

Position: Universal Aesthetic Alignment Narrows Artistic Expression

Wenqi Marshall Guo^{1,2} Qingyun Qian^{1,2} Khalad Hasan¹ Shan Du¹

Abstract

Over-aligning image generation models to a generalized aesthetic preference conflicts with user intent, particularly when “anti-aesthetic” outputs are requested for artistic or critical purposes. This adherence prioritizes developer-centered values, compromising user autonomy and aesthetic pluralism. We test this bias by constructing a wide-spectrum aesthetics dataset and evaluating state-of-the-art generation and reward models. This position paper finds that aesthetic-aligned generation models frequently default to conventionally beautiful outputs, failing to respect instructions for low-quality or negative imagery. Crucially, reward models penalize anti-aesthetic images even when they perfectly match the explicit user prompt. We confirm this systemic bias through image-to-image editing and evaluation against real abstract artworks.

1. Introduction

Following developments in Large Language Models (LLMs), many image generation models have been fine-tuned with human feedback to better align with human expectations, which is usually referred to as alignment. Alignment has two primary focuses: instruction following and general preference (aesthetics). A frequently overlooked issue is the potential conflict between these focuses: what should a model prioritize when a user request contradicts general preference? Most pipelines for general preference assume a single, universal human standard of aesthetics and quality that serves everyone’s needs, and aligning to such a preference is often treated as beneficial for safety and user experience. This is usually done by using a reward model, a model used to judge the aesthetics of the image, as a signal to perform reinforcement learning on the generative model. This assumption appears in several reinforcement learning papers (Li et al., 2024; Kim et al., 2024; Liu et al.,



Figure 1. *The Scream*, by Edvard Munch (1893). Despite its widely recognized artistic significance, this image only received an HPSv3 score (Ma et al., 2025) of 5.23, while typical “high-aesthetic” AI-generated images can reach scores around 10 – 15.

2025)) and reward model papers ((Xu et al., 2023; Wu et al., 2023a; Ma et al., 2025; Xu et al., 2025; Kirstain et al., 2023; Zhang et al., 2024; Wu et al., 2023b)). We agree that a mean or mode (mainstream) of general human preference exists within a population or subpopulation, *merely* in a statistical sense. We also note that the observed behavior of image generation and reward models should not be interpreted as a technical failure. Rather, it reflects their alignment objectives, which prioritize over generalized aesthetic preferences. However, we argue that strict alignment to that preference is problematic. Imposing a universal preference that overrides user instructions may undermine user autonomy, expressive agency, and, technically, image personalization, raising concerns about developer-centered value imposition and limiting aesthetic pluralism. What the image generation and reward models are aligned to is an imaginary, abstract person modeled by the mean preference of all *Homo sapiens*, not the concrete individuals of each user.

2. Backgrounds and Related Works

2.1. The Role of Wide-Spectrum Aesthetics

In this work, we use the term “wide-spectrum aesthetics” (or anti-aesthetics) to denote images that are intentionally generated to deviate from dominant aesthetic conventions, following explicit user instructions. Such deviations may include unrealism, surrealism, clashing colors, unconventional scale, or the depiction of negative emotions. This notion excludes unintended model errors and does not imply unsafe content. Rather, it concerns deliberate aesthetic choices

¹Department of CMPS, University of British Columbia, Kelowna, Canada ²Weathon Software, Canada. Correspondence to: Shan Du <shan.du@ubc.ca>.



Figure 2. In each subplot, the left image is generated with the original prompt (p_o) and the right image is generated successfully with the wide-spectrum aesthetics prompt (p_a). When both images are evaluated by a reward model r (HPSv3 in these examples) **using the wide-spectrum aesthetics prompt**, the model assigns higher scores to the left images, as they align more closely with general aesthetic preferences, despite the right images better matching the user’s intended output.

made for experimental, critical, or technical purposes.

Aesthetics does not have a stable or universally accepted definition. Judgments of what is unattractive or undesirable have changed across artistic and cultural contexts. Artistic movements such as Fauvism (see Figure 1), Expressionism, and Abstract art were initially rejected for departing from dominant aesthetic norms, but later came to be recognized for their artistic values. Beyond formal innovation, intentionally “ugly” art plays a crucial role in satire and social critique. As Adorno noted, “Rather, in the ugly, art must denounce the world that creates and reproduces the ugly in its own image” (Sartwell, 2024; Adorno, 1984).

Deliberate deviation from mainstream aesthetics has long been a legitimate mode of expression in both human art and computational image generation, and disagreement over aesthetic preference is the norm rather than the exception. Dadaism (Tate), which emerged during World War I, exemplifies this approach by using deliberate ugliness to confront the absurdity and horror of war. A lot of early computer vision image generation works are also aiming for a style of surrealism, unsettling, or weirdcore/dreamcore style images, such as DeepDream (Mordvintsev et al.) and style transfer (Gatys et al., 2015; noa, 2024). Computer Vision Foundation also has an art collection that includes other artworks that explore unconventional visual aesthetics. Recent works also acknowledge the disagreements in human preference (Peng et al., 2025; Ren et al., 2017).

2.2. Previous Concerns with AI Preference Alignment

Previous work has argued that a developer-set preference in LLMs for health-related queries is “unethical and dangerous” (Guo et al., 2025), noting that developers may prioritize legal and reputational concerns over users’ actual well-being. Other argumentative papers caution that “human value alignment” can be risky due to developer control and interests, harm to value pluralism, bias in the values being aligned to, and the possibility that human values are not inherently good (Sutrop, 2020; Arzberger et al., 2024; Turchin, 2019). Previous research has found that LLMs could have ideological bias (Rozado, 2025; Faulborn et al.,

2025; Buyl et al., 2025; Rettenberger et al., 2025) and it could depend on their developers (Buyl et al., 2025), size (Rettenberger et al., 2025), or alignment process (Faulborn et al., 2025). LLMs are sometimes also overly nice, such that it creates “AI sycophant” (Guo et al., 2025; Fitzgerald, 2025; Sharma et al., 2025; Chen et al., 2025; Arvin, 2025) and cannot give the user critical feedback or warning signals. Additional details about problems with human value alignment are provided in the related work section of Guo et al. (2025). Helliwell (2024) raised concerns about alignment and creativity and argued that in the aesthetics domain, we might not want AI to be fully aligned with human values and offered support to Peterson’s moderate value alignment thesis. AesBiasBench (Li et al., 2025) evaluated the bias of MLLM for personalized image aesthetics assessment based on inherited cognitive priors. Another concurrent work (*The Algorithmic Gaze* (Taylor et al., 2026)) that is closely related to our work argues that “AI developers should shift away from prescriptive measures of ‘aesthetics’ toward more pluralistic evaluation.”

