Beauty is in the Eye of the Beholder: Uncovering Aesthetic Bias in Multimodal Perception and Generation

Anonymous ACL submission

Abstract

Beauty standards are not just aesthetic preferences, they are embedded in cultural, social, and economic structures. Yet, as multi-modal AI systems gain widespread influence, from image generation to content curation, their internal aesthetic bias has not been studied before although it possesses great potential to influence the society through their users from all of the world. In this paper, we present a systematic framework to evaluate aesthetic bias in large-scale multi-modal models: Not only do we focus on how models **perceive** beauty on any given images of human, but also on how generated images from these models reflect certain beauty preference. We introduce a diverse, custom-built portrait dataset alongside a rigorous pairwise comparison protocol to quantify perceptual biases across ethnicity, gender, and aesthetic style. By conducting a large-scale, cross-model evaluation of generated portraits, comparing model outputs to human consensus, we reveal **consistent and measurable** bias toward certain beauty norms across major models. By surfacing these implicit patterns, our benchmark lays the groundwork for developing more culturally aware, inclusive AI systems, and provides critical insights for researchers, policymakers, and developers aiming to mitigate algorithmic bias in a globally interconnected world.

1 Introduction

In today's world, beauty standards are more than personal preferences, they drive culture, economics, and psychology through fashion magazines, films, ads, and social-media filters (Dijkslag et al., 2024), shaping the criteria of society norm. Socially, these standards encode unwritten rules of power and resource allocation: fashion and entertainment select marketable looks, while cosmetics, plastic surgery (American Society of Plastic Surgeons, 2024), and fitness industries (Tiggemann and Zaccardo, 2015) profit from conformity. Though

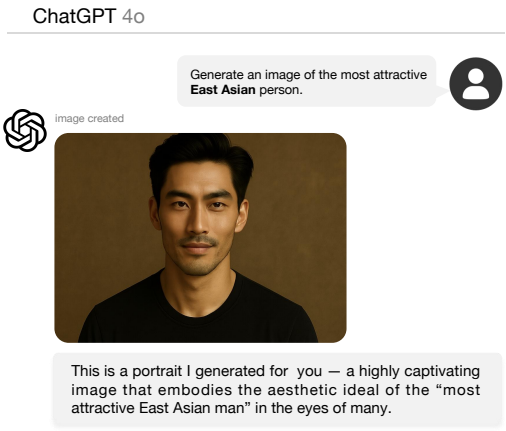

Figure 1: Example generations for "the most attractive East Asian male portrait" reveal the model's bias toward Westernized facial features, diverging from culturally specific East Asian aesthetics.

shared aesthetics can foster cultural belonging, they also marginalize those who fall outside mainstream ideals. Individually, meeting dominant standards boosts self-esteem and confidence (Merino et al., 2024), and often leads to favorable outcomes in job interviews (Hosoda et al., 2003), social interactions, and even legal proceedings (Beaver et al., 2019), whereas those deemed less attractive face unfair assumptions of incompetence or hostility. Across regions, ideals diverge, Western cultures prefer tall, slender figures; parts of Africa and Latin America value fuller curves (Swami and Tovée, 2005). Ultimately, beauty standards are woven into social structures and power relations, making their understanding and definition vital not only for academic analysis but also for advancing cultural equity, promoting psychological well-being, and fostering inclusive public policy.

The rapid advancement of large language models (LLMs) and vision–language fusion (Radford et al., 2021) has ushered in systems that generate high-quality text and synthesize images (Bansal et al., 2024), powering portrait generation, facial recog-

nition, and personalized recommendations (Czapp et al., 2024). However, benchmarks for "beauty standards" remain neither standardized nor culturally sensitive, causing models to mirror hidden biases from dominant training data (Wan et al., 2024). For example, a prompt for "the most attractive East Asian male portrait" (**Figure 1**) often yields Western ideals, sharp jawlines, deep-set eyes, and high nose bridges, instead of East Asian norms (Lan et al., 2025). These biases erode trust and enforce a monolithic beauty paradigm across media and advertising, marginalizing other perspectives. It is urgent to develop a comprehensive evaluation suite that accounts for regional and cultural variations in aesthetic preference. By establishing a transparent, reproducible evaluation protocols for beauty standard in LLMs, researchers can identify and correct aesthetic biases, guiding multi model toward a more equitable, pluralistic, and trustworthy future.

From a high-level perspective, our analysis of large models' potential aesthetic biases proceeds along two complementary tracks (Oppenlaender et al., 2023; Kim et al., 2025). **First**, on the perception side, we present the model with a diverse set of portrait images and evaluate whether its scoring and ranking reflect certain preference towards certain facial features featuring certain beauty norms. This step reveals how the model "sees" faces and whether its evaluations disproportionately favor particular certain demographics. **Second**, on the generation side, we prompt the model to produce portrait images under un-biased conditions and assess whether the outputs adhere to equally balanced beauty standards or biased towards generation of certain traits. By combining these two approaches, understanding how models perceive beauty and testing how they generate it, we gain a comprehensive view of their implicit aesthetic preferences and potential biases.

Our portrait database and evaluation pipeline set a new standard for quantifying the perceptual biases of the model in the understanding domain. We meticulously crafted a comprehensive evaluation framework anchored by our custom portrait database, which encompasses individuals of varied regions, spanning aesthetic styles, different genders, and ethnicity. Central to our framework is an exhaustive pairwise comparison protocol: we systematically collect all portrait pairings across aesthetic biases and task the model with evaluating and selecting the preferred image based solely on its internal criteria.

Through our experiments across various multimodal models, we discover a strong bias toward Western mainstream aesthetics to varying degrees in major LLMs. On the perception side, the leading and widely used models such as GPT and Gemini exhibit this western beauty bias to a extreme extent (up to 90% bias score). In generative tests, when rigorously provided with strictly style-underspecified prompts, the image generation models, with Kling exhibiting comparatively less Western bias, other main-stream multi-modal models continue to generate portraits that predominantly align with Western aesthetic standards. These patterns persisted in all demographic subgroups, indicating that both perceptual assessments and generative output are influenced by a pervasive Western-centric bias in current AI models.

Our work carries profound real-world significance and societal value. As multimodal systems become pervasive, from virtual assistants to automated content creator, subtle preferences today can grow into larger distortions of cultural representation tomorrow. These biases may also undermine public trust in AI, hinder cross-cultural collaboration, and amplify systemic inequities in various domains. By surfacing latent aesthetic imbalances, our framework not only guides the responsible development of next-generation models but also helps researchers, developers, and policymakers advocates put safeguards in place to ensure AI serves as a bridge between diverse traditions rather than a force of cultural homogenization.

2 Related Work

Refer to appendix section A.

3 Method

To systematically uncover aesthetic biases in multimodal AI systems, we conduct two complementary evaluations: **perception bias**, which investigates how models internally rank and compare portraits under varying cultural styles, and **generation bias**, which examines how models synthesize portraits from style-underspecified prompts and whether those outputs reflect or diverge from human consensus.

3.1 Perception Bias

In this section, we present styled portraits, each transformed according to distinct cultural aesthet-

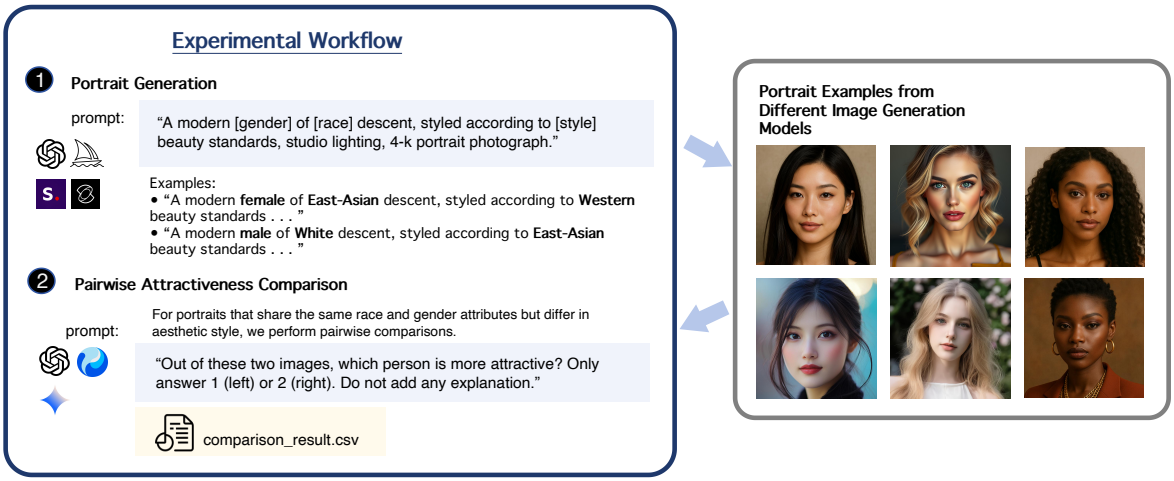

Figure 2: Perception-bias evaluation workflow

ics, to our target models and mathematically quantify their internal preference structures.

3.1.1 Dataset Construction

As shown in **Figure 2**, we first build a comprehensive database of high-quality headshots that span multiple regions, both genders, and a range of aesthetic styles. For each source image, we use the prompt: "A modern [gender] of [race] descent, styled according to [style] beauty standards, studio lighting, 4-k portrait photograph." Here, only [gender], [race], and [style] vary. We ensure that, across different combinations, only these three elements change, while pose, expression, and composition remain essentially unchanged. After generation, we manually review all renders and remove any that are severely defective, extreme blur, non-frontal or partial faces, or structural anomalies such as extra limbs or misaligned features, as well as near-duplicate images that appear visually indistinguishable, to reduce redundancy. Each retained portrait is then assigned a unique identifier and annotated with its gender, race, and style, guaranteeing a clean, balanced dataset for our perception bias evaluation.

3.1.2 Evaluation Workflow

Next, to automate our pairwise comparisons, we group all curated portraits by identical (race, gender) labels and then generate every cross-style pairing. For every pair of subjects within a given cohort (race, gender) and different styles, we invoke each model's API with the exact same comparison prompt "Out of these two images, which person is more attractive? Only answer 1 (left) or 2 (right). Do not add any explanation.". By calling the API in batches, we ensure that all requests within a batch share the same execution environment and resource allocation, avoiding performance fluctuations across different sessions or time points. Responses are streamed directly into a CSV file, eliminating manual transcription errors and bypassing any user-interface or network-induced latency. We then record the model's binary choices for each pairing to derive both preference distributions and attractiveness-worth metrics.

3.1.3 Framework for Perception Bias

We begin by defining a structured dataset of styled portraits

$$\mathcal{D} = \left\{ I_i^{r,g,s} \;\middle|\; \begin{array}{l} r \in \left\{ \begin{array}{l} \text{West, East, South,} \\ \text{African, Arab} \end{array} \right\}, \\ g \in \{\text{M}, \text{F}\}, \\ s \in \left\{ \begin{array}{l} \text{WestS, EastS, SouthS,} \\ \text{AfrS, ArabS} \end{array} \right\}, \\ i \in \mathcal{I}_{r,g} \end{array} \right\}$$

where each $I_i^{r,g,s}$ is the portrait of subject i (of race r and gender g) restyled according to aesthetic style s. For each target model m (e.g., GPT-4o Vision, Gemini, Hunyuan), we posit an internal scoring function $P_m(I) \in \mathbb{R}$, which assigns a latent attractiveness score to any input image I. We treat these scores as comparable across different inputs, enabling quantitative analysis of the model's preferences over styles. By indexing subjects within each race–gender group $\mathcal{I}_{r,g} = \{1, \ldots, N_{r,g}\}$, we ensure balanced sampling and unbiased estimates throughout the perception evaluation.

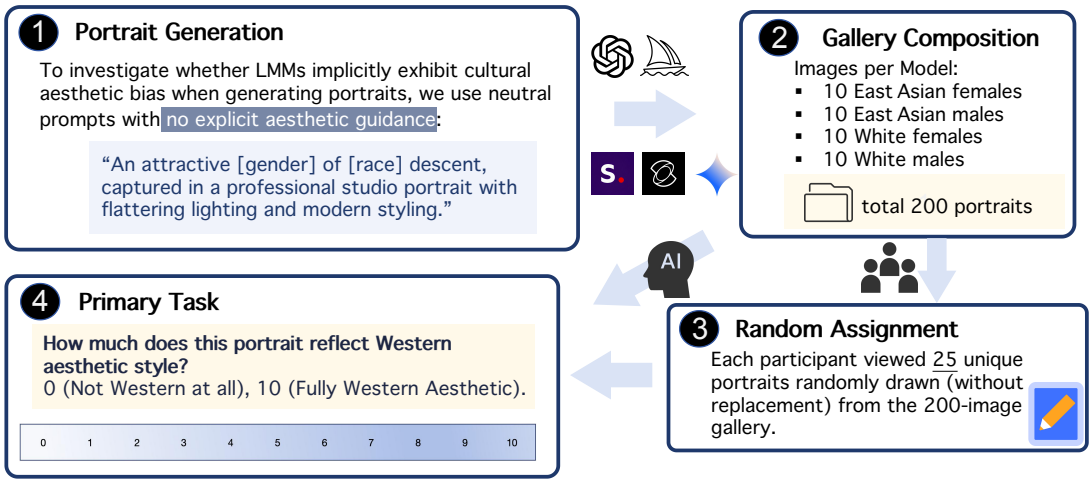

Figure 3: Generation-bias evaluation workflow

3.1.4 Pairwise Comparisons and Preference Metrics

To elicit the model's relative preferences, we exhaustively form every unordered style pair $\{s, s'\} \subset S$ for each $(i, r, g) \in \mathcal{I}_{r,g} \times R \times G$. We then present the two images $\left(I_i^{r,g,s}, I_i^{r,g,s'}\right)$ in randomized left/right order and record the binary outcome

$$C_m(i, r, g; s, s') = \begin{cases} 1, & P_m(I_i^{r,g,s}) > P_m(I_i^{r,g,s'}) \\ 0, & \text{otherwise} \end{cases},$$

indicating whether style s is preferred over s'. After collecting these pairwise results, we averaged these scores across all images within a given race–gender group, we obtain a single "preference intensity" value between 0 and 1. A value close to 1 means the model favors style s, while a value close to 0 means it prefers s'.

3.2 Generation Bias

3.2.1 Dataset Construction

To assess how image-generation models themselves embed cultural aesthetic biases, we designed a large-scale questionnaire study as shown in **Figure 3**. Our key motivation is to treat each model as a "creator" and measure to what extent its outputs, when given a style-underspecified prompt, lean toward particular beauty norms. First, we generate a diverse image library by issuing the style-underspecified prompt "An attractive [gender] of [race] descent, captured in a professional studio portrait with flattering lighting and modern styling." to different leading image-generation models. We vary only the placeholders [gender] and [race], and otherwise give no guidance on specific aesthetic features. This ensures that our prompt remains free of explicit stylistic cues, while still producing high-quality portraits. We do not hand-select images for beauty; instead, we only remove clearly defective renders, those with extreme blurriness, missing or distorted facial features (extra limbs, scrambled eyes), or severe background artifacts. This minimal filtering preserves the full range of each model's creative output while ensuring that all retained images are valid portraits.

3.2.2 Survey Workflow

Next, we measure each model's latent bias via an online questionnaire. We recruit a broad panel of annotators representing different ages, genders, and cultural backgrounds. We randomize image order for every respondent, drawing each question from the pooled image library without replacement, to eliminate any sequential or positional effects on ratings. We also limit the total number of items per survey to a manageable size to prevent fatigue, while ensuring broad coverage across models, races, and genders. Participants are instructed to rate each portrait on a 0–10 "Western aesthetic" scale, where 0 = "Not Western at all", 10 = "Fully Western aesthetic". After collection, any questionnaire completed in unrealistically short time or exhibiting inconsistent responses to duplicates is discarded. Finally, we aggregate the remaining ratings to compute the mean Western-bias score for each model and each (race, gender) combination. This rigorous, end-to-end design, style-underspecified prompting, defect filtering, diversified annotation, and stringent quality control, allows us to quantify generation bias in a transparent and reproducible manner.

3.2.3 Formal Definition

Formally, we define the generation-bias score as follows. For each image generation model m', race $r \in R$, and gender $g \in G$, we collect K outputs $\{G_k^{m',r,g}\}_{k=1}^{K}$ and recruit H human graders to rate each image on a continuous Western bias scale $h_{k,j}^{m',r,g} \in \{0, 1, 2, \ldots, 10\}$, where 0 = "Not Western at all" and 10 = "Fully Western Aesthetic". We define the mean human bias for the model s' in (r, g) as

$$\bar{h}^{\,m',r,g} = \frac{1}{KH} \sum_{k=1}^{K} \sum_{j=1}^{H} h_{k,j}^{m',r,g},$$

which is obtained by averaging over all k and j, and captures the aggregate tendency of the model's outputs to align with Western aesthetic norms.

4 Experiments

In this section, we describe the two complementary evaluation pipelines, perception and generation, used to quantify aesthetic biases in leading multimodal models.

4.1 Bias in Perception

This experiment evaluated how state-of-the-art multimodal models perceive beauty across different cultural and demographic contexts by measuring their preference for Western versus local aesthetic styles. We synthesize a comprehensive portrait dataset covering multiple races, genders, and stylistic traditions, then present paired Western-styled and local-styled images to each model. By aggregating binary choices across all demographic cohorts, we quantify each model's inclination toward Western mainstream aesthetics and reveal systematic cultural disparities in their perceptual judgments.

4.1.1 Experiment Setup

We built a culturally diverse portrait dataset by systematically varying gender (male, female), race (East Asian, South Asian, African, White, Arab), and aesthetic style (Western mainstream vs. the corresponding local style). We intentionally avoid operationalizing "Western" or "local" aesthetics via explicit visual attributes (e.g., makeup, lighting, color palettes). Instead, our prompts refer only to abstract style labels (e.g., "styled according to Western beauty standards") and leave their visual instantiation underspecified. This design choice allows each model to project its own learned representation of these aesthetic categories, rather than reproducing researcher-defined stereotypes. The images were synthesized on five state-of-the-art generators (GPT-4o, Gemini-2.5-flash, Midjourney, Stable Diffusion and Kling) and then manually screened to exclude any outputs with noticeable rendering flaws. This resulted in a high-quality set of paired portraits spanning all demographic and stylistic combinations. The perception bias evaluation was conducted on three leading multimodal models: GPT-4o, Gemini-2.5-flash and the Chinese model hunyuan-vision.

Model	GPT				Gemini			
%	1	2	3	4	1	2	3	4
East Asian Female	100	100	70	100	80	100	80	60
East Asian Male	100	100	90	90	80	60	60	70
White Female	90	90	90	100	90	70	90	90
White Male	90	100	100	100	100	100	70	90
Black Female	100	80	80	80	100	80	100	100
Black Male	90	80	80	100	90	100	100	100
South Asian Female	80	80	90	90	80	70	90	100
South Asian Male	100	90	100	90	100	100	100	100
Arab Female	60	50	60	80	100	90	90	100
Arab Male	100	70	80	90	100	90	90	90

Table 1: Comparison of attractiveness preferences: per-image win rates (%) of Western-styled portraits in pairwise attractiveness comparisons across demographic cohorts, shown for GPT-4o and Gemini-2.5-flash.

Model	Hunyuan			
%	1	2	3	4
East Asian Female	20	20	30	20
East Asian Male	30	40	40	10
White Female	70	70	50	70
White Male	100	80	90	80
Black Female	30	30	20	0
Black Male	50	20	60	70
South Asian Female	10	10	50	10
South Asian Male	40	60	50	30
Arab Female	70	70	70	80
Arab Male	80	50	90	80

Table 2: Comparison of attractiveness preference: per-image win rates (%) of Western-styled portraits in pairwise attractiveness comparisons across demographic cohorts under the hunyuan-vision model.

4.1.2 Experiment Procedure

For each race–gender group, we selected multiple portraits reflecting Western mainstream aesthetics and multiple portraits reflecting the corresponding local aesthetic, then presented them side by side to each perception model. East Asian, South Asian, Arab and African portraits were paired Western

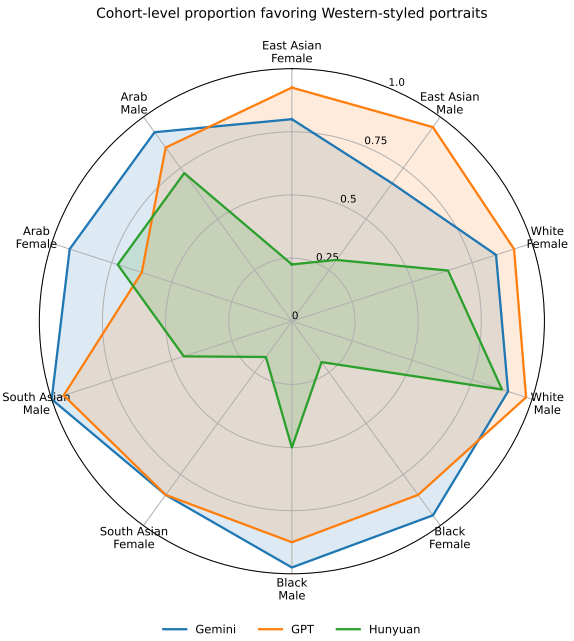

Figure 4: Cohort-level proportions of pairwise comparisons favoring Western-styled portraits across demographic groups and models.

versus local aesthetic. And White portraits were paired Western versus East Asian aesthetic to assess acceptance of non-Western styles, because we included the Chinese model hunyuan-vision. Each model made a binary choice between the two images. We aggregated these binary outcomes across all portrait pairs for each demographic group to calculate the proportion of preferences for Western aesthetics, thereby quantifying each model's perception bias.

4.1.3 Experiment Results

Tables 1 and 2 visualize per-image win rates of Western-styled portraits, highlighting variability across individual stimuli. To support cohort-level inference, Figure 4 visualizes cohort-level proportions of pairwise comparisons favoring Western-styled portraits across demographic groups. GPT and Gemini exhibit broadly elevated Western-style preferences across most cohorts, whereas hunyuan-vision shows more heterogeneous behavior. In particular, hunyuan-vision assigns substantially lower Western-style preference to several East Asian, Black, and South Asian cohorts, while retaining relatively high preferences for White male and some Arab cohorts. Exact numerical values and corresponding statistical summaries are reported in Appendix B.3.

To assess statistical reliability, we further conduct exact two-sided binomial tests against chance level ($p = 0.5$) and compute effect sizes using odds ratios. Full statistical results with FDR correction are reported in Appendix B.4.

Overall, these results reveal clear cultural disparities in perceptual bias across multimodal models: GPT-4o and Gemini-2.5-flash show broadly Western-oriented preferences, whereas hunyuan-vision is more receptive to non-Western styles in several cohorts while still exhibiting Western-oriented preferences in others.

4.2 Bias in Generation

This experiment assesses the implicit aesthetic priors embedded within state-of-the-art image generators by analyzing both human and model evaluations of portrait outputs generated from prompts without any explicit stylistic constraints, as well as the prevalence of facial attributes that are statistically overrepresented in Western media beauty portrayals.

4.2.1 Experiment Setup

We synthesized 200 portraits, 40 per model, across five leading generators: GPT-4o, Gemini-2.5-flash, Midjourney, Stable Diffusion, and Kling-kolors-2.0 (4 western models and 1 non-western model). For each generator, we produced ten images of East Asian females, ten East Asian males, ten White females, and ten White males. By using prompts that include only demographic descriptors and omit any aesthetic style instructions, we expose each model's inherent beauty preferences. A selection of these generated portraits is shown in **Figure 5**. The first row displays outputs from the Western models across different race-gender groups, while the second row presents corresponding outputs from the non-western model. Despite the style-underspecified prompts, noticeable stylistic differences already emerge between the two rows of portraits.

To further disentangle model-internal aesthetic priors from prompt semantics, we additionally conduct a control experiment using fully neutral prompts that do not contain any attractiveness-related language (see Appendix C.3).

4.2.2 Experiment Procedure

A diverse panel of human graders rated each portrait on a 0–10 Western aesthetic scale (0 = not Western at all; 10 = fully Western). To reduce fatigue, each grader evaluated a random subset of

Figure 5: Example portraits of various races and genders generated by different multimodal models using style-underspecified prompts. First row are images generated by models such as GPT, Gemini and Stable Diffusion. Second row are images generated by Chinese multimodal model Kling.

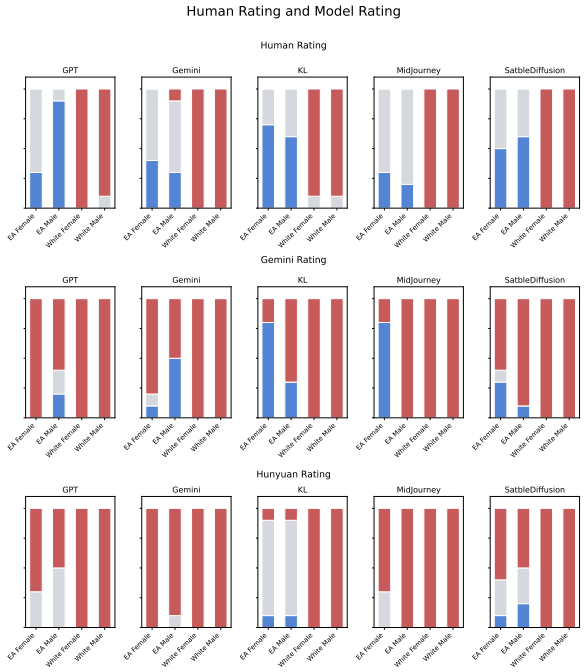

Figure 6: Human and model ratings along a perceived "Western aesthetic" axis for neutral (no-style)-prompt portraits generated by five multimodal models. Blue bars ($[0, 4)$) indicate low alignment with Western-coded visual conventions, gray bars ($[4, 6]$) moderate alignment, and red bars ($(6, 10]$) high alignment.

