen, F. W., Groissboeck, W., & Richter, R. (2008). Modeling human aesthetic perception of visual textures. *ACM Transactions on Applied Perception (TAP)*, *8*(4), 1–29.

Van Paasschen, J., Zamboni, E., Bacci, F., & Melcher, D. (2014). Consistent emotions elicited by low-level visual features in abstract art. *Art & Perception*, *2*(1-2), 99–118.

Vijendran, M., Deng, J., Chen, S., Ho, E. S., & Shum, H. P. (2024). Artificial intelligence for geometry-based feature extraction, analysis and synthesis in artistic images: A survey. *Artificial Intelligence Review*, *58*(2), 64.

Wan, E. W., & Chen, R. P. (2021). Anthropomorphism and object attachment. *Current Opinion in Psychology*, *39*, 88–93.

Wang, J., & Hsu, Y. (2020). Gender difference in preference for apple watch dial interface. *Human Interface and the Management of Information. Designing Information: Thematic Area, HIMI 2020, Held as Part of the 22nd International Conference, HCII 2020, Copenhagen, Denmark, July 19–24, 2020, Proceedings, Part I 22*, 170–182.

Weisberg, S. (2005). Applied linear regression.

Wiltsher, N. (2024). The aesthetic constitution of genders. *Ergo: An Open Access Journal of Philosophy*, *11*.

Woodfield, R. (1996). Gombrich's story of art. *The British Journal of Aesthetics*, *36*(3), 313–316.

Wu, W., Dai, T., Chen, Z., Huang, X., Xiao, J., Ma, F., & Ouyang, R. (2025). Adaptive patch contrast for weakly supervised semantic segmentation. *Engineering Applications of Artificial Intelligence*, *139*, 109626.

Yanulevskaya, V., Uijlings, J., Bruni, E., Sartori, A., Zamboni, E., Bacci, F., Melcher, D., & Sebe, N. (2012). In the eye of the beholder: Employing statistical analysis and eye tracking for analyzing abstract paintings. *Proceedings of the 20th ACM international conference on multimedia*, 349–358.

Yarbus, A. L. (2013). *Eye movements and vision*. Springer.