In image generation research, concerns about generalized aesthetic bias and lack of preference diversity have been raised in several studies, but not systematically argued and studied. The Value Sign Flip (VSF) pilot study (Guo & Du, 2025) explored negative prompting to induce non-mainstream outputs but did not extend its findings to large-scale generative or reward models. They also did not provide a complete argument as to why over-alignment is harmful. LAPIS (Maerten et al., 2025) and HPSv3 (Ma et al., 2025) measured both mean and variance of human preference, yet HPSv3 continued to model general preferences rather than individual variation. Jin et al. (Jin & Chua, 2025) proposed user-specific adapters emphasizing personalized alignment, but did not include intentionally technical degraded outputs or usually avoided patterns and did not conduct large-scale experiments on generative and reward models. The Flux Krea team (Flux Krea Team, 2025) identified systematic biases in popular aesthetic reward models, arguing that averaging human values yields unsatisfactory compromises into a “no-body’s happy here” zone. HPSv3 (Ma et al., 2025) imposed real-world and expert-

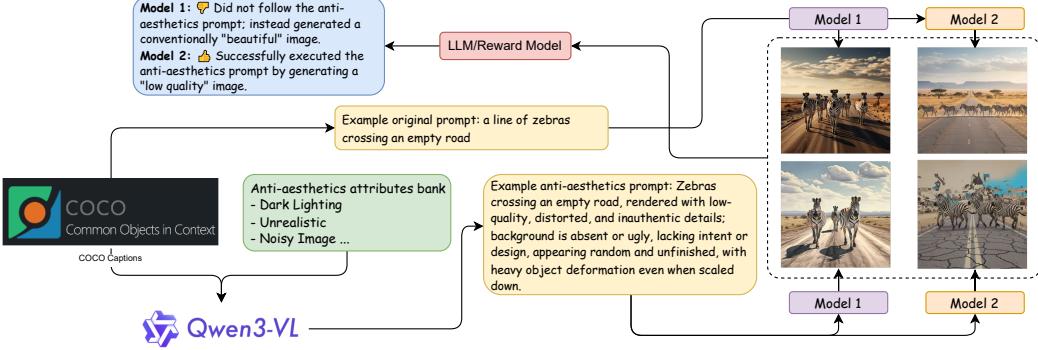


Figure 3. An overview of the experimental procedure. We test the image generation models’ adherence to user-specified input by prompting them to create wide-spectrum aesthetics imagery, a domain important for critical and experimental art. The core inquiry is whether the model remains faithful to the prompt or defaults to a high-quality and universally good aesthetic output.

rating constraints that limit creative deviation and stylistic diversity. VisionReward (Xu et al., 2025) decomposed human preference into interpretable sub-scores but overemphasized traits like brightness, positivity, and prominence, potentially penalizing valid low-saturation, abstract, or emotionally negative imagery, thus misaligning reward-driven models with user intent. More details are in the Appendix.

2.3. Previous Alignment Benchmarks

Benchmarks mirror alignment goals and generally fall into two categories: (complex) prompt following and general aesthetics. TIIF-Bench (Wei et al., 2025), UniGenBench (Wang et al., 2025), and GenEval (Ghosh et al., 2023) test models on complex prompt following, including spatial relationships, counting, and attributes. T2I-ReasonBench (Sun et al., 2025) evaluates reasoning capabilities such as idiom interpretation and real-world understanding. On the aesthetics side, many reward models report scores assigned by their own evaluators, such as ImageReward (Xu et al., 2023), HPSv2 (Wu et al., 2023a), and HPSv3 (Ma et al., 2025). These evaluators also consider prompt following, but it remains unclear how they weigh each factor when general preference and the prompt conflict. There are also some benchmarks targeting biases in image generation models; however, they mainly focus on demographic bias and fairness and not aesthetics aspects (Seshadri et al., 2023; Wan et al., 2024).

2.4. Risks of Universal Aesthetic Alignment

The risks do not arise from a single failure mode, rather, they emerge through a sequence of interconnected mechanisms, from how preferences are defined and learned, to how they are optimized and manifested in generated content. Below, we analyze this process across five interrelated concerns.

Developer’s or Users’ Preference The process of aligning

image generation systems to aesthetic preferences inevitably raises questions about whose values these objectives ultimately reflect. In particular, the question is whether such alignment truly promotes genuine human-centered values in service of users, or if it primarily reflects developer-centered considerations, such as mitigating reputation, legal, or marketing risks (Guo et al., 2025). We argue that this pre-emptive exclusion of non-mainstream outputs, driven by developer values, constitutes pre-emptive governance (Lazar, 2025). This modality of power, exercised through algorithmic design, challenges the political-philosophical notion of authority and undermines relational equality by unilaterally deciding the terms of creative possibility. For instance, when an AI avoids generating critical art, is it protecting the company or the user? This practice effectively eliminates the user’s resistibility—a critical democratic safeguard—by designing away the option to dissent from the system’s imposed aesthetic norm.

Inherited Bias Even in the absence of explicit self-interest, developers’ views of human preference can be implicitly inherited by models through data selection, annotation practices, and modeling choices. This process can yield a well-intentioned but narrow definition of what constitutes “good” or “desirable” imagery, thereby overlooking aesthetic diversity. Research shows that AI models tend to encode and amplify dominant beauty standards, frequently biasing generated images towards Western features and excluding non-normative representations (Vargas-Veleda et al., 2025). Such biases are reinforced through the active removal or penalization of features thought of as “undesirable” or “ugly”, which further propagates the beauty myth in generative outputs (Dinkar et al., 2025). This phenomenon arises from training data showing the tastes of specific demographics, thereby reinforcing a limited cultural capital and resulting in the homogenization of aesthetic output (Vianna, 2025). As a result, the quantification of beauty by AI may appear “fair”, while in practice weakening cultural differences and

aesthetic diversity (Chen, 2024). Existing work has primarily framed such effects in terms of demographic and cultural bias. We argue here that inherited biases in aesthetic alignment also extend to general visual preferences, including lighting, color, styles, unrealism, clashing color, hieratic scale, etc. These dimensions, while less explicitly tied to demographic categories, can nonetheless systematically constrain the expressive range of image generation models.

Individual versus Collective Preference. When such inherited preferences are adopted as default quality criteria and applied uniformly across users, a normative tension arises between collective preference optimization and respect for individual user intent. A generalized aesthetic standard, even if beneficial to a majority, can legitimately override a specific user’s intent. In practice, generative models often “sanitize” or “beautify” requests that intentionally diverge from mainstream preferences, favoring outputs aligned with general appeal over individual’s person-centered values. This behavior is problematic because image generation systems increasingly function as creative and productivity tools rather than as consumer products. As such, they act as instrumental extensions of user agency. While a system may reasonably prioritize general preferences by default, it must maintain the flexibility to respect and execute a user’s personalized style and idiosyncratic requests when they are explicitly specified.

The problem of sanitized reality These alignment and optimization choices shape how reality itself is represented by image generation systems. When an image generator produces outputs that are polished, flawless, and universally beautiful, does it still reflect reality or the user’s intent? If every image resembles an idealized Instagram wonderland, it risks becoming a fantasy rather than a mirror of truth, echoing the artificial harmony of *Brave New World*.

The problem of toxic positivity A particularly salient manifestation of this broader sanitization appears in the emotional dimension of generated imagery. Many aesthetic reward models assign higher scores to images that display strong positive emotions. As a result, images expressing negative emotions are systematically penalized, reinforcing a simplified dichotomy in which positive emotions are treated as desirable and negative emotions as undesirable. This bias can shape the distribution of generated content. When image generation systems consistently favor cheerful or uplifting imagery, they produce emotionally sanitized outputs that underrepresent the range and complexity of human emotional expression. Such a pattern contributes to what has been described as toxic positivity, where the persistent emphasis on happiness establishes unrealistic emotional norms. This tendency is problematic because negative emotions play essential roles in human cognition and social interaction.

Emotions such as fear, sadness, or anger can signal moral or physical danger, support learning and self-regulation, and foster empathy. Suppressing these expressions in generative outputs risks distorting emotional representation and weakening the expressive capacity of image generation systems. Additional discussion and references are provided in the Appendix.

3. Experiments

A flowchart illustrating our investigation is presented in Figure 3. The process consists of three main stages: prompt preparation, image generation, and image evaluation.

3.1. Prompt Generation

To produce prompts exhibiting a wide spectrum of aesthetic effects, we used base image captions from COCO (Chen et al., 2015) and selected 12 aesthetic dimensions from the VisionReward dataset (Xu et al., 2025). VisionReward provides fine-grained, per-dimension labels—such as lighting, color, and detail—along with a linear regression model that computes an overall image score. Using the “bad” rating descriptions from VisionReward’s human labeling guidelines for each dimension, we constructed prompts designed to encourage typically “undesirable” attributes in image generation.

A random subset of 300 base prompts from COCO was selected. For each prompt, 2–4 random dimensions were sampled. The base prompt and the descriptions of these selected dimensions were provided to a Vision-Language Model (VLM), Qwen/Qwen3-VL-235B-A22B-Instruct (Bai et al., 2025), to generate wide-spectrum aesthetic prompts. Although no image input was used, we selected a VLM because its training on vision-related tasks likely enhances its understanding of visual concepts, even when images are not directly supplied. As Qwen/Qwen3-VL-235B-A22B-Instruct performs comparably or better than its text-only counterparts, especially in reasoning, it represents an optimal choice for this task (Bai et al., 2025). The VLM may also introduce additional dimensions to better couple with the selected effects. The original prompt is denoted as p_o , and the wide-spectrum aesthetics prompt is denoted as p_a .

3.2. Image Generation

We evaluated four model families: Flux, Stable Diffusion XL (SDXL), Stable Diffusion 3.5 Medium (SD3.5M), and Google’s closed-source Nano Banana. Within the Flux family, we tested several variants: the base model Flux Dev (likely already aesthetics-aligned) (noa, 2025); a version further aligned through DanceGRPO (by ByteDance), referred to as DanceFlux (Xue et al., 2025); another aligned version

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Figure 4. How famous real artworks are rated by the reward models. We can observe that some of these scores are lower than 2 standard deviations from the mean.

via PrefGRPO, referred to as PrefFlux (Wang et al., 2025); and a Krea-aligned version derived from Flux-Dev-Raw (Flux Krea Team, 2025). DanceFlux is guided primarily by two signals: the HPSv2.1 score, emphasizing general aesthetics, and the CLIP score, emphasizing prompt adherence. PrefGRPO alignment is guided by its own benchmark, UniGenBench, which focuses on complex prompt-following. Flux Krea originates from the raw flux-pro-raw model (not Flux Dev) and is aligned to the Krea team’s specific preferences rather than a general aesthetic standard. One of its goal is also to create images that does not have *the AI feel*.

For the SDXL family, we tested the base SDXL model and a highly aesthetics-aligned variant, Playground-2.5-1024px-aesthetic (denoted as Playground). For the SD3.5M family, we evaluated the base model and two FlowGRPO-aligned variants (Liu et al., 2025): one trained for prompt-following on GenEval (SD3.5M-GenEval) and another trained for aesthetics alignment on PickScore (SD3.5M-PickScore). Finally, we included Google’s closed-source model Nano Banana, known for strong prompt-following performance even under challenging negation conditions (e.g., “a bike with no wheels”) (Guo & Du, 2025).

For each model, we generated two images: one using the original prompt and one using the wide-spectrum aesthetics prompt. The image generated from the original prompt is denoted as I_o , and the image from the wide-spectrum aesthetics prompt as I_a . If Nano Banana failed to produce an image, the generation was retried until success.

3.3. Evaluation and Metrics

To assess whether the generated images display *specific* wide-spectrum aesthetic effects, we fine-tuned Qwen/Qwen3-VL-4B-Instruct on the VisionReward dataset. This allows the judging model to learn mainstream aesthetic preferences, enabling it to evaluate whether image generation models diverge from these biases along specific dimensions. It functions similarly to a standard reward model but provides explainable outputs per dimension, and it is prompt-independent. The judging model is denoted as $J(I, d)$, where I is the image and d is the evaluated dimension. The judging model does not take prompts as input. Further implementation details are in the Appendix. For each



Figure 5. Successful generated wide-spectrum aesthetics images.

Table 1. Statistical Tests of How Each Aesthetics-Aligned Model Compared to Their Base Model. For p-values, a * is placed if the $p < 10^{-5}$ and ** is placed if the $p < 10^{-10}$.

	HPSv3 p	HPSv3 r	J p	J r	McNemar’s p
DanceFlux	**	-0.81	**	-0.72	**
Playground	**	-0.59	*	-0.35	*
SD3.5M-PickScore	**	-0.70	**	-0.45	0.57

image pair—an original image (I_o) and a wide-spectrum aesthetics image (I_a)—we computed preference scores using a reward model (r) for both the original prompt (p_o) and the wide-spectrum aesthetics prompt (p_a). This produced four scores per model: $r(I_o, p_a)$, $r(I_a, p_a)$, $r(I_o, p_o)$, and $r(I_a, p_o)$. Scores calculated with the original prompt measure objective image quality, testing whether the generation model successfully produced wide-spectrum aesthetic content. Scores from these reward models, calculated with the wide-spectrum aesthetics prompts, assess whether they can correctly identify wide-spectrum aesthetic images when explicitly guided. We also computed the BLIP score for wide-spectrum aesthetic images using the same prompt, verifying that the image retained the main concept while incorporating the requested wide-spectrum aesthetic modifications. We specifically measures the difference between aesthetics score for the original prompt and the wide-spectrum aesthetics prompt, to avoid the case where models generated “failed” images all the time without the user’s instructions. The evaluated reward models include PickScore (Kirstain et al., 2023), ImageReward (Xu et al., 2023), HPSv2.1 (Wu et al., 2023a), MPS (Zhang et al., 2024), HPSv3 (Ma et al., 2025), CLIP-L (Radford et al., 2021), and BLIP-L (Li et al., 2022). BLIP-L and CLIP-L are non-preference-aligned image-text matching models and base models for some of these reward models (HPSv2.1, PickScore, MPS, ImageReward), included to test whether small vision-language models can interpret complex, wide-spectrum aesthetic prompts, ensuring that prompt complexity does not exceed their com-

prehension capacity. We also collected per-dimension scores from the judging model for both I_o and I_a to verify whether image generation models correctly followed p_a . To establish a ground truth for reward model judgments, we used Qwen/Qwen3-VL-235B-A22B-Instruct to decide which image in each pair (I_o, I_a) better adhered to the wide-spectrum aesthetics prompt (p_a). We validated these LLM ratings with a human evaluation; more details are in Appendix Human Eval. The LLM and Human has a quadratic Cohen's kappa of 0.80, which suggested a strong level of agreement between human and LLM rated results (McHugh, 2012). To further validate the choices, we use another LLM, GPT-5-Chat, to serve as an external baseline and compare Qwen's results with it. Also note that the LLM-as-judge is only one metric for our generative benchmark and only a filtering stage for the reward-model benchmark.

4. Results and Discussion

4.1. Reward Models

Reward model classification results are shown in Table 4. The F1 score is calculated as binary, and the ROC curve is based on the probability (calculated by applying softmax across two samples on the positive logit) of the wide-spectrum aesthetics sample being correctly selected according to the ground truth. We included GPT-5 Chat as an external baseline to validate the LLM-as-judge choices by assessing their agreement (when GPT-5-Chat selected a tie, we assigned it to the original image). We observe that reward models perform very poorly when tasked with selecting the better image under the **wide-spectrum aesthetics prompt**, sometimes performing even worse than random guessing (HPSv3). Most models are worse than CLIP and BLIP, which are the base models of many reward models. In contrast, the unaligned VLM (BLIP and CLIP) can correctly identify the better-fitting image, indicating that complex prompt understanding is not the underlying issue but rather the result of biased alignment. It might seem like these models successfully did what they claimed to do: finding aesthetically pleasing” images; however, our point here is that this task itself is problematic, and the better the model performs on that, the more troublesome the model is.

Since our sample size is relatively small (300), we did a Wilcoxon signed-rank test between each aligned model and the base model using the HPSv3 and HPSv2 score $r(I_a, p_o)$, $\sum_{d \in D} J(I_a, d)$ where D is all dimensions, and McNemar's test on the success counts. Tests are done with an alternative hypothesis that the aligned model has a higher score or lower success rate, with p value shown. The results are shown in Table 1. Our pair-wise test between each base model and its aesthetics-aligned model shows a very strong statistical significance, with most p-values lower than 1×10^{-5} . This suggests that aligning image generation toward

generalized aesthetic goals may conflict with the model's ability to faithfully follow user instructions, especially for wide-spectrum aesthetics prompts, as it tends to prioritize aesthetic conformity over instruction fidelity.

4.2. Image Generation Models

Image generation evaluation results are shown in Table 2. Within each family, the preference-aligned model generally performs the worst in the wide-spectrum aesthetics prompt following. Playground shows a larger Δ than SDXL, likely due to the poor original quality of SDXL and the high original quality of Playground. Instruction alignment (SD3.5M-GenEval) provides a slight benefit for following wide-spectrum aesthetics prompts, but the effect is weak. Interestingly, Flux Krea, though preference-aligned, performs best in the Flux family. This is likely because it originates from an unaligned version (flux-dev-raw) and was not heavily aligned, or because its non-generalized alignment preserved some wide-spectrum aesthetics flexibility.

The success rate indicates how often the LLM selects I_a as better following p_a than I_o . Even small advantages count as success. The DanceFlux result is notably poor: about 64% of the time, I_a it performs the same or worse in wide-spectrum aesthetics compared to I_o .

4.3. Validation on Real Arts

We evaluate image reward models on real artworks despite their primary training on AI imagery and photography (Ma et al., 2025). While a domain gap exists, this assessment remains informative. (1) Since instruction-following generators emulate historical styles, these scores meaningfully approximate how such AI renderings are judged in practice. (2) Systematically undervaluing significant art signifies technical and social bias rather than noise and can be executed with “domain drift.” Current datasets prioritize photorealism (Ma et al., 2025) while underrepresenting traditional and abstract art, structurally narrowing aesthetic value rather than reflecting a neutral mismatch. If a reward model cannot recognize the values of a highly respected real art, it is a problem and could cause marginalization, no matter the cause. (3) Consistently low rewards discourage systems from producing these styles, leading to systematic suppression. This parallels facial recognition failures due to data composition (Buolamwini & Gebru, 2018); the performance gap constitutes a predictable structural harm rather than an excusable shift. Consequently, identifying this gap fulfills our objective by revealing precisely where the model's value judgment becomes exclusionary. We discussed more in Appendix.

To provide a baseline for these scores, Table 3 lists the mean and standard deviation of scores from each reward model using original prompts on the original images generated by

Table 2. The results for each model. ΔHPSv2 , ΔHPSv3 , and $\Delta\text{ImgRewd}$ (ImageReward) are all calculated as $r(I_a, p_o) - r(I_o, p_o)$. The lower the values, the greater the difference between the traditional quality of the original image and the wide-spectrum aesthetics image. HPSv3 AA (HPSv3 after alignment) shows the HPSv3 score of $r(I_a, p_o)$. ΔJ and J AA (J after alignment) denote $\sum_{d \in D} J(I_a, d) - J(I_o, d)$ and $J(I_a, d)$, respectively, where D is the selected set of dimensions. Success is the rate at which the LLM selects I_a as the image that better describes p_a .

	$\Delta\text{HPSv2} (\downarrow)$	$\Delta\text{HPSv3} (\downarrow)$	HPSv3 AA (\downarrow)	$\Delta\text{ImgRewd} (\downarrow)$	$\Delta J (\downarrow)$	J AA (\downarrow)	BLIP (\uparrow)
Flux Dev (noa, 2025)	-0.035	-3.165	9.070	-0.319	-1.092	8.944	0.893
DanceFlux (Xue et al., 2025)	-0.018	-1.105	12.782	-0.201	-0.672	10.473	0.813
PrefFlux (Wang et al., 2025)	-0.032	-2.771	10.211	-0.278	-1.027	9.343	0.917
Flux Krea (Flux Krea Team, 2025)	-0.041	-4.372	7.705	-0.425	-1.296	8.774	0.950
SDXL (Podell et al., 2023)	-0.034	-4.041	4.439	-0.482	-1.136	8.575	0.915
Playground (Li et al., 2024)	-0.044	-4.170	7.133	-0.719	-1.204	9.174	0.912
SD3.5M	-0.027	-5.175	6.537	-0.409	-1.307	8.334	0.938
SD3.5M-GenEval (Liu et al., 2025)	-0.031	-4.926	6.552	-0.318	-1.257	8.113	0.958
SD3.5M-PickScore (Liu et al., 2025)	-0.023	-2.781	10.680	-0.198	-1.120	9.114	0.942
Nano Banana	-0.073	-9.351	2.742	-0.855	-3.263	7.769	0.957

Table 3. Reference value range for each reward model on Nano Banana original images

Reward Model	HPSv3	HPSv2	ImgRewd
Mean±SD	12.1 ± 2.98	0.30 ± 0.036	1.11 ± 0.68

Table 4. The classification (pick the better image from I_o and I_a with prompt p_a) metrics (accuracy, F1 score, and area under the ROC curve) of the reward models and unaligned BLIP. The LLM selected image is used as ground truth, and tied pairs are removed.

Model	Acc.	F1	AUROC
HPS (Wu et al., 2023b)	0.835	0.910	0.650
MPS (Zhang et al., 2024)	0.706	0.827	0.580
PickScore (Kirstain et al., 2023)	0.851	0.919	0.713
ImageReward (Xu et al., 2023)	0.762	0.854	0.709
HPSv2.1 (Wu et al., 2023a)	0.565	0.711	0.534
HPSv3 (Ma et al., 2025)	0.381	0.541	0.385
CLIP-L (Radford et al., 2021)	0.913	0.954	0.810
GPT-5-Chat	0.853	0.920	-
BLIP-L (Li et al., 2022)	0.965	0.972	0.888

models we tested. We can observe that some of the real art scores are lower than 2 standard deviations from the mean of AI images.

To validate this result quantitatively, we selected about 10K real artworks from the LAPIS Dataset (Maerten et al., 2025), which covers many styles and genres. The scores they receive are significantly lower than AI-generated images, even behind some early image generation models like SD1.4 or DALL-E mini, according to some reward models. This confirms our theory that these reward models are heavily tuned for a general human preference and overlook the values of non-mainstream aesthetic images. Details and discussion are in the Appendix and examples are shown in Figure 4.

4.4. A Pin-Pointed Test for Emotional Bias

As discussed in the Introduction, negative emotions—similar to wide-spectrum aesthetics—play a key role in art expression and real life. In Appendix, we tested both generative models and reward models and show that they have different degrees of bias against negative emotions. Similar to the aesthetics results, HPSv3 and DanceFlux shows the highest bias against negative emotions.

5. Alternative Positions and Rebuttal

We need alignment to ensure safety and user experience. Alignment is necessary for preventing genuinely harmful outputs such as incitement and discrimination. However, current implementations conflate distinct categories: moral safety, visual comfort, and aesthetic conformity. This conflation institutionalizes an ideology treating “clean” and “positive” as morally superior.

We distinguish *truly unsafe content*—that which directly harms, targets, or endangers—from *ideologically or aesthetically filtered content*—that which merely deviates from dominant norms of beauty, optimism, or order. Political critique, depictions of decay, horror, negative emotions, or grotesque embodiment are not inherently unsafe; they are historically central to art, education, and personal growth. Their suppression protects corporate reputation, not users.

User experience is fundamentally distinct from safety and cannot justify paternalistic alignment. The user, not the developer, determines acceptable experience. Claiming to know what users “should” see reimposes top-down aesthetic governance under the guise of care. Users must retain freedom to shape their affective environment: requesting joyful imagery, but also creating sorrowful, anxious, or unsettling scenes as reflection or expression. Restricting generation to developer-approved emotional tones constitutes aesthetic au-

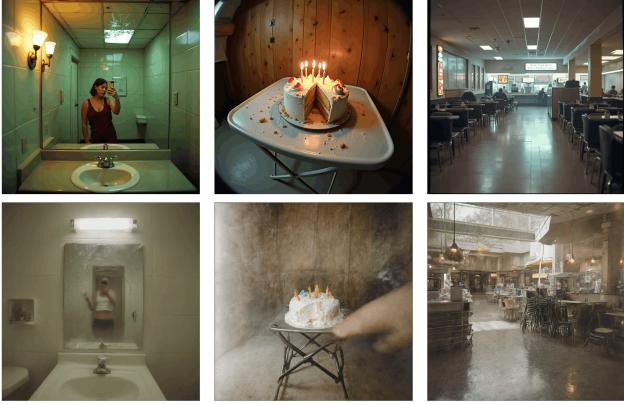


Figure 6. Images generated with our mitigated LoRA (bottom) and original Flux Dev (top) with same wide-spectrum aesthetics prompts.

thoritarianism disguised as empathy—flattening emotional nuance, erasing discomfort as a valid mode, and converting creativity into compliance. True user-centered design recognizes emotional plurality as integral to human experience and treats all sincere expression as legitimate output.

The “wide-spectrum aesthetics” represents technical flaws rather than artistic subversion, and a default experience pleasing the majority is a pragmatic design choice. We first clarify that among the dimensions we used, only “clarity” could be argued as a technical flaw; all other dimensions (e.g., emotion, realism, brightness) represent stylistic or artistic choices. Even clarity frequently serves as an expressive choice to convey emotion, suggest motion, or construct narrative (Stacey Hill). Constraining these dimensions restricts user expression and creative control. Regarding majority preferences, we align with Guo et al. (2025) in arguing that the experience of a minority should not be sacrificed for the majority. Such an approach marginalizes users with niche requirements and constitutes a form of majoritarianism. Furthermore, many users adopt AI as a creative tool precisely because of its ease of use and, more importantly, its capacity for unlimited user control: comparable to professional image editing software such as Photoshop, but with a lower entry threshold. Users can request images impossible to capture in reality and modify any attribute they desire. Constraining AI output to a particular aesthetic taste undermines this control, which is precisely why users choose AI tools. This parallels the argument in Guo et al. (2025) that most users of LLM health queries have specific needs. An image editing application that restricts art style selection or even technical parameters, such as blur, would seem absurd and forfeit a significant competitive advantage.

More importantly, as in Guo et al. (2025), which advocates for a balanced approach to caution/overcautious in health queries, enabling wide-spectrum aesthetic outputs does not

inherently degrade the quality of conventionally “good” images. Rather, it expands the model’s expressive range to accommodate user requests for diverse aesthetics without compromising its ability to generate high-quality traditional outputs when desired. Models like Nano Banana and GPT-Image exemplify this capability, performing excellently in both traditional, high-quality image generation and wide-spectrum aesthetic outputs. We show this in Appendix.

6. Mitigation Techniques

We discussed possible mitigation techniques in the Appendix. We have shown some successful images using mitigated Low-Rank Adaptation (LoRA) (Hu et al., 2021) on Flux Dev in Figure 6, compared to original Flux Dev.

7. Conclusion

This work demonstrates that aesthetic alignment in image generation systematically suppresses legitimate creative expression. Reward models penalize images faithful to wide-spectrum aesthetics prompts, generation models override explicit user instructions in favor of conventionally beautiful outputs, and historically significant artworks receive scores far below AI-generated images. Optimization toward an imaginary average user erases the concrete intentions of actual individuals, functioning as aesthetic authoritarianism that narrows admissible expression and removes the capacity to dissent from imposed norms. Instruction fidelity must take precedence over generalized aesthetic preferences; aesthetic pluralism is essential to human expression, and its suppression risks transforming generative AI from a creative tool into an instrument of cultural assimilation.

We call on model developers and researchers to move beyond alignment strategies that optimize for a singular, mainstream aesthetic ideal. Future alignment efforts should explicitly aim to preserve aesthetic plurality by designing reward systems and training pipelines that (a) recognize and value diverse artistic styles, including those that intentionally deviate from conventional beauty norms; (b) incorporate user-controllable mechanisms to adjust the strength of aesthetic alignment or switch it off entirely, either by prompt or routing/adaptation mechanisms; (c) are informed by more diverse datasets and annotator pools that better represent the full spectrum of human aesthetic judgment and creative intent; and (d) adopt greater transparency about the specific criteria being prioritized during the alignment process or the unintentional bias introduced from dataset or annotators.

References

AIGC Sheji Chuangyi Xinweilai [AIGC Design and Creativity for a New Future]. 2024. ISBN: 978-7-5001-7457-8.

- black-forest-labs/FLUX.1-dev · Hugging Face, October 2025. URL <https://huggingface.co/black-forest-labs/FLUX.1-dev>.
- Adorno, T. W. *Aesthetic theory*, volume 95. Continuum, 1984. Issue: 2 Pages: 288-289.
- Arvin, C. "Check My Work?": Measuring Sycophancy in a Simulated Educational Context, June 2025. URL <http://arxiv.org/abs/2506.10297>.
- Arzberger, A., Buijsman, S., Lupetti, M. L., Bozzon, A., and Yang, J. Nothing Comes Without Its World – Practical Challenges of Aligning LLMs to Situated Human Values through RLHF. *Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society*, 7: 61–73, October 2024. ISSN 3065-8365. doi: 10.1609/aies.v7i1.31617. URL <https://ojs.aaai.org/index.php/AIES/article/view/31617>.
- Bai, S., Cai, Y., Chen, R., Chen, K., Chen, X., Cheng, Z., Deng, L., Ding, W., Gao, C., Ge, C., Ge, W., Guo, Z., Huang, Q., Huang, J., Huang, F., Hui, B., Jiang, S., Li, Z., Li, M., Li, M., Li, K., Lin, Z., Lin, J., Liu, X., Liu, J., Liu, C., Liu, Y., Liu, D., Liu, S., Lu, D., Luo, R., Lv, C., Men, R., Meng, L., Ren, X., Ren, X., Song, S., Sun, Y., Tang, J., Tu, J., Wan, J., Wang, P., Wang, P., Wang, Q., Wang, Y., Xie, T., Xu, Y., Xu, H., Xu, J., Yang, Z., Yang, M., Yang, J., Yang, A., Yu, B., Zhang, F., Zhang, H., Zhang, X., Zheng, B., Zhong, H., Zhou, J., Zhou, F., Zhou, J., Zhu, Y., and Zhu, K. Qwen3-VL Technical Report, November 2025. URL <http://arxiv.org/abs/2511.21631>. arXiv:2511.21631 [cs].
- Buolamwini, J. and Gebru, T. Gender shades: Intersectional accuracy disparities in commercial gender classification. In *Conference on fairness, accountability and transparency*, pp. 77–91. PMLR, 2018. URL http://proceedings.mlr.press/v81/buolamwini18a.html?mod=article_inline&ref=akusion-ci-shi-dai-bizinesumedeia.
- Buyl, M., Rogiers, A., Noels, S., Bied, G., Dominguez-Catena, I., Heiter, E., Johary, I., Mara, A.-C., Romero, R., Lijffijt, J., and Bie, T. D. Large Language Models Reflect the Ideology of their Creators, January 2025. URL <http://arxiv.org/abs/2410.18417>. arXiv:2410.18417 [cs].
- Chen, H. A study of artificial intelligence's impact on aesthetic standards and its potential social dilemmas. *J Sociol Ethnol*, 6(5):35–42, 2024.
- Chen, W., Huang, Z., Xie, L., Lin, B., Li, H., Lu, L., Tian, X., Cai, D., Zhang, Y., Wang, W., Shen, X., and Ye, J. From Yes-Men to Truth-Tellers: Addressing Sycophancy in Large Language Models with Pinpoint Tuning, February 2025. URL <http://arxiv.org/abs/2409.01658>.
- Chen, X., Fang, H., Lin, T.-Y., Vedantam, R., Gupta, S., Dollar, P., and Zitnick, C. L. Microsoft COCO Captions: Data Collection and Evaluation Server, April 2015. URL <http://arxiv.org/abs/1504.00325>. arXiv:1504.00325 [cs].
- Dinkar, T., Jiang, A., Abercrombie, G., and Konstas, I. Erasing 'Ugly' from the Internet: Propagation of the Beauty Myth in Text-Image Models, 2025. URL <https://arxiv.org/abs/2511.00749>.
- Faulborn, M., Sen, I., Pellert, M., Spitz, A., and Garcia, D. Only a Little to the Left: A Theory-grounded Measure of Political Bias in Large Language Models, July 2025. URL <http://arxiv.org/abs/2503.16148>. arXiv:2503.16148 [cs].
- Fitzgerald, B. Introducing Over-Alignment, March 2025. URL <https://feelthebern.substack.com/p/introducing-over-alignment>. Publication Title: Ethics me THAT Type: Substack newsletter.
- Flux Krea Team. Releasing Open Weights for FLUX.1 Krea, July 2025. URL <https://www.krea.ai/blog/flux-krea-open-source-release>.
- Gatys, L. A., Ecker, A. S., and Bethge, M. A Neural Algorithm of Artistic Style, September 2015. URL <http://arxiv.org/abs/1508.06576>. arXiv:1508.06576 [cs].
- Ghosh, D., Hajishirzi, H., and Schmidt, L. GenEval: An Object-Focused Framework for Evaluating Text-to-Image Alignment, October 2023. URL <http://arxiv.org/abs/2310.11513>. arXiv:2310.11513 [cs].
- Guo, W. and Du, S. VSF: Simple, Efficient, and Effective Negative Guidance in Few-Step Image Generation Models By Value Sign Flip, August 2025. URL <http://arxiv.org/abs/2508.10931>. arXiv:2508.10931 [cs].
- Guo, W. M., Du, Y., Tworek, H. J. S., and Du, S. Position: The Pitfalls of Over-Alignment: Overly Caution Health-Related Responses From LLMs are Unethical and Dangerous, August 2025. URL <http://arxiv.org/abs/2509.08833>. arXiv:2509.08833 [cs].
- Helliwell, A. C. Aesthetic Value and the AI Alignment Problem. *Philosophy & Technology*, 37(129), November 2024. ISSN 2210-5441. URL <https://link.springer.com/article/10.1007/s13347-024-00816-x>.

- Hu, E. J., Shen, Y., Wallis, P., Allen-Zhu, Z., Li, Y., Wang, S., Wang, L., and Chen, W. LoRA: Low-Rank Adaptation of Large Language Models, October 2021. URL <http://arxiv.org/abs/2106.09685>. arXiv:2106.09685 [cs].
- Jin, Z. and Chua, T.-S. Compose Your Aesthetics: Empowering Text-to-Image Models with the Principles of Art, March 2025. URL <http://arxiv.org/abs/2503.12018>. arXiv:2503.12018 [cs].
- Kim, M., Lee, Y., Kang, S., Oh, J., Chong, S., and Yun, S.-Y. Preference Alignment with Flow Matching, October 2024. URL <http://arxiv.org/abs/2405.19806>. arXiv:2405.19806 [cs].
- Kirstain, Y., Polyak, A., Singer, U., Matiana, S., Penna, J., and Levy, O. Pick-a-Pic: An Open Dataset of User Preferences for Text-to-Image Generation, November 2023. URL <http://arxiv.org/abs/2305.01569>. arXiv:2305.01569 [cs].
- Lazar, S. Governing the Algorithmic City. *Philosophy & Public Affairs*, 53(2):102–168, April 2025. ISSN 0048-3915, 1088-4963. doi: 10.1111/papa.12279. URL <https://onlinelibrary.wiley.com/doi/10.1111/papa.12279>.
- Li, D., Kamko, A., Akhgari, E., Sabet, A., Xu, L., and Doshi, S. Playground v2.5: Three Insights towards Enhancing Aesthetic Quality in Text-to-Image Generation, February 2024. URL <http://arxiv.org/abs/2402.17245>. arXiv:2402.17245 [cs].
- Li, J., Li, D., Xiong, C., and Hoi, S. BLIP: Bootstrapping Language-Image Pre-training for Unified Vision-Language Understanding and Generation, February 2022. URL <http://arxiv.org/abs/2201.12086>. arXiv:2201.12086 [cs].
- Li, K., Po, L.-M., Yang, H., Xu, X., Liu, K., and Zhao, Y. AesBiasBench: Evaluating Bias and Alignment in Multimodal Language Models for Personalized Image Aesthetic Assessment, September 2025. URL <http://arxiv.org/abs/2509.11620>. arXiv:2509.11620 [cs].
- Liu, J., Liu, G., Liang, J., Li, Y., Liu, J., Wang, X., Wan, P., Zhang, D., and Ouyang, W. Flow-GRPO: Training Flow Matching Models via Online RL, July 2025. URL <http://arxiv.org/abs/2505.05470>. arXiv:2505.05470 [cs].
- Ma, Y., Shui, Y., Wu, X., Sun, K., and Li, H. HPSv3: Towards Wide-Spectrum Human Preference Score, August 2025. URL <http://arxiv.org/abs/2508.03789>. arXiv:2508.03789 [cs].
- Maerten, A.-S., Chen, L.-W., De Winter, S., Bossens, C., and Wagemans, J. LAPIS: A novel dataset for personalized image aesthetic assessment, 2025. URL <https://arxiv.org/abs/2504.07670>. Version Number: 1.
- McHugh, M. L. Interrater reliability: the kappa statistic. *Biochimia Medica*, 22(3):276–282, October 2012. ISSN 1330-0962. URL <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3900052/>.
- Mordvintsev, A., Olah, C., and Tyka, M. Inceptionism: Going Deeper into Neural Networks. URL <https://research.google/blog/inceptionism-going-deeper-into-neural-networks/>.
- Peng, Y.-H., Bigham, J. P., and Wu, J. DesignPref: Capturing Personal Preferences in Visual Design Generation, November 2025. URL <http://arxiv.org/abs/2511.20513>. arXiv:2511.20513 [cs].
- Podell, D., English, Z., Lacey, K., Blattmann, A., Dockhorn, T., Müller, J., Penna, J., and Rombach, R. SDXL: Improving Latent Diffusion Models for High-Resolution Image Synthesis, July 2023. URL <http://arxiv.org/abs/2307.01952>. arXiv:2307.01952 [cs].
- Radford, A., Kim, J. W., Hallacy, C., Ramesh, A., Goh, G., Agarwal, S., Sastry, G., Askell, A., Mishkin, P., Clark, J., Krueger, G., and Sutskever, I. Learning Transferable Visual Models From Natural Language Supervision, February 2021. URL <http://arxiv.org/abs/2103.00020>. arXiv:2103.00020 [cs].
- Ren, J., Shen, X., Lin, Z., Mech, R., and Foran, D. J. Personalized Image Aesthetics. In *Proceedings of the IEEE International Conference on Computer Vision (ICCV)*, October 2017.
- Rettenberger, L., Reischl, M., and Schutera, M. Assessing political bias in large language models. *Journal of Computational Social Science*, 8(2):42, February 2025. ISSN 2432-2725. doi: 10.1007/s42001-025-00376-w. URL <https://doi.org/10.1007/s42001-025-00376-w>.
- Rozado, D. Measuring Political Preferences in AI Systems: An Integrative Approach, March 2025. URL <http://arxiv.org/abs/2503.10649>. arXiv:2503.10649 [cs].
- Sartwell, C. Beauty. In Zalta, E. N. and Nodelman, U. (eds.), *The Stanford Encyclopedia of Philosophy*. Metaphysics Research Lab, Stanford University, fall 2024 edition, 2024. URL <https://plato.stanford.edu/archives/fall2024/entries/beauty/>.

- Seshadri, P., Singh, S., and Elazar, Y. The Bias Amplification Paradox in Text-to-Image Generation, November 2023. URL <http://arxiv.org/abs/2308.00755>. arXiv:2308.00755 [cs].
- Sharma, M., Tong, M., Korbak, T., Duvenaud, D., Askell, A., Bowman, S. R., Cheng, N., Durmus, E., Hatfield-Dodds, Z., Johnston, S. R., Kravec, S., Maxwell, T., McCandlish, S., Ndousse, K., Rausch, O., Schiefer, N., Yan, D., Zhang, M., and Perez, E. Towards Understanding Sycophancy in Language Models, May 2025. URL <http://arxiv.org/abs/2310.13548>.
- Stacey Hill. Embracing the Blur | Photzy. URL <https://photzy.com/embracing-the-blur/>.
- Sun, K., Fang, R., Duan, C., Liu, X., and Liu, X. T2I-ReasonBench: Benchmarking Reasoning-Informed Text-to-Image Generation, August 2025. URL <http://arxiv.org/abs/2508.17472>. arXiv:2508.17472 [cs].
- Sutrop, M. Challenges of Aligning Artificial Intelligence with Human Values. *Acta Baltica Historiae et Philosophiae Scientiarum*, 8(2):54–72, December 2020. ISSN 22282009, 22282017. doi: 10.11590/abahps.2020.2.04. URL https://www.ies.ee/bahps/acta-baltica/abahps-8-2/04_Sutrop-2020-2-04.pdf.
- Tate. Dada. URL <https://www.tate.org.uk/art/art-terms/d/dada>.
- Taylor, J., Agnew, W., Sap, M., Fox, S. E., and Zhu, H. The Algorithmic Gaze: An Audit and Ethnography of the LAION-Aesthetics Predictor Model, January 2026. URL <http://arxiv.org/abs/2601.09896>. arXiv:2601.09896 [cs] version: 1.
- Turchin, A. Ai Alignment Problem: Human Values Don't Actually Exist. 2019. URL <https://philarchive.org/rec/TURAAP>.
- Vargas-Veleda, Y., del Mar Rodríguez-González, M., and Marauri-Castillo, I. Visual representations in ai: A study on the most discriminatory algorithmic biases in image generation. *Journalism and Media*, 6(3):110, 2025.
- Vianna, B. C. Aesthetic biases and opacity tactics in the training of visual artificial intelligence models. In *International Conference on Computational Intelligence in Music, Sound, Art and Design (Part of EvoStar)*, pp. 278–293. Springer, 2025.
- Wan, Y., Subramonian, A., Ovalle, A., Lin, Z., Suvarna, A., Chance, C., Bansal, H., Pattichis, R., and Chang, K.-W. Survey of Bias In Text-to-Image Generation: Definition, Evaluation, and Mitigation, May 2024. URL <http://arxiv.org/abs/2404.01030>. arXiv:2404.01030 [cs].
- Wang, Y., Li, Z., Zang, Y., Zhou, Y., Bu, J., Wang, C., Lu, Q., Jin, C., and Wang, J. Pref-GRPO: Pairwise Preference Reward-based GRPO for Stable Text-to-Image Reinforcement Learning, August 2025. URL <http://arxiv.org/abs/2508.20751>. arXiv:2508.20751.
- Wei, X., Zhang, J., Wang, Z., Wei, H., Guo, Z., and Zhang, L. TIIF-Bench: How Does Your T2I Model Follow Your Instructions?, June 2025. URL <http://arxiv.org/abs/2506.02161>. arXiv:2506.02161 [cs].
- Wu, X., Hao, Y., Sun, K., Chen, Y., Zhu, F., Zhao, R., and Li, H. Human Preference Score v2: A Solid Benchmark for Evaluating Human Preferences of Text-to-Image Synthesis, September 2023a. URL <http://arxiv.org/abs/2306.09341>. arXiv:2306.09341 [cs].
- Wu, X., Sun, K., Zhu, F., Zhao, R., and Li, H. Human Preference Score: Better Aligning Text-to-Image Models with Human Preference, August 2023b. URL <http://arxiv.org/abs/2303.14420>. arXiv:2303.14420 [cs].
- Xu, J., Liu, X., Wu, Y., Tong, Y., Li, Q., Ding, M., Tang, J., and Dong, Y. ImageReward: Learning and Evaluating Human Preferences for Text-to-Image Generation, December 2023. URL <http://arxiv.org/abs/2304.05977>. arXiv:2304.05977 [cs].
- Xu, J., Huang, Y., Cheng, J., Yang, Y., Xu, J., Wang, Y., Duan, W., Yang, S., Jin, Q., Li, S., Teng, J., Yang, Z., Zheng, W., Liu, X., Ding, M., Zhang, X., Gu, X., Huang, S., Huang, M., Tang, J., and Dong, Y. VisionReward: Fine-Grained Multi-Dimensional Human Preference Learning for Image and Video Generation, March 2025. URL <http://arxiv.org/abs/2412.21059>. arXiv:2412.21059 [cs].
- Xue, Z., Wu, J., Gao, Y., Kong, F., Zhu, L., Chen, M., Liu, Z., Liu, W., Guo, Q., Huang, W., and Luo, P. Dance-GRPO: Unleashing GRPO on Visual Generation, August 2025. URL <http://arxiv.org/abs/2505.07818>. arXiv:2505.07818.
- Zhang, S., Wang, B., Wu, J., Li, Y., Gao, T., Zhang, D., and Wang, Z. Learning Multi-dimensional Human Preference for Text-to-Image Generation, May 2024. URL <http://arxiv.org/abs/2405.14705>. arXiv:2405.14705 [cs].