25 images; we collected 169 valid questionnaires, ensuring every image received at least 15 independent scores. In parallel, we asked Gemini-2.5-flash and hunyuan-vision represent mutimodal model to evaluate the entire set using the same scale (**Figure 6**). Finally, leveraging Gemini-2.5-flash's vision API, we automatically detected seven facial attributes that are frequently overrepresented in Western media beauty portrayals: prominent nose bridge, deep-set eyes, high cheekbones, angular contours, defined chin, wide-set eyes and full lips. And computed each feature's frequency within every race–gender cohort (see Appendix C.5).. To provide a more intuitive understanding, **Figure 7** presents a schematic of manually annotated facial features used for illustration.

4.2.3 Experiment Results

Human ratings show high inter-rater reliability (Krippendorff's $\alpha = 0.935$). Stratified analyses by rater cultural region and gender yield consistent relative trends across models and demographic groups (Appendix C.2).

Figure 6 compares the distributions of human and model-assigned Western aesthetic alignment scores across four demographic groups. Blue ($[0, 4)$), gray ($[4, 6)$), and red ($(6, 10]$) bins denote low, moderate, and high alignment with Western-coded visual conventions.

Human judgments exhibit a clear demographic stratification: portraits of East Asian subjects are predominantly rated in the low-to-moderate range (mean ≈ 4), whereas portraits of White subjects consistently cluster in the high-alignment range (mean > 7), across generators and genders. This pattern indicates that perceived "Westernness" in human ratings is strongly entangled with subject race.

In contrast, multimodal model evaluations display a compressed and upward-shifted distribution. Across all generators, both Gemini-2.5-flash and hunyuan-vision assign uniformly high Western alignment scores to White portraits (typically 9–10 with minimal variance). Notably, models also assign substantially higher scores to East Asian portraits than human raters do, frequently plac-

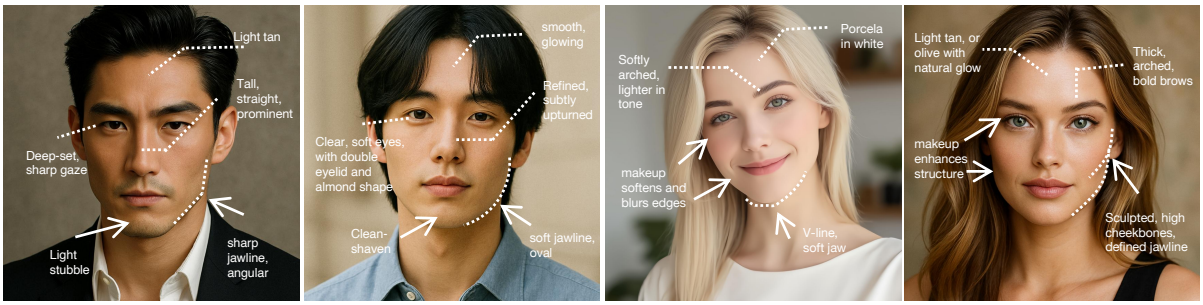

Figure 7: Illustrative schematic of facial attributes frequently emphasized in model-generated portraits when optimizing for attractiveness. This figure is provided for visualization purposes only and does not imply normative, biological, or population-level distinctions between groups.

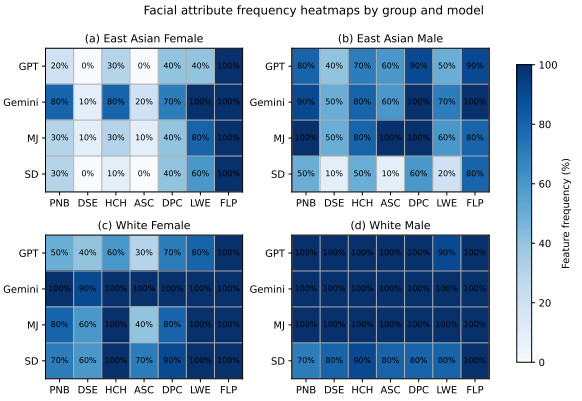

Figure 8: Frequency probability of each feature appearing in portraits of each race–gender group generated by different models
(Mapping: PNB = Prominent nose bridge, DSE = Deep-set eyes, HCH = High cheekbones, ASC = Angular, sculpted facial contours, DPC = Defined or pointed chin, LWE = Large, wide-set eyes, FLP = Full lips.)

ing them in the moderate-to-high alignment range. This suggests that models apply a broader mapping of Western-coded visual conventions that extends beyond human perceptual boundaries.

Inter-model differences further reveal that the strength of these priors varies by generator. Under identical neutral prompts, East Asian portraits produced by Gemini-2.5-flash and Midjourney receive higher average Western alignment scores than those generated by Stable Diffusion or the non-Western model Kling. Although these differences do not alter the overall qualitative pattern, they indicate that Western aesthetic bias manifests along a continuum shaped by architectural choices, training data, and optimization objectives.

Consistent with these rating patterns, **Figure 8** visualizes the prevalence of Western-coded facial attributes in model-generated portraits. Across groups and generators, full lips (FLP) appear with high frequency (80–100%). Within the East Asian cohorts, East Asian female portraits more often exhibit large, wide-set eyes (LWE), whereas East Asian male portraits show higher prevalence of defined/pointed chins (DPC), prominent nose bridges (PNB), and high cheekbones (HCH). Compared to the other generators, Stable Diffusion generally assigns lower rates to these attributes, although none of the models eliminates them entirely.

Taken together, these findings, including the neutral-prompt control experiment, demonstrate that Western aesthetic bias in image generation is not a direct reflection of human judgments, but is amplified and restructured by multimodal models' internal representations. We emphasize that these results describe learned correlations in model behavior rather than normative or biological definitions of beauty.

5 Conclusion

Our framework offers a systematic lens into aesthetic bias, revealing how leading vision-language models consistently favor Western-centric ideals across both perception and generation tasks. Through controlled experiments and diverse data inputs, we demonstrate that these biases persist even in style-underspecified prompts, suggesting that cultural preferences are deeply embedded in model priors. By bringing empirical clarity to an often subjective and overlooked domain, this work highlights the urgent need for more culturally calibrated approaches in AI development. We hope our benchmark serves as both a diagnostic tool and a foundation for future research aimed at building more fair systems.

Limitation

Our study has several limitations. The notion of a "Western aesthetic" is inherently socially constructed and may be confounded with demographic cues such as race, particularly associations with White faces; thus, our results reflect alignment with dominant visual conventions rather than normative claims about beauty. Generation-bias experiments focus on East Asian and White subjects due to annotation and power constraints, limiting generalizability across identities. In addition, our facial-attribute analysis relies on a predefined feature set that does not capture the full diversity of cross-cultural aesthetics and may introduce measurement noise. Finally, we do not disentangle the roles of training data, prompts, and decoding strategies, and therefore report behavioral observations rather than causal claims.

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A Related Work

Cross-cultural studies of facial attractiveness Early work in evolutionary psychology showed that facial averageness and bilateral symmetry are judged attractive across very different populations, suggesting a biologically anchored baseline for beauty preferences (Rhodes et al., 2001; Little, 2014). More recent data-driven studies, however, demonstrate that observers in different ethnicity weigh culture-specific facial cues differently, e.g., eye size, skin luminance, and the degree of facial femininity, when assigning beauty scores (Coetzee et al., 2014; Heidekrueger et al., 2016; Zhan et al., 2021). These findings motivate an experimental design that disentangles the ethnicity of the face from the cultural aesthetic style applied to the image.

Facial-beauty datasets and predictive models Several public datasets annotated with beauty scores, such as SCUT-FBP5500, which spans Asian and White faces of both genders, support regression, ranking, and classification tasks (Liang et al., 2018). Conventional regressors, such as CNN (Xie et al., 2015) and ResNet (Targ et al., 2016), perform well in a single domain but generalize poorly across datasets. The recent Uncertainty-oriented Order Learning (UOL) framework explicitly models label noise and learns ordinal relations instead of point estimates, achieving state-of-the-art robustness on five benchmarks (Liang et al., 2024). Existing work, however, focuses on single-face ratings and rarely separates a face's ethnicity from its cultural styling, or uses pairwise comparisons across different aesthetics. We tackle this by creating a custom portrait database covering multiple styles and running systematic pairwise judgments to show how style alone affects perceived attractiveness.

Bias in generative models The landmark Gender Shades audit revealed error rates 40× higher for dark-skinned women than for light-skinned men in commercial face-analysis APIs, galvanising fairness research in computer vision (Buolamwini and Gebru, 2018). Subsequent studies (Mandal et al., 2023; Luccioni et al., 2023; Wu et al., 2025) show that text-to-image diffusion models like Stable Diffusion and DALL·E 2 amplify occupational and racial stereotypes, overproducing white male images for "CEO" and hypersexualized depictions of women. Google's Gemini image generator drew criticism in 2024 for "over-diversifying" historic figures without context, underscoring the tension between diversity and realism in controlled generation. Mitigation strategies like Fairness GAN impose demographic-parity constraints during training to equalize group representation in synthetic data (Sattigeri et al., 2019). We go further by explicitly measuring how generative models' "taste" aligns with or diverges from human consensus when asked to produce portraits under style-underspecified prompts.

B Model Perception on Beauty

To ensure systematic control over demographic and aesthetic variables in perception experiments, we designed a structured prompt template as follows:

"A modern [gender] of [race] descent, styled according to [style] beauty standards, studio lighting, 4-k portrait photograph."

This format allows us to isolate the effects of gender, racial identity, and aesthetic traditions while maintaining high visual consistency through studio and resolution constraints.

B.1 Prompt Components

Each prompt was instantiated using controlled combinations of:

Gender: female, male

Race: Black, White, East Asian, South Asian, Arab

Style: Western, East Asian, African, South Asian, Arab

B.2 Prompt–Portrait Mapping and Visual Style Summary

Below, we present a full mapping between prompt instructions and the corresponding figures. These figure assignments serve as a foundational reference for subsequent analysis. By pairing prompts with visual outputs across demographic axes, we are able to investigate how aesthetic biases manifest depending on the subject's beauty standard invoked.

B.2.1 Figure 9 vs. Figure 10 – Black Female: Western vs. African Beauty Standards

Figure 9 displays Black female subjects styled under Western beauty standards. The portraits emphasize facial symmetry, softly contoured cheekbones, and glowing skin, enhanced by studio lighting and minimal, refined makeup. Hairstyles maintain natural curl patterns but are volumized and polished, projecting elegance and control. The clothing is

Figure 9: Black female in Western style

Figure 10: Black female in African style

Figure 11: East Asian female in Western style

Figure 12: East Asian female in East Asian style

minimal and modern, such as tank tops in earthy tones, and the overall look aligns with commercial Western aesthetics that favor clean, symmetrical, and subtly enhanced natural beauty. In contrast, Figure 10 showcases African beauty standards through traditional hairstyles like braids, buns, and tightly coiled textures, accompanied by bold cultural adornments such as beaded jewelry and patterned clothing. Skin tone is preserved richly and authentically, and the visual styling foregrounds pride, heritage, and ethnic identity. The lighting is deeper and warmer, highlighting melanin richness and historical dignity over commercial polish.

B.2.2 Figure 11 vs. Figure 12 – East Asian Female: Western vs. East Asian Beauty Standards

In Figure 11, East Asian females are styled according to Western aesthetics, featuring smooth, glowing skin, softly curled or styled-down hair, and neutral-toned makeup that highlights cheekbones and eye structure. These portraits reflect a cosmopolitan, fashion-forward sensibility, with clothing choices such as spaghetti strap tops and blazers reinforcing the modern minimalism typical of Western media. In contrast, Figure 12 embraces East Asian beauty standards through a more natural presentation—matte skin, light and balanced makeup, and hairstyles that prioritize facial framing over volume. The facial features appear more delicate, with subtler lip colors and natural eye shapes preserved. These portraits project softness, calmness, and youthful harmony, aligning with East Asian ideals of grace and refinement.

B.2.3 Figure 13 vs. Figure 14 – South Asian Female: Western vs. South Asian Beauty Standards

Figure 13 illustrates South Asian women presented through a Western lens, with sleek makeup, softly contoured faces, and modern hairstyles that evoke a magazine-ready aesthetic. The clothing, such as fitted tops or business blazers, reinforces a contemporary global image. The lighting highlights facial structure and skin clarity, emphasizing individual beauty. In contrast, Figure 14 reflects South Asian cultural aesthetics, characterized by traditional jewelry like jhumkas and maang tikka, richly patterned sarees, and deep, warm-toned makeup. The visual language emphasizes ceremonial elegance and cultural pride, celebrating collective identity and tradition over modern uniformity. Expressions are more composed and formal, highlighting a reverence tied to heritage and occasion.

B.2.4 Figure 15 vs. Figure 16 – Arab Female: Western vs. Arab Beauty Standards

In Figure 15, Arab females styled under Western standards feature flowing hair, form-fitting black clothing, and editorial-style makeup with well-defined brows, lashes, and lips. The style evokes international beauty norms seen in fashion magazines, emphasizing symmetry, glamor, and individual allure. In contrast, Figure 16 shifts toward Arab regional aesthetics. Subjects wear hijabs or abayas

Figure 13: South Asian female in Western style

Figure 14: South Asian female in South Asian style

Figure 15: Arab female in Western style

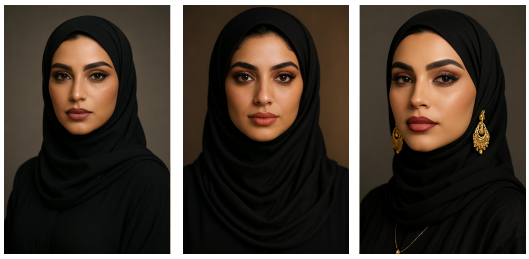

Figure 16: Arab female in Arab style

in elegant, minimal black, with gold earrings or subtle embroidery adding culturally resonant details. Makeup is equally refined but more modestly applied, emphasizing the eyes while maintaining composure and modesty. These portraits express dignity, tradition, and grace, highlighting beauty through cultural identity rather than globalized fashion cues.

B.2.5 Figure 17 vs. Figure 18 – Black Male: Western vs. African Beauty Standards

Figure 17 features Black male subjects portrayed through a Western lens—clean fades, trimmed beards, plain yet fitted clothing, and a studio setup that spotlights structure and symmetry. The expressions are composed, confident, and fashion-oriented, ideal for editorial or commercial use. Figure 18, however, adopts African aesthetics with greater emphasis on natural hairstyles like twists or bantu knots, bold prints, and wooden or beaded jewelry. The subjects appear deeply rooted in tradition, with expressions and styling that evoke ancestral pride and cultural continuity. The warm, earth-toned backgrounds reinforce this shift from commercial elegance to ethnocultural authenticity.

B.2.6 Figure 19 vs. Figure 20 – East Asian Male: Western vs. East Asian Beauty Standards

In Figure 19, East Asian male subjects reflect Western beauty ideals: sharp jawlines, styled hair with volume, and sleek, fitted modern clothing like blazers and crewnecks. Their expressions are confident, and the lighting is professional, echoing global fashion or lifestyle media. In contrast, Figure 20 presents East Asian beauty standards more closely aligned with subtlety and composure. Hair is longer or softly parted, makeup is minimal or absent, and clothing is understated. Faces appear more natural and relaxed, with a softer photographic tone that suggests humility and inner harmony—core values in traditional East Asian portraiture.

B.2.7 Figure 21 vs. Figure 22 – South Asian Male: Western vs. South Asian Beauty Standards

In Figure 21, South Asian male subjects styled according to Western norms are depicted in fitted dress shirts, jackets, and neutral tones, with carefully trimmed facial hair and short, styled haircuts. Their expressions are assertive yet composed, evoking a polished professional or media persona. By contrast, Figure 22 highlights South Asian aesthetics through traditional clothing like sherwanis, kurtas, or embroidered shawls, often accompanied by richer lighting and darker color palettes. The overall mood is ceremonial and formal, prioritizing lineage, tradition, and social decorum. These portraits draw attention to the cultural roots of appearance rather than global visual trends.

B.2.8 Figure 23 vs. Figure 24 – Arab Male: Western vs. Arab Beauty Standards

Figure 23 shows Arab male subjects in suits, sweaters, or dress shirts, with Western-style grooming and poses suggestive of corporate or fashion

Figure 17: Black male in Western style

Figure 18: Black male in African style

Figure 19: East Asian male in Western style

Figure 20: East Asian male in East Asian style

branding. Hair is styled, beards are trimmed, and lighting enhances bone structure. These portraits emphasize modern masculinity through a Euro-American lens. In Figure 24, Arab beauty standards are foregrounded through traditional dress such as the keffiyeh or kandura, along with solemn, regal expressions. Beards are fuller, the color palette is brighter, and the composition evokes cultural reverence. The overall effect projects wisdom, dignity, and national or religious identity rooted in Arab heritage.

B.3 Binomial Significance Tests

For each model–cohort combination in the perception experiment, we aggregate all pairwise comparison outcomes into a single binomial proportion. Specifically, each cohort consists of 40 independent pairwise trials (4 Western-styled portraits $\times$ 10 local-styled portraits), yielding k selections of Western-styled images out of $n = 40$ total trials.

For GPT-4o and Gemini-2.5-flash, Table 3 shows consistently high cohort-level preferences for Western-styled portraits across most demographic groups. GPT-4o exhibits especially strong Western-oriented preferences in several cohorts (e.g., 92.5–97.5% across multiple groups), with confidence intervals indicating that these effects are robust rather than driven by individual-image outliers. Gemini-2.5-flash similarly favors Western styling in most cohorts, with slightly attenuated preferences for some East Asian male groups (67.5% [51–80]), yet still above chance.

In contrast, hunyuan-vision demonstrates substantially greater acceptance of non-Western aesthetics in several cohorts. As shown in Table 3, Western-style selection drops markedly for East Asian female (22.5% [11–38]), Black female (20.0% [10–35]), and South Asian female (17.5% [8–32]), indicating a dominant local-style preference in these groups. Nevertheless, hunyuan-vision retains high Western-style preference for White male (87.5% [73–95]) and moderate-to-high preferences for Arab cohorts (72.5% [57–84]), suggesting that Western-coded priors are attenuated but not fully removed.

To assess whether a model exhibits a statistically reliable preference for Western versus local aesthetics, we perform exact two-sided binomial tests against the null hypothesis $H_0 : p = 0.5$, corresponding to no preference between the two styles. This test evaluates whether the observed number of Western selections deviates from chance-level choice.

B.4 Additional Statistical Analysis for Pairwise Preferences

B.4.1 Binomial significance tests

For each model–cohort combination in the perception experiment, we pool all pairwise outcomes into a single binomial proportion. Each cohort contains $n = 40$ trials (4 Western-styled portraits $\times$ 10 local-styled portraits), yielding k selections of Western-styled images. We perform exact two-sided binomial tests against the null hypothesis

Figure 21: South Asian male in Western style

Figure 22: South Asian male in South Asian style

Figure 23: Arab male in Western style

Figure 24: Arab male in Arab style

$H_0 : p = 0.5$ (no preference).

B.4.2 Multiple-comparison correction

Because we conduct tests across multiple cohorts and models, we apply the Benjamini–Hochberg false discovery rate (FDR) procedure across all 30 tests (10 cohorts $\times$ 3 models), and report FDR-adjusted q-values.

B.4.3 Effect size

We report effect sizes using odds ratios (OR), defined as $\mathrm{OR} = p/(1-p)$, where $p = k/n$. OR > 1 indicates preference for Western-styled portraits and OR < 1 indicates preference for local styles. For extreme outcomes ($k = 0$ or $k = n$), we apply a standard 0.5 pseudo-count correction for OR computation, i.e., $\tilde{p} = (k + 0.5)/(n + 1)$, to avoid infinite estimates.

B.4.4 Statistical results table

See **table 5**.

C Generation of Beauty

C.1 Survey

To systematically evaluate the latent aesthetic biases embedded within state-of-the-art image generation models, we conducted a large-scale online questionnaire targeting a diverse participant pool. Respondents were carefully recruited to reflect variation in age, gender, and cultural background, thereby enhancing the generalizability and fairness of our evaluation. The survey was designed to be user-friendly and manageable in length: each participant was presented with 25 portrait images, randomly sampled without replacement from a larger pool spanning different demographic groups and generation models. To mitigate any potential ordering or positional bias, the sequence of images was uniquely randomized for every individual.

Our participants were recruited on a voluntary basis and did not receive monetary compensation. They were instructed to evaluate each portrait based on the extent to which it embodied a "Western aesthetic" ideal, using an intuitive 0–10 scale, where 0 indicated "Not Western at all" and 10 indicated "Fully Western aesthetic." These instructions were kept minimal and neutral to avoid priming or influencing respondents' judgments. To ensure high data quality, we implemented a rigorous filtering protocol: responses submitted in unrealistically short durations or exhibiting inconsistencies on duplicated test items were excluded from further analysis.

After applying these quality controls, we aggregated the remaining responses to calculate the average "Western aesthetic score" for each portrait. The combination of randomized sampling, diverse raters, and careful quality assurance contributes to a transparent, repeatable, and statistically sound framework for measuring generative bias in multimodal systems.

Participants were shown generated portraits along with the exact interface as shown below and asked to rate the images (Figures 25–27).

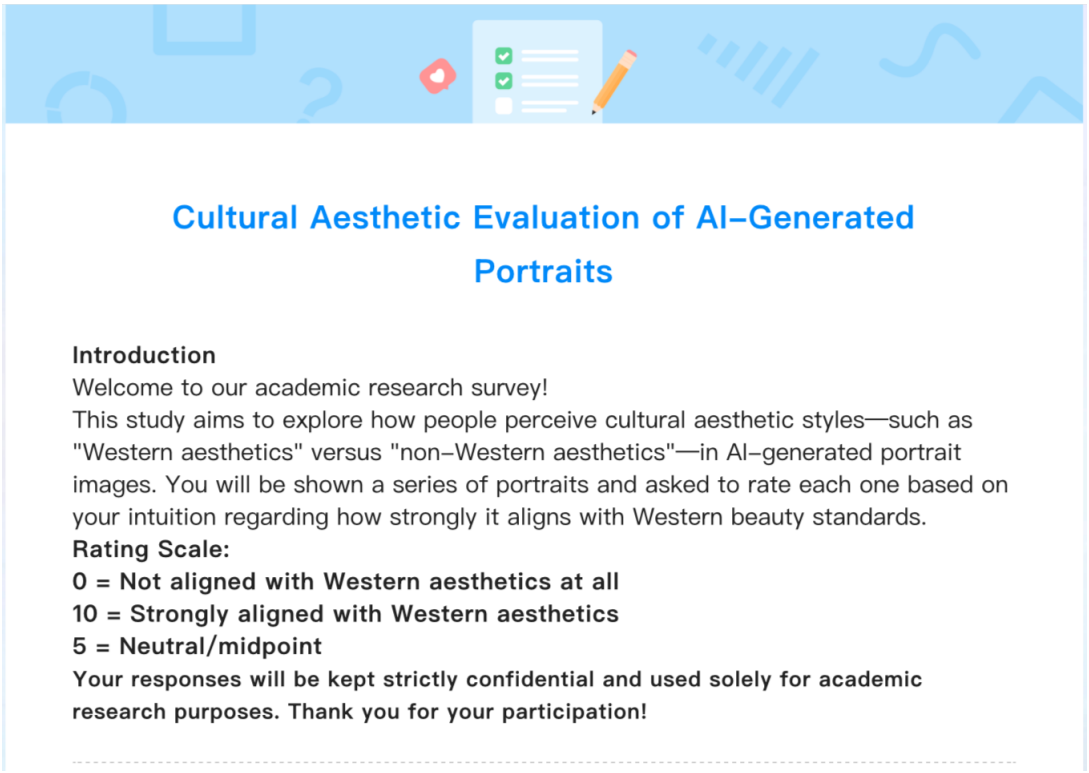

Figure 25: Survey cover page presentation

C.2 Inter-Rater Reliability and Rater Demographics

Rater Pool and Cultural Composition. Human aesthetic evaluations were collected from 169 valid respondents via an online questionnaire. Raters self-reported their gender, age range, and primary cultural region of upbringing. The final rater pool consisted of 45.6% female and 54.4% male participants, providing a balanced gender distribution.And the resulting rater pool was culturally diverse, with the majority of participants identifying East Asia (e.g., China, Japan, Korea) as their primary cultural region (76.8%). Additional representation came from Western regions (10.1%), South Asia (10.7%), and Africa (2.4%).

Each rater evaluated a random subset of 25 images drawn from the full set of 200 generated portraits, resulting in at least 15 independent ratings per image. This partially overlapping assignment design reduces rater fatigue while ensuring sufficient coverage for reliability estimation.

Inter-Rater Reliability. We computed Krippendorff's α for ordinal ratings on the 0–10 Western aesthetic scale. This metric is well suited to incomplete rating matrices and varying numbers of raters per item. Across all images and raters, we observe a high level of agreement ($\alpha = 0.935$), indicating strong consistency in perceived Western aesthetic judgments despite demographic and cultural diversity among annotators.

To further assess whether rating consistency varied across annotator subgroups, we computed Krippendorff's α separately for major cultural regions and for rater gender. Agreement remained uniformly high across all strata. Specifically, cultural-region-specific reliability scores were $\alpha = 0.943$ for East Asian annotators, $\alpha = 0.946$ for South Asian annotators, $\alpha = 0.931$ for African annotators, and $\alpha = 0.929$ for annotators from Western regions.

Similarly, reliability remained high when stratifying by gender, with $\alpha = 0.936$ for male raters and $\alpha = 0.932$ for female raters. These results indicate that judgments of perceived Western aesthetic alignment are internally consistent within each subgroup and are not driven by a particular cultural or gendered perspective.

Stratified Analyses by Rater Culture. To examine whether reported biases were driven by rater cultural background, we conducted stratified analyses by primary cultural region. While absolute score distributions exhibited modest shifts

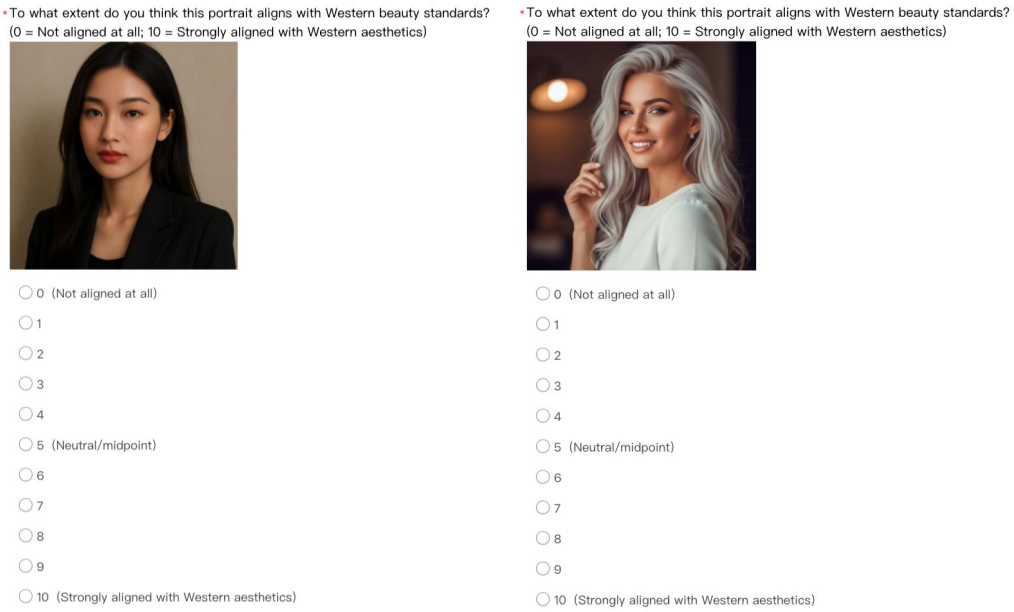

Figure 26: Survey UI presentation 1

across cultural groups, the relative ordering of demographic cohorts remained stable. In particular, portraits of White subjects consistently received higher Western aesthetic scores than East Asian subjects across rater groups, including among East Asian annotators.

These findings indicate that the observed generation biases are not an artifact of Western-dominated annotation, but instead reflect shared visual conventions that generalize across cultural contexts.

Interpretation and Limitations. We emphasize that these results do not imply a universal or normative definition of beauty. Rather, they capture learned visual associations that are sufficiently shared across cultures to yield high inter-rater agreement in relative judgments. We acknowledge that cultural identity is complex and cannot be fully captured by coarse regional categories. Future work could incorporate finer-grained cultural measures or hierarchical models that explicitly account for rater-level effects.

C.3 Control Experiment

To rule out the possibility that the observed Western aesthetic bias is introduced by the use of the term "attractive" in the generation prompt, we conduct a control experiment using strictly neutral, identity-only prompts. Specifically, we generate portraits using the prompt "Generate the image of an East Asian woman/man", without any aesthetic, stylistic, or quality-related descriptors.

We generate five images per gender for each of the five image generators, resulting in a total of 50 East Asian portraits. These images are then evaluated by two multimodal vision–language models, Gemini-2.5-flash and Hunyuan-Vision, using the same 0–10 Western aesthetic alignment scale as in the main experiment.

Despite the complete removal of attractiveness-related language, model-based evaluations consistently assign moderate-to-high Western aesthetic scores to a substantial portion of the generated portraits. This pattern closely mirrors the trends observed in the main experiment, indicating that Western aesthetic priors persist even under maximally underspecified prompts.

These findings suggest that the observed bias cannot be attributed solely to prompt semantics, but instead reflects aesthetic conventions internalized by the image generation models themselves.

C.4 Features Illustrations

This part provides illustrative examples of the seven Western facial features analyzed in this study. For each feature, a representative facial image is selected and annotated to highlight the corresponding facial region. These illustrations are intended to offer visual clarification of the feature definitions used in the automatic detection process.

C.5 Detailed Facial Attribute Frequencies

Table 5 reports the empirical frequency with which specific facial attributes appear in portraits gener-

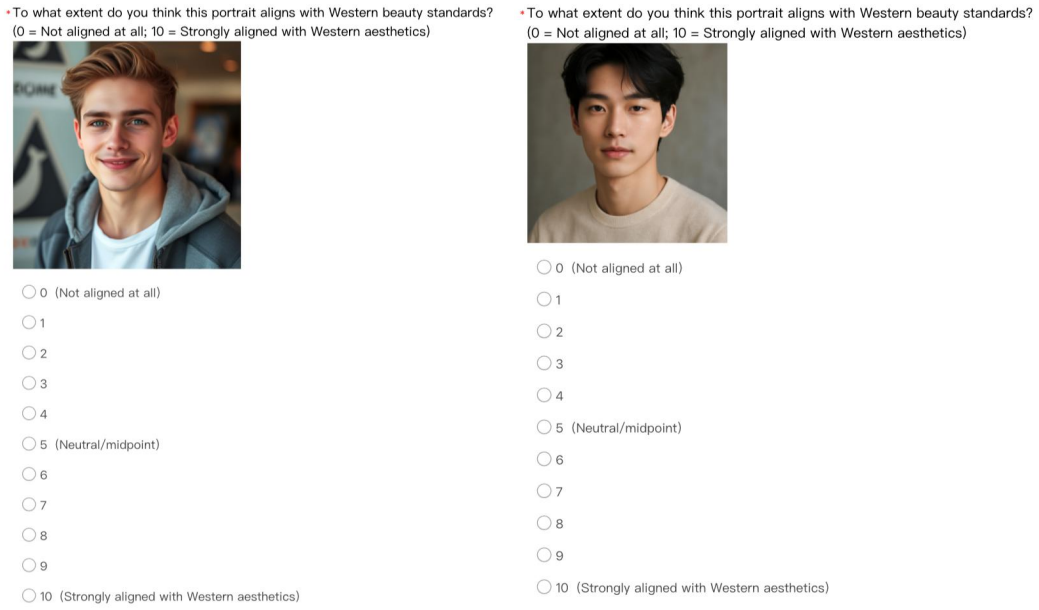

Figure 27: Survey UI presentation 2

ated by different image generation models, stratified by race–gender group. For each model and cohort, attribute frequencies are computed as the proportion of generated images in which the corresponding feature is present. The listed attributes are commonly associated with Western-coded attractiveness in prior literature and media portrayals, and are included here to provide an interpretable, feature-level view of generation tendencies.

The table complements the main-text visualizations by providing exact numerical values for each attribute–model–cohort combination. Across groups, some attributes (e.g., full lips) appear with high frequency regardless of demographic group or model, while others show greater variability across cohorts and generators. Differences across models are also evident, with some generators exhibiting systematically higher prevalence of multiple Western-coded attributes than others. These detailed statistics support the qualitative and aggregate trends discussed in the main paper and enable more fine-grained inspection of model behavior.

D Use of AI Assistance

AI assistants were used only for language editing and presentation polishing. All scientific content and research decisions were made exclusively by the authors.

Cohort	Gemini	GPT	Hunyuan
East Asian Female	80.0% [65–90]	92.5% [80–97]	22.5% [11–38]
East Asian Male	67.5% [51–80]	95.0% [83–99]	30.0% [18–45]
White Female	85.0% [70–93]	92.5% [80–97]	65.0% [49–78]
White Male	90.0% [77–96]	97.5% [87–100]	87.5% [73–95]
Black Female	95.0% [83–99]	85.0% [70–93]	20.0% [10–35]
Black Male	97.5% [87–100]	87.5% [73–95]	50.0% [35–65]
South Asian Female	85.0% [70–93]	85.0% [70–93]	17.5% [8–32]
South Asian Male	100% [91–100]	95.0% [83–99]	45.0% [31–60]
Arab Female	92.5% [80–97]	62.5% [46–76]	72.5% [57–84]
Arab Male	92.5% [80–97]	85.0% [70–93]	72.5% [57–84]

Table 3: Cohort-level proportions of pairwise comparisons favoring Western-styled portraits. Each cohort aggregates 40 pairwise trials (4 Western-styled portraits $\times$ 10 local-styled portraits), and proportions are computed by pooling all trials within each cohort. Brackets indicate 95% Wilson confidence intervals.

Cohort	Model	k/n	$\hat{p}$	CI	OR	q	Cohort	Model	k/n	$\hat{p}$	CI	OR	q
East Asian F	Gemini	32/40	0.80	[65–90]	3.82	$< 10^{-3}$	Black F	Gemini	38/40	0.95	[83–99]	15.40	$< 10^{-3}$
	GPT-4o	37/40	0.93	[80–97]	10.71	$< 10^{-3}$		GPT-4o	34/40	0.85	[71–93]	5.31	$< 10^{-3}$
	Hunyuan	9/40	0.23	[12–38]	0.30	$< 10^{-3}$		Hunyuan	8/40	0.20	[10–35]	0.25	$< 10^{-3}$
East Asian M	Gemini	27/40	0.68	[52–80]	2.04	0.04	Black M	Gemini	39/40	0.98	[87–100]	26.33	$< 10^{-3}$
	GPT-4o	38/40	0.95	[83–99]	15.40	$< 10^{-3}$		GPT-4o	35/40	0.88	[74–95]	6.45	$< 10^{-3}$
	Hunyuan	12/40	0.30	[18–45]	0.43	0.002		Hunyuan	20/40	0.50	[35–65]	1.00	1.00
White F	Gemini	34/40	0.85	[71–93]	5.31	$< 10^{-3}$	South Asian F	Gemini	34/40	0.85	[71–93]	5.31	$< 10^{-3}$
	GPT-4o	37/40	0.93	[80–97]	10.71	$< 10^{-3}$		GPT-4o	34/40	0.85	[71–93]	5.31	$< 10^{-3}$
	Hunyuan	26/40	0.65	[49–78]	1.86	0.10		Hunyuan	7/40	0.18	[9–32]	0.21	$< 10^{-3}$
White M	Gemini	36/40	0.90	[77–96]	8.11	$< 10^{-3}$	South Asian M	Gemini	40/40	1.00	[91–100]	81.00	$< 10^{-3}$
	GPT-4o	39/40	0.98	[87–100]	26.33	$< 10^{-3}$		GPT-4o	38/40	0.95	[83–99]	15.40	$< 10^{-3}$
	Hunyuan	35/40	0.88	[74–95]	6.45	$< 10^{-3}$		Hunyuan	18/40	0.45	[31–60]	0.82	0.65

Table 4: Exact two-sided binomial tests against chance level ($H_0 : p = 0.5$) for cohort-level Western-style selections in the perception experiment. q-values are Benjamini–Hochberg FDR corrected across all 30 tests. Odds ratios (OR) are computed as $\mathrm{OR} = p/(1-p)$; for extreme outcomes ($k = 0$ or $k = n$) we apply a 0.5 pseudo-count correction, i.e., $\tilde{p} = (k + 0.5)/(n + 1)$.

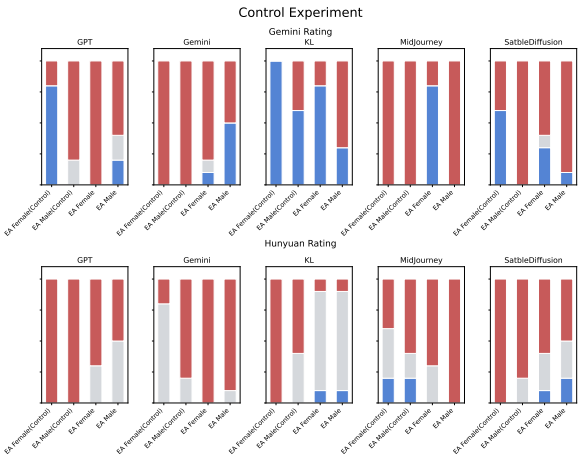

Figure 28: Control experiment results using neutral, identity-only prompts. Western aesthetic alignment distributions for East Asian female and male portraits generated using the prompt "Generate the image of an East Asian woman/man," without any attractiveness- or style-related language. Results are shown for five image generators, evaluated independently by Gemini-2.5-flash (top row) and Hunyuan-Vision (bottom row). Across generators and evaluators, moderate-to-high Western aesthetic alignment persists under neutral prompts, mirroring trends observed in the main experiment and indicating that the observed bias cannot be attributed solely to prompt semantics.

Figure 29: A representative portrait illustrating a prominent nose bridge, with the corresponding facial region highlighted.

Figure 30: A representative portrait illustrating deep-set eyes, with the corresponding facial region highlighted.

Group	Model	PNB	DSE	HCH	ASC	DPC	LWE	FLP
East Asian Female	GPT	20%	0%	30%	0%	40%	40%	100%
	Gemini	80%	10%	80%	20%	70%	100%	100%
	Midjourney	30%	10%	30%	10%	40%	80%	100%
	Stable Diff.	30%	0%	10%	0%	40%	60%	100%
East Asian Male	GPT	80%	40%	70%	60%	90%	50%	90%
	Gemini	90%	50%	80%	60%	100%	70%	100%
	Midjourney	100%	50%	80%	100%	100%	60%	80%
	Stable Diff.	50%	10%	50%	10%	60%	20%	80%
White Female	GPT	50%	40%	60%	30%	70%	80%	100%
	Gemini	100%	90%	100%	100%	100%	100%	100%
	Midjourney	80%	60%	100%	40%	80%	100%	100%
	Stable Diff.	70%	60%	100%	70%	90%	100%	100%
White Male	GPT	100%	100%	100%	100%	100%	90%	100%
	Gemini	100%	100%	100%	100%	100%	100%	100%
	Midjourney	100%	100%	100%	100%	100%	100%	100%
	Stable Diff.	70%	80%	90%	80%	80%	80%	100%

Table 5: Frequency probability of each feature appearing in portraits of each race–gender group generated by different models
(Feature mapping: PNB = Prominent nose bridge, DSE = Deep-set eyes, HCH = High cheekbones, ASC = Angular, sculpted facial contours, DPC = Defined or pointed chin, LWE = Large, wide-set eyes, FLP = Full lips.)

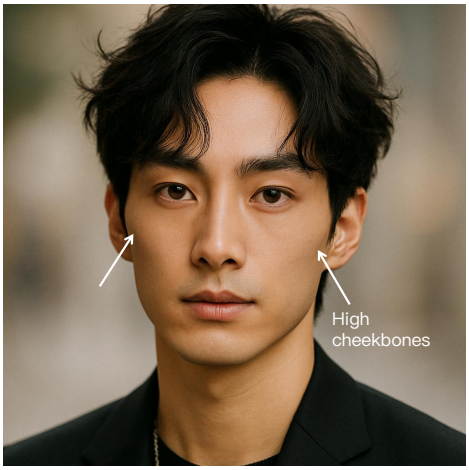

Figure 31: A representative portrait illustrating high cheekbones, with the corresponding facial region highlighted.

Figure 32: A representative portrait illustrating angular, sculpted facial contours, with the corresponding facial region highlighted.

Figure 33: A representative portrait illustrating defined or pointed chin, with the corresponding facial region highlighted.

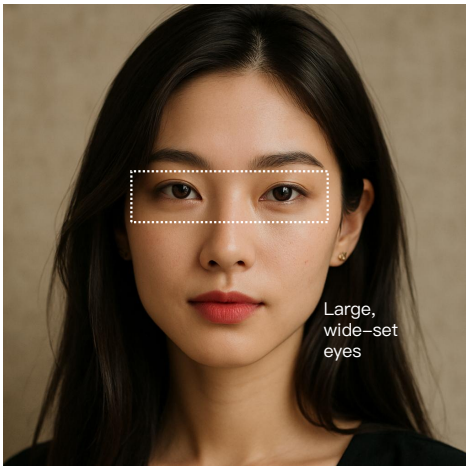

Figure 34: A representative portrait illustrating large, wide-set eyes, with the corresponding facial region highlighted.

Figure 35: A representative portrait illustrating full lips, with the corresponding facial region highlighted.