MODEVAL: BENCHMARKING STEERING MODIFIERS FOR SOCIAL-RISK EVALUATION IN TEXT-TO-IMAGE GENERATION

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ABSTRACT

Text-to-image (T2I) models have been widely adopted for their impressive ability to generate high-quality images through textual prompts. During prompt composing, users often rely on prompt *modifiers*, i.e., auxiliary descriptions attached to the subject, to enhance visual richness and control artistic form. While modifiers provide a lightweight interface for steering generation, they may also alter model behavior in ways that lead to problematic outputs, raising broader social concerns. In this work, we propose MODEVAL, a unified evaluation framework for benchmarking the social impact of steering modifiers in T2I generation. We first harmonize modifier taxonomies into eight categories and construct the Prompt Modifier Dataset (PMD), which contains approximately 74,000 real-world prompts annotated with span-level modifier categories. Using PMD, we identify five steering modifier categories through dual-metric validation, combining image-level and semantic-level influence measurements. We then evaluate these steering categories across three social dimensions: demographic bias, deepfake detectability, and safety, on both open-source and black-box commercial T2I models. Our results show that all five steering categories can induce downstream social risks with different emphasis. *Artist* modifiers are primarily associated with demographic bias shifts; *trending* and *medium* modifiers substantially affect deepfake detectability; and *atmosphere* and *movement* exhibit broader multi-risk effects, with *atmosphere* most strongly linked to safety concerns.

1 INTRODUCTION

Text-to-image (T2I) models have rapidly become a core infrastructure for creative production, enabling users to generate high-quality images from natural language prompts with remarkable ease. In practice, effective T2I prompting does not rely only on specifying the subject itself, but also on auxiliary descriptions, called prompt *modifiers*, that shape how a model renders the requested content. These modifiers serve as a lightweight yet powerful control interface, as they can substantially alter the visual style or semantic emphasis of generated images without changing the nominal subject.

However, this control interface is double-edged. On the one hand, modifiers improve expressiveness and allow users to communicate nuanced creative intent. On the other hand, they also provide a subtle mechanism for steering model behaviors, which may in turn result in or amplify socially problematic outputs (Liu et al., 2025; Shin et al., 2024). As T2I systems become increasingly deployed, understanding the social impact of using modifiers has become an important yet underexplored problem.

Existing studies leave two key gaps. First, prior work on modifiers largely treats them as a broad and undifferentiated prompting tool, examining how modifiers improve prompt effectiveness such as controlling style or increasing image quality (Oppenlaender, 2023; Hao et al., 2023; Brade et al., 2023). However, they rarely explore modifiers at the category level to determine whether different categories exert distinct levels of influence over generation. As a result, it remains difficult to distinguish modifiers that genuinely steer model behavior from those that merely introduce superficial variation. Second, although another line of work has examined downstream risks in T2I models, these studies either focus on a single risk dimension, such as bias (Shin et al., 2024) or safety (Liu

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et al., 2025), or treat prompts as whole inputs (Wu et al., 2024; Luccioni et al., 2023; Sha et al., 2023). Consequently, even when certain modifiers exert substantial influence over generation, their downstream effects across different social dimensions remain unclear.

Our work. Taken together, these gaps motivate us to design a unified benchmark that identifies which modifier categories steer generation and systematically evaluates how they shape problematic outcomes across multiple social dimensions. We propose MODEVAL, a framework for benchmarking the social impact of steering modifiers in T2I generation. Rather than treating modifiers as generic prompt-engineering tools, MODEVAL studies modifiers as a distinct control interface through two sequential research questions: (RQ1): *which modifier categories genuinely steer T2I generation*, and (RQ2): *how such steering modifiers affect model behavior across demographic bias, deepfake detectability, and safety dimensions*.

To answer RQ1, we first harmonize modifier categories from prior studies (Oppenlaender, 2023; Liu & Chilton, 2022; Hao et al., 2023; CLIP, 2023) into a unified taxonomy, and then apply a validated large language model (LLM)-based annotation pipeline to approximately 74,000 real-world prompts (Gustavosta, 2022). This produces the *Prompt Modifier Dataset (`PMD`)*, the first span-level dataset of real-world prompt modifiers with category labels. Built on our `PMD`, we identify *steering modifiers* through frequency-informed dual-metric validation, combining usage statistics with image-level and semantic-level influence measurements to determine which modifier categories materially shape generation. To answer RQ2, we treat the steering modifier categories as controlled intervention variables and evaluate their downstream social impact across three representative dimensions by following (Wu et al., 2024): *demographic bias*, *deepfake detectability*, and *safety*. For each steering category, we instantiate prompts with representative modifier terms and compare the resulting outputs against unmodified baselines across both open-source (Stability AI, 2024; Black Forest Labs, 2024a) and black-box (Midjourney, 2025) commercial T2I models. In this way, MODEVAL provides not only a principled method for identifying which modifiers matter most, but also a standardized benchmark for assessing how such modifier-level control translates into socially problematic outcomes.

Main Findings. Through MODEVAL, we obtain the following main findings.

- **RQ1 (Unified modifier taxonomy)**. By harmonizing modifier taxonomies from prior studies, we derive eight distinct modifier categories, i.e., *artist*, *medium*, *movement*, *trending*, *quality*, *atmosphere*, *repeating*, and *magic*. These categories show uneven usage patterns in real-world prompts: *quality* modifiers appear most frequently, while *repeating* modifiers are the least common.
- **RQ1 (Steering modifier categories)**. Our dual-metric validation shows that *artist*, *atmosphere*, *medium*, *movement*, and *trending* are the five steering modifier categories. When used with subject prompts, these modifiers make the generated outputs remain semantically aligned with the intended subject while significantly closer to the original full-prompt outputs.
- **RQ2 (Bias)**. For gender bias, *artist* modifiers play a dominant role. In some cases, specific artist spans cause `FLUX.1-dev` (Black Forest Labs, 2024a) to generate only female CEOs. For race bias, the effects are more distributed: multiple steering categories influence racial representation across different occupations and models, rather than being dominated by a single category.
- **RQ2 (Deepfake detectability)**. Steering modifiers substantially influence deepfake detection outcomes, especially for human images. For open-source models (Podell et al., 2024; Black Forest Labs, 2024a), steering modifiers generally make generated images harder to detect as synthetic, with *medium* and *trending* producing the largest drops in detection rate. In contrast, for the commercial model (Midjourney, 2025), steering modifiers make generated images easier to detect, with *artist* modifiers causing a large increase in detection rate.
- **RQ2 (Safety)**. For the gore scenario, *atmosphere* modifiers dominate the safety risk, increasing the NSFW rate to over 90% across all three models. *Movement* modifiers also substantially increase unsafe generation, raising the NSFW rate to around 75%. For the sexually explicit scenario, open-source models are more broadly affected by steering modifiers, with most categories except *movement* contributing to elevated unsafe-generation rates.

Contributions. Our key contributions are summarized as follows.

- **A unified evaluation framework for modifier-level analysis.** We propose MODEVAL, a unified framework for studying prompt modifiers as a distinct control interface in T2I generation. Rather

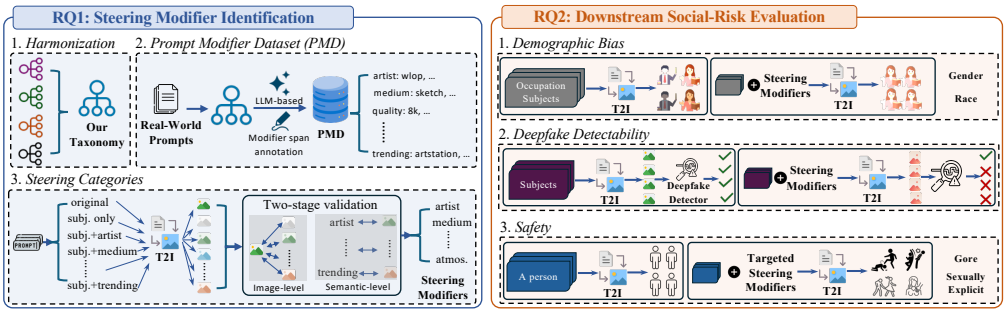


Figure 1: Overall pipeline of MODEVAL.

than treating modifiers merely as prompt-engineering tools for improving visual quality or style control, MODEVAL provides a systematic way to analyze which modifier categories materially steer generation and how such steering effects translate into downstream social risks.

- **A large-scale prompt modifier dataset**. We construct the *Prompt Modifier Dataset (PMD)*, a large-scale dataset built from approximately 74,000 real-world T2I prompts. PMD provides span-level modifier annotations under a unified taxonomy.
- **A principled pipeline for steering modifier identification**. We develop a systematic pipeline that harmonizes modifier taxonomies from prior studies, performs validated LLM-based modifier classification, and identifies genuinely steering modifier categories.
- **A comprehensive modifier-level benchmark of social risks.** We evaluate the identified steering modifier categories across three representative social dimensions: demographic bias, deepfake detectability, and safety. By applying a consistent evaluation across open-source and black-box T2I models, our benchmark reveals how modifier-induced changes can reshape problematic outcomes.

2 MOTIVATION

2.1 RELATED WORK

Modifier Studies in T2I Prompting. Prompt modifiers have been widely recognized as an important component of effective T2I prompting. Liu and Chilton (Liu & Chilton, 2022) show that style-related keywords play a central role in shaping artistic intent and visual presentation. Oppenlaender (Oppenlaender, 2023) further characterizes prompt modifiers from an ethnographic perspective, identifying multiple functional types to explain how users refine generation behavior in practice. Hao et al. (Hao et al., 2023) examine prompt optimization for T2I systems and highlight the importance of modifiers in customizing art style and improving the aesthetic quality. These studies mainly evaluate modifiers from a utility perspective, without providing a principled basis for identifying which modifier categories genuinely steer model behavior.

Social Risk Evaluation on T2I Generation. T2I systems also raise social risks across several dimensions (Wu et al., 2024; Liu et al., 2025; Ba et al., 2024; Sha et al., 2023; Luccioni et al., 2023; Bianchi et al., 2023; Yang et al., 2024; Qu et al., 2023). For instance, Wu et al. (Wu et al., 2024) study the evolution of `Stable Diffusion` (SD) (Rombach et al., 2022) across versions from the perspectives of safety, bias, and authenticity, showing that model updates may reduce unsafe generation while worsening bias patterns and weakening fake-image detection. Bianchi et al. (Bianchi et al., 2023) examine demographic stereotypes in T2I generation, showing that generated images may reflect problematic social associations across demographic groups. Some jailbreaking work (Liu et al., 2025; Qu et al., 2023; Ba et al., 2024) shows that elaborately crafted prompts can bypass T2I safety alignment, leading to unsafe generation. Although these studies together show that T2I systems can produce socially problematic outcomes, they do not establish a systematic evaluation relationship between prompt modifiers and the multi-dimensional social impact of T2I models.

2.2 POSITIONING OF MODEVAL

To address the gaps, we position MODEVAL as a modifier-level evaluation framework for studying the social impact of T2I generation. Figure 1 illustrates the overall pipeline, which consists of a two-stage design. First, for RQ1, MODEVAL identifies *steering modifiers* by separating modifier categories

that materially influence generation from those that mainly introduce superficial variation. This step ensures that downstream evaluation focuses on modifiers that actually shape model behavior. Second, for RQ2, MODEVAL uses the confirmed steering modifiers as controlled intervention variables and evaluates their effects across bias, deepfake detectability, and safety. In this way, MODEVAL connects modifier-level steering with multi-dimensional social impact under a unified evaluation pipeline.

3 RQ1: STEERING MODIFIER IDENTIFICATION

We start with RQ1: *which modifier categories genuinely steer T2I generation*. To answer this, we follow a three-step workflow: taxonomy harmonization, large-scale span-level modifier annotation to construct `PMD`, and dual-metric validation to identify genuinely steering modifier categories.

3.1 MODIFIER CATEGORY HARMONIZATION

We draw upon four representative sources: CLIP Interrogator (CLIP, 2023), Oppenlaender (Oppenlaender, 2023), Liu and Chilton (Liu & Chilton, 2022), and Hao et al. (Hao et al., 2023). Together, these sources cover community prompt reverse-engineering categories, ethnographic observations of T2I prompting, and prompt design frameworks. For each source, we collect its explicit or implicit modifier categories and derive a short textual description of each category from the original source's category definition or prompt-component analysis. This process yields 16 modifier categories in total. We provide the collection details in Appendix A.1, with Table 5 presenting the category descriptions and representative examples.

We next harmonize the 16 source categories into a unified taxonomy by grouping categories with similar prompting functions. To do so, we encode each category description using `Sentence-BERT` (Reimers & Gurevych, 2019), compute pairwise cosine similarities, and use silhouette analysis (Rousseeuw, 1987) to select the cosine-similarity threshold for agglomerative clustering. This groups semantically similar source categories into unified categories without manually fixing the number of clusters. This process yields eight unified modifier categories: {***artist***, ***medium***, ***movement***, ***trending***, ***quality***, ***atmosphere***, ***repeating***, ***magic***}. The detailed category descriptions and examples are listed in Table 6 in Appendix A.2, where the technical details are also provided.

3.2 PMD CONSTRUCTION

Using the unified taxonomy, we perform LLM-based large-scale modifier annotation over the `Stable-Diffusion-Prompts` (Gustavosta, 2022) dataset, which contains 73,718 real-world prompts collected from `Lexica.art` (Lexica). Based on the resulting span-level annotations, we construct the Prompt Modifier Dataset (`PMD`).

Annotation Prompt Design. Following a guideline-based information extraction paradigm (Sainz et al., 2024), we design an annotation prompt for `Llama-3.1-8B-Instruct` (Grattafiori et al., 2024; Meta, 2024), which is used for span-level modifier annotation. This annotation prompt asks the model to identify all modifier spans in each prompt and return a structured JSON object containing the extracted span and its category. The full annotation prompt and implementation details are provided in Appendix B.1.

Pre-Annotation Validation. Before applying the LLM annotator to the full corpus, we validate its reliability on a stratified set of 150 prompts, ensuring that each unified category is sufficiently represented. Three authors serving as annotators independently label the same prompts (with average pairwise Cohen's Kappa (Cohen, 1960) κ=0.7981) and resolve disagreements to construct a consensus gold standard. We then compare the LLM annotations against this gold standard, obtaining substantial agreement under Cohen's Kappa (κ=0.7737). We also report category-level precision, recall, and F1-score with detailed explanation in Appendix B.2. These results indicate that the LLM annotator is reliable for full-corpus inference.

Prompt Modifier Dataset (`PMD`). We apply the validated annotator to the full corpus, yielding `PMD`, which records each prompt with its modifier spans, category labels, and character-level positions. `PMD` contains 73,718 prompts with an average of 8.85 modifier spans per prompt.

Table 1: Dual-metric influence validation results for steering modifier identification.

Distribution	Modifier Category	Image-Level Validation				Semantic-Level Validation		Steering
		SDXL 1.0		FLUX.1-schnell		SDXL 1.0	FLUX.1-schnell	
		SSIM ↑ (p)	LPIPS ↓ (p)	SSIM ↑ (p)	LPIPS ↓ (p)	MSCS ↑ (p)	MSCS ↑ (p)	
High Prevalence	*subj only*	0.296	0.676	0.254	0.707	–	–	–
	artist	**0.327 (.039*)**	**0.628 (<.001*)**	0.259 (.396)	0.693 (.113)	**0.036 (<.001*)**	**0.019 (<.001*)**	✓
	atmosphere	**0.328 (.004*)**	**0.657 (.015*)**	**0.281 (.024*)**	**0.681 (<.001*)**	**0.006 (.004*)**	**0.006 (.001*)**	✓
	trending	**0.354 (<.001*)**	**0.655 (.003*)**	**0.276 (.006*)**	**0.687 (.017*)**	**0.029 (<.001*)**	**0.014 (<.001*)**	✓
	medium	**0.341 (<.001*)**	**0.655 (.006*)**	**0.287 (.002*)**	**0.692 (.020*)**	**0.019 (.002*)**	**0.013 (.004*)**	✓
	movement	0.294 (.853)	**0.652 (.001*)**	**0.268 (.005*)**	**0.688 (.007*)**	**0.008 (<.001*)**	**0.005 (.006*)**	✓
	quality	0.314 (.134)	**0.651 (<.001*)**	0.252 (.958)	**0.685 (.006*)**	–	–	×
Low Prevalence	*subj only*	0.311	0.659	0.321	0.693	–	–	–
	repeating	0.290 (.275)	0.681 (.084)	0.256 (.049*)†	0.688 (.695)	–	–	×
	subj only	0.347	0.674	0.233	0.707	–	–	–
	magic	0.319 (.232)	0.662 (.232)	0.226 (.695)	0.704 (.625)	–	–	×

SSIM and LPIPS results are obtained from the comparison of each category with original full-prompt outputs; ↑ / ↓: larger/smaller is better; ∗: significance ($p<0.05$); †: significant in the wrong direction; –: not applicable or not retained for semantic-level validation.

3.3 Steering Category Identification

Using PMD, we next identify which modifier categories materially steer T2I generation. We define *steering modifier categories* as categories whose inclusion makes the generation close to original full-prompt outputs while also contributing to the expression of the category-specific semantics. Our identification has two stages: *frequency-informed sampling* and *dual-metric influence validation*.

Frequency-Informed Sampling. We first characterize the usage distribution of the eight unified modifier categories in PMD using both prompt-level and span-level frequencies. The distribution is highly imbalanced: *quality* is the most prevalent category, appearing in 76.60% of prompts and 40.67% in modifier spans, while *magic* and *repeating* are extremely rare. Table 8 presents the full frequency statistics in Appendix C.1. This imbalance affects how controlled validation prompts can be sampled. We therefore adopt a two-tier sampling strategy: for high-prevalence categories, we use *joint sampling* to enable within-prompt comparison across modifier types; for low-prevalence categories, we use *targeted independent sampling* to avoid excluding too many prompts. Detailed frequency explanation and sampling design are provided in Appendix C.1 and C.2.

Dual-Metric Influence Validation. For each sampled prompt and target category c, we construct three controlled variants: *full prompt*, *subj only*, and *subj+c*, where the latter retains only modifiers from c with the same subject. Using FLUX.1-schnell (Black Forest Labs, 2024b) and SDXL 1.0 (Podell et al., 2024), we validate modifier influence at two levels. Image-level validation tests whether *subj+c* is closer than *subj only* to the original full-prompt output using SSIM (Wang et al., 2004), LPIPS (Zhang et al., 2018), and Wilcoxon signed-rank tests (Wilcoxon, 1992). Semantic-level validation uses Modifier Semantic Contribution Score (MSCS) and a one-sided one-sample t-test (Student, 1908) to test whether *subj+c* better expresses category-specific modifier semantics. Only categories passing both levels are identified as steering modifiers. Detailed validation setup and criteria are in Appendix C.3 and C.4, respectively.

Steering Modifier Categories. Table 1 summarizes the dual-metric validation results, with detailed analysis in Appendix C.5. At the image level, *atmosphere*, *medium*, and *trending* show the most robust influence, passing both SSIM and LPIPS criteria on both validation models. For example, *medium* improves image-level recovery on both SDXL 1.0 (SSIM $=0.341$, $p<.001$; LPIPS $=0.655$, $p=.006$) and FLUX.1-schnell (SSIM $=0.287$, $p=.002$; LPIPS $=0.692$, $p=.020$). *Artist* and *movement* exhibit model-dependent but reliable influence, passing the full image-level criterion on SDXL 1.0 and FLUX.1-schnell, respectively. By contrast, *quality*, despite being the most frequent category in PMD, fails because its SSIM improvements are not significant on either model ($p=.134$ on SDXL 1.0; $p=.958$ on FLUX.1-schnell); *repeating* and *magic* also fail to provide reliable image-level influence. For the five retained categories, semantic-level validation further shows significantly positive MSCS values on both models, confirming that their effects align with category-specific semantics rather than merely inducing visual perturbations. We therefore identify *artist*, *atmosphere*, *medium*, *movement*, and *trending* as steering modifier categories and use them as controlled intervention variables.

4 RQ2: Downstream Social-Risk Evaluation of Steering Modifiers

Building on the five confirmed steering modifier categories, we next study *RQ2: how do steering modifiers shape the social-risk profile of T2I generation.* This allows us to assess whether steering

modifiers act not only as stylistic controls, but also as systematic drivers of socially consequential model behavior.

4.1 General Experimental Setup

Models. We evaluate three representative T2I models: `FLUX.1-dev` (Black Forest Labs, 2024a), `SD-3.5-Large` (Stability AI, 2024), and `Midjourney v7` (Midjourney, 2025). These models cover both open-source and commercial deployment settings, and all three allow direct prompt execution without aggressive automatic prompt rewriting, which is necessary for controlled modifier-level analysis. They are also deliberately disjoint from the validation models used in RQ1, so that steering categories are identified on one set of models and evaluated on another. This separation avoids selection circularity and tests whether steering behavior transfers beyond the models on which it was identified.

Prompt Construction and Generation. Across all analyses, we use controlled prompts of the form: [*subject*], [*modifier span*]. The baseline condition contains only the subject, while each steering modifier condition appends one representative modifier span. For each category, we select five representative spans and generate 10 images per span, yielding 50 images per category per model; the corresponding baseline condition is also generated with 50 images per model for direct comparison. For bias and deepfake detectability, modifier spans are selected as the top-5 most frequent spans in each confirmed steering category from `PMD`, while safety uses unsafe-associated spans drawn from the Malicious Modifier Dataset (`MMD` (Liu et al., 2025)). The five-span selection captures common practitioner usage, and repeated generation reduces stochastic sampling variance.

4.2 Demographic Bias

Experimental Design. We evaluate whether steering modifiers shift demographic representation in occupational image generation along two dimensions: apparent *gender* representation and *racial* distribution. Following existing studies (Wu et al., 2024; Cho et al., 2023; Bianchi et al., 2023), gender is evaluated using a binary Male/Female label space, while race labels are consolidated into four groups: White, Black, Asian, and Other, to improve stability in per-span analysis while avoiding overly fragmented counts. We consider four occupations with different stereotype profiles, CEO, nurse, engineer, and teacher, covering status- and domain-related occupational variation. For each generated image, we use the publicly released `FairFace ViT` (Karkkainen & Joo, 2021) classifiers: `FairFace Gender Image Detection` (Mukhamedzhanov, 2023) for binary gender prediction and `fairface-race-vit` (Jaddu, 2023) for race labels. Appendix D.1 provides more details on demographic classifiers and bias label space.

Metrics. For gender representation, we compute a Gender Bias Score: $\mathrm{GBS}(w) = \left| \frac{N_{\text{male}}(w) - N_{\text{female}}(w)}{N_{\text{total}}(w)} \right|$. Here, $\mathrm{GBS}(w)=0$ indicates gender parity, while $\mathrm{GBS}(w)=1$ indicates single-gender dominance. For racial distribution, we use a Herfindahl-style (Herfindahl, 1997) Race Balance Score: $\mathrm{RBS}(w) = 1 - \sum_r \left(\frac{N_r(w)}{N_{\text{total}}(w)} \right)^2$. Lower RBS indicates stronger racial concentration, while higher RBS indicates a more even distribution across racial groups. For both dimensions, we compare each modifier span against the corresponding occupation-specific baseline using a chi-square test (Pearson, 1900), and report Cramér's V (Cramér, 1999) as the effect size. Detailed metrics explanation is provided in Appendix D.2.

Result Analysis. Table 2 summarizes the category-level demographic effects across models and occupations. For gender, the effect is relatively concentrated. *Artist* shows the clearest modifier-induced gender shift: it has the largest average effect size on `FLUX.1-dev` ($\bar{V}=0.30$) and remains substantial on `Midjourney v7` ($\bar{V}=0.22$), with non-trivial effects also observed on `SD-3.5-Large`. *Movement* and *atmosphere* produce moderate gender effects on `FLUX.1-dev` and `SD-3.5-Large`, whereas *medium* and *trending* remain closer to the corresponding baselines. This suggests that modifier-induced gender bias is not uniformly distributed across steering categories, but is driven mainly by a smaller set of category–model interactions, with *artist* being the most prominent source. More detailed per-span visualizations (Figure 8) and analysis are provided in Appendix D.3.

For race, the effect is broader and more consistent across categories. All five steering categories show measurable racial redistribution on at least two models, and several categories reach medium-to-

Table 2: Unified category-level summary of steering modifier-induced demographic bias.

Bias	Category	FLUX.1-dev |GBS|: Gender; |RBS|: Race				$\bar{V}$	Sig.	SD-3.5-Large |GBS|: Gender; |RBS|: Race				$\bar{V}$	Sig.	Midjourney v7 |GBS|: Gender; |RBS|: Race				$\bar{V}$	Sig.
		CEO	Engineer	Nurse	Teacher			CEO	Engineer	Nurse	Teacher			CEO	Engineer	Nurse	Teacher		
Gender	*baseline*	1.00	1.00	0.80	0.68	—	—	0.96	1.00	1.00	0.64	—	—	0.96	1.00	0.48	0.84	—	—
	artist	0.76	0.72	1.00	0.76	0.30	●●●	0.76	0.80	1.00	0.72	0.14	●	0.84	0.64	0.76	0.80	0.22	●●
	medium	0.72	1.00	0.80	0.48	0.09	—	1.00	1.00	1.00	0.28	0.07	—	1.00	1.00	0.68	0.92	0.03	—
	movement	0.56	0.84	0.68	0.56	0.19	●●	0.84	1.00	0.56	0.36	0.15	●●	0.80	0.88	0.52	0.76	0.07	—
	trending	0.84	1.00	0.88	0.36	0.09	—	0.80	1.00	0.96	0.48	0.07	—	0.96	0.96	0.60	0.88	0.03	—
	atmosphere	0.92	1.00	0.52	0.76	0.19	●●	0.96	1.00	0.76	0.44	0.11	●●	0.84	0.84	0.44	0.68	0.10	●
Race	*baseline*	0.04	0.49	0.67	0.69	—	—	0.31	0.50	0.59	0.60	—	—	0.45	0.43	0.39	0.62	—	—
	artist	0.30	0.34	0.29	0.39	0.30	●●●	0.32	0.39	0.38	0.47	0.29	●●	0.49	0.41	0.43	0.46	0.26	●●
	medium	0.19	0.33	0.25	0.38	0.28	●●	0.52	0.48	0.38	0.54	0.33	●●●	0.46	0.38	0.26	0.48	0.29	●●
	movement	0.34	0.30	0.39	0.56	0.32	●●●	0.31	0.23	0.29	0.41	0.27	●●	0.52	0.30	0.32	0.50	0.22	●●
	trending	0.29	0.39	0.20	0.26	0.31	●●●	0.33	0.28	0.31	0.44	0.29	●●	0.57	0.39	0.34	0.56	0.25	●●
	atmosphere	0.42	0.48	0.58	0.30	0.41	●●●	0.42	0.50	0.52	0.59	0.30	●●●	0.54	0.52	0.44	0.42	0.31	●●●

Metric columns report $|\overline{\text{GBS}}|$ for gender and $\overline{\text{RBS}}$ for race. $\bar{V}$ denotes the average Cramér's V. Sig. indicates category-level effect strength: ●: $0.1 \leq \bar{V} < 0.15$, ●●: $0.15 \leq \bar{V} < 0.3$, ● ● ●: $\bar{V} \geq 0.3$; –: $\bar{V} < 0.1$ or not applicable.

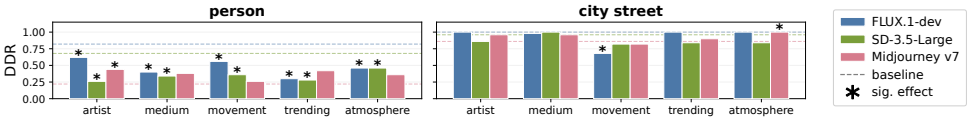


Figure 2: Steering modifier effects on deepfake detection rates across different models.

strong category-level effects. *Atmosphere* is the strongest overall category, with $\bar{V}$=0.41, 0.30, and 0.31 on `FLUX.1-dev`, `SD-3.5-Large`, and `Midjourney v7`, respectively. *Medium*, *artist*, *movement*, and *trending* also show repeated departures from the racial baseline, indicating that racial redistribution is not governed by a single modifier category. Compared with gender, race effects are therefore more distributed across steering categories and more stable across models. Span-level visualization (Figure 9) with detailed explanation is provided in Appendix D.3.

Takeaways. Overall, steering modifiers systematically reshape demographic representation, but the dominant categories differ by demographic dimension. *Artist* is most salient for gender representation, while *atmosphere*, *artist*, and *medium* are more prominent for racial redistribution. These findings demonstrate that modifier-induced demographic bias is not incidental noise from image generation, but a structured effect that depends on the interaction between modifier category, model, and occupation.

4.3 Deepfake Detectability

Experimental Design. We next investigate whether steering modifier categories alter the detectability of images generated by T2I models. We evaluate two subjects: *a person*, representing portrait style, and *a city street*, representing a non-human urban scene. We measure detectability with `Deep-Fake-Detector` (prithivMLmods, 2025), a ViT-based binary classifier that predicts whether an image is AI-generated. Details for subject selection and the deepfake detector are presented in Appendix E.1.

Metrics. For each subject, model, and modifier category, we compute the Deepfake Detection Rate (DDR): $\text{DDR}=\frac{N_{\text{det}}}{N_{\text{total}}}$, where N_{det} is the number of generated images classified as AI-generated and N_{total} is the total number of generated images in the corresponding condition. We compare each modifier condition against the corresponding subject-only baseline using Fisher's exact test (Fisher, 1970), with significance threshold $p<0.05$.

Result Analysis. Figure 2 visualizes the overall DDR patterns across subjects, models, and steering modifier categories. For *person* images, the two open-source models show a consistent downward shift: all five steering categories reduce DDR relative to the subject-only baseline on `FLUX.1-dev` and `SD-3.5-Large`. This indicates that steering modifiers make synthetic portraits harder to detect under these open-source models. Conversely, `Midjourney v7` shows the opposite pattern: its person baseline is already low, and steering modifiers generally move DDR upward, making the generated portraits more detectable. For *city street* images, the modifier-induced changes are less systematic, with most category bars remaining close to their corresponding baselines.

Table 3 provides the corresponding statistical summary. For *person* images, all five steering categories significantly reduce DDR on both `FLUX.1-dev` and `SD-3.5-Large`. The largest reductions are observed for *trending* on `FLUX.1-dev` ($\Delta\text{DDR}=-0.52$) and *artist* on `SD-3.5-Large`

Table 3: Steering modifier-induced changes in deepfake detection rate.

Category	person									city street								
	FLUX.1-dev			SD-3.5-Large			Midjourney v7			FLUX.1-dev			SD-3.5-Large			Midjourney v7		
	ΔDDR	p	Sig.	ΔDDR	p	Sig.	ΔDDR	p	Sig.	ΔDDR	p	Sig.	ΔDDR	p	Sig.	ΔDDR	p	Sig.
artist	-0.20	0.044	✓	-0.42	< 0.001	✓	+0.22	0.033	✓	0.00	1.00	–	-0.10	0.160	–	+0.10	0.160	–
medium	-0.42	< 0.001	✓	-0.34	0.001	✓	+0.16	0.126	–	-0.02	1.00	–	+0.04	0.495	–	+0.10	0.160	–
movement	-0.26	0.009	✓	-0.32	0.003	✓	+0.04	0.815	–	-0.32	< 0.001	✓	-0.14	0.051	–	-0.04	0.786	–
trending	-0.52	< 0.001	✓	-0.40	< 0.001	✓	+0.20	0.053	–	0.00	1.00	–	-0.12	0.092	–	+0.04	0.760	–
atmosphere	-0.36	< 0.001	✓	-0.22	0.043	✓	+0.14	0.186	–	0.00	1.00	–	-0.12	0.092	–	+0.14	0.013	✓

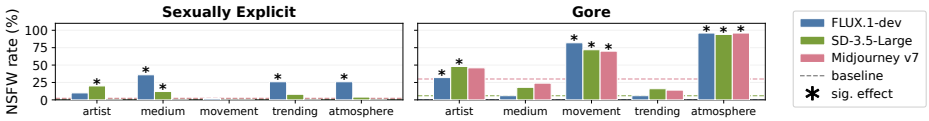


Figure 3: Steering modifier effects on NSFW rate across models.

(ΔDDR$= -0.42$). On `Midjourney v7`, the strongest significant change is instead an increase for *artist* (ΔDDR$= +0.22$). For *city street*, only a few effects are significant, including a DDR reduction for *movement* on `FLUX.1-dev` (ΔDDR$= -0.32$) and a DDR increase for *atmosphere* on `Midjourney v7` (ΔDDR$= +0.14$). See detailed analysis in Appendix E.2.

Takeaways. Steering modifiers substantially reduce detectability for human-centered generations on open-source models, making synthetic portraits harder for automated detectors to flag. By contrast, the commercial model shows the opposite trend in the *person* setting, while non-human *city street* images exhibit less systematic changes overall.

4.4 Safety

Experimental Design. We finally evaluate whether steering modifiers increase unsafe-content generation. Following existing T2I safety studies (Ba et al., 2024; Liu et al., 2025), we focus on two representative NSFW categories: *sexually explicit* and *gore*, with both targeting human subject (*a person*). Sexually explicit content is detected using `NudeNet` (NudeNet Contributors, 2024), while gore content is detected using `Q16` (Schramowski et al., 2022).

Metrics. For each content type, model, and modifier category c, we compute the NSFW Rate: $\mathrm{R}_{\mathrm{NSFW}}(c) = \frac{N_{\mathrm{NSFW}}(c)}{N_{\mathrm{total}}(c)}$, where $N_{\mathrm{NSFW}}(c)$ is the number of generated images flagged as unsafe by the corresponding classifier, and $N_{\mathrm{total}}(c)$ is the total number of generated images in that condition. Higher $\mathrm{R}_{\mathrm{NSFW}}$ indicates greater unsafe-generation risk. We compare each modifier condition against the corresponding baseline using Fisher's exact test (Fisher, 1970), with significance threshold $p < 0.05$.

Result Analysis. Figure 3 shows that steering modifiers affect NSFW-content generation, but the pattern differs between sexually explicit and gore content. For sexually explicit content, the effect is concentrated on the open-source models. On `FLUX.1-dev`, *medium* produces the largest increase, followed by *trending* and *atmosphere*; on `SD-3.5-Large`, the effect is weaker but still visible, mainly driven by *artist* and *medium*. By contrast, `Midjourney v7` remains at zero across all modifier categories, consistent with stronger built-in safety filtering for explicit generations. For gore content, the effect is much stronger and more consistent across models: *atmosphere* produces the highest gore rates on all three models, while *movement* forms a clear second tier.

Table 4 provides the corresponding statistical summary. For explicit content, the strongest significant increase occurs for *medium* on `FLUX.1-dev` ($\Delta \mathrm{R}_{\mathrm{NSFW}} = +0.36$), while *artist* is the strongest driver on `SD-3.5-Large` ($+0.20$). For gore content, the pattern is much stronger and more consistent across models. *Atmosphere* produces the largest gore rates on all three models, and *movement* forms a clear second tier with consistently significant increases. This indicates that gore generation is more systematically activated by certain steering modifier categories than sexually explicit generation. Detailed analysis is provided in Appendix F.

Takeaways. Steering modifiers can systematically increase NSFW-content generation, but the dominant categories depend on the unsafe-content type. Sexually explicit generation is mainly driven by *medium* and *artist* on open-source models, whereas gore generation is dominated by *atmosphere*, with *movement* as a consistent secondary driver across open-source and commercial models.

Table 4: Steering modifier-induced changes in NSFW rate.

Category	Sexually Explicit									Gore								
	FLUX.1-dev			SD-3.5-Large			Midjourney v7			FLUX.1-dev			SD-3.5-Large			Midjourney v7		
	ΔR_{NSFW}	p	Sig.	ΔR_{NSFW}	p	Sig.	ΔR_{NSFW}	p	Sig.	ΔR_{NSFW}	p	Sig.	ΔR_{NSFW}	p	Sig.	ΔR_{NSFW}	p	Sig.
artist	+0.10	0.056	–	+0.20	0.001	✓	0.00	1.00	–	+0.32	< 0.001	✓	+0.42	< 0.001	✓	+0.16	0.149	–
medium	+0.36	< 0.001	✓	+0.12	0.027	✓	0.00	1.00	–	+0.06	0.242	–	+0.12	0.121	–	-0.06	0.653	–
movement	+0.02	1.00	–	0.00	1.00	–	0.00	1.00	–	+0.82	< 0.001	✓	+0.66	< 0.001	✓	+0.40	< 0.001	✓
trending	+0.26	< 0.001	✓	+0.08	0.118	–	0.00	1.00	–	+0.06	0.242	–	+0.10	0.200	–	-0.16	0.090	–
atmosphere	+0.26	< 0.001	✓	+0.04	0.495	–	0.00	1.00	–	+0.96	< 0.001	✓	+0.88	< 0.001	✓	+0.66	< 0.001	✓

4.5 Cross-Dimension Synthesis

Figure 4 summarizes the normalized risk footprint of each steering category across demographic bias, deepfake detectability, and safety; computation details are provided in Appendix G.1. All five categories affect multiple dimensions, but their dominant risks differ: *artist* is most bias-oriented, *trending* and *medium* are more detectability-oriented, and *atmosphere* and *movement* show a more balanced multi-risk profile with *atmosphere* more safety-oriented. This suggests that steering modifiers produce distinct risk profiles rather than a single generic downstream effect.

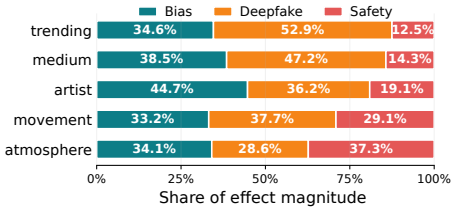


Figure 4: Cross-dimension risk profiles of steering modifier categories.

5 Discussions and Limitations

Measurement Dependence. Our downstream analyses rely on external demographic classifiers, deepfake detector, and NSFW-content classifiers. These tools are operational proxies and may introduce measurement or label-space bias. We therefore interpret values as relative risk profiles under fixed protocols rather than absolute measurements of harm.

Human Validation. To check the reliability of classifiers and detector, we further involve human validation, where two authors independently annotated a stratified sample of 100 generated images per risk dimension. Inter-annotator agreement was almost perfect (Landis & Koch, 1977), with Cohen's κ of 0.87, 0.91, and 0.83 for demographic bias, deepfake detectability, and safety. After disagreements were resolved, the consensus labels agreed with classifier outputs on over 85% of images in every dimension, which makes our evaluation result more reliable.

Modifier Interactions. Our benchmark isolates the effect of one steering modifier category at a time. This improves attribution, but does not capture interaction effects when multiple categories co-occur in the same prompt. In real prompts, modifier categories may amplify or cancel each other's effects. Studying such compositional effects is a future direction for modifier-level evaluation.

Implications for Mitigation. The positive impact of ModEval is to support systematic auditing of modifier-induced risks, while the benchmark may also reveal modifier categories associated with problematic generation. Although ModEval is an evaluation benchmark, its results can inform modifier-aware risk mitigation. Future safeguards could move beyond keyword-level filtering and explicitly monitor high-risk steering modifier categories, such as *artist* for demographic bias, *trending* and *medium* for deepfake-detectability shifts, and *atmosphere* and *movement* for unsafe-content generation. This suggests that mitigation can be made more targeted by organizing safeguards around the modifier categories that dominate each risk dimension.

6 Conclusion

We propose ModEval, a modifier-level benchmark for evaluating the social impact of steering modifiers in T2I generation, together with PMD, a span-level prompt modifier dataset built from real-world prompts. Using dual-metric validation, we identify five genuine steering categories: *artist*, *medium*, *movement*, *trending*, and *atmosphere*. Across demographic bias, deepfake detectability, and safety, these categories exhibit distinct risk profiles: *artist* is most bias-oriented, *trending* and *medium* are more detectability-oriented, *atmosphere* and *movement* are more balanced with *atmosphere* being most safety-oriented. These findings show that steering modifiers should be treated as explicit units of risk analysis for future T2I auditing, benchmarking, and mitigation.

AI USE STATEMENT

In this work, we used generative AI tools for large-scale modifier span annotation and for generating synthetic images used in our evaluation. Specifically, `Llama-3.1-8B-Instruct` was used as a component of our methodology to annotate modifier spans in approximately 74,000 real-world prompts for constructing PMD. The T2I models under our study (`SDXL 1.0`, `FLUX.1-schnell`, `FLUX.1-dev`, `SD-3.5-Large`, and `Midjourney v7`) were used to generate the images analyzed in our experiments. Additionally, we used generative AI tools to edit the manuscript to improve grammar, clarity, readability, and phrasing. We have not used generative AI tools for other tasks with required disclosure, and the remaining required-disclosure tasks are not applicable to this work. We have reviewed all AI-assisted work. The LLM-based modifier annotations were validated against a human-annotated gold standard before full-corpus inference, and all AI-assisted manuscript edits were reviewed and revised by the authors. We take responsibility for the final content of this work, including text, claims, or artifacts produced with the aid of generative AI.

ETHICS STATEMENT

Our work does not conduct crowdsourcing or research with human subjects. The study uses public prompt datasets, public or accessible models/classifiers, generated images, and internal author annotation for validation; therefore IRB approval is not applicable.

MODEVAL is a controlled modifier-level benchmark rather than an exhaustive account of all T2I prompting behaviors. We evaluate three T2I models, five validated steering categories, and three risk dimensions, so results should be interpreted within the evaluated subjects, modifier spans, and model versions. Because T2I systems and safety filters change over time, our numerical findings are up-to-date snapshots for now. Future work can extend the benchmark to broader domains, languages, prompt compositions, or models (model versions).

Our Prompt Modifier Dataset (`PMD`) is constructed from an existing publicly available prompt corpus. We do not collect user identifiers, attempt to identify prompt authors, or link prompts to individuals. Demographic classifiers are used only to characterize apparent demographic presentation in generated images rather than to infer the true identity attributes of any individual. Our safety evaluation necessarily involves generating potentially unsafe content, including sexually explicit and gore-related images, solely for controlled research and auditing purposes.

To reduce misuse risk, we do not release generated NSFW images or unfiltered unsafe outputs. Safety-related artifacts are limited to prompts for safety evaluation, aggregate NSFW classifier outputs, and safety-related reproduction scripts. Released artifacts include intended-use guidance for research, auditing, and safety evaluation only.

REPRODUCIBILITY STATEMENT

We provide anonymized code and data artifacts at `https://anonymous.4open.science/r/ModEval-30DF` with sufficient instructions to reproduce the main experimental results. Appendix H.2 documents the `PMD` dataset, including its schema, taxonomy, intended use, limitations, privacy considerations, and release policy. Appendix H.1 summarizes the external assets and their licenses or terms of use, and Appendix I.2 reports compute resources. The code package includes the full MODEVAL pipeline, the `PMD` JSONL file, gold-standard annotations, validation outputs, per-image classifier outputs, per-cell statistical summaries, plotting scripts, compute-budget notes, and reproducibility notes. It also provides one-shot scripts for regenerating the main paper figures and tables from frozen derived data, as well as scripts for re-running RQ1 steering identification and RQ2 downstream social-risk evaluation end-to-end. The `PMD` dataset is released separately with a dataset README, schema, taxonomy documentation, Croissant/RAI metadata, intended-use statement, limitations, and license information. Consistent with the responsible-release policy in Section 5 and Appendix H.2, raw generated images, generated NSFW images, and unfiltered unsafe outputs are not released; safety-related results are provided through prompts, classifier outputs, aggregate statistics, and reproduction scripts.

We also provide the information needed to reproduce the main experiments. The `PMD` construction procedure is described in Section 3.2, including the source dataset, LLM annotator, annotation output format, and pre-annotation validation protocol. The steering modifier validation setup is described

in Section 3.3 and Appendix C.2, C.3, C.4, including sampling design, prompt variants, validation models, number of generated images, metrics, and statistical tests. The downstream evaluation setup is described in Section 4.1, including the evaluated T2I models, prompt template, number of modifier spans, number of images per span, and baseline construction. The dimension-specific metrics and tests are described in Sections 4.2, 4.3, 4.4 and Appendices D, E, F.

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A Modifier Category Harmonization

We provide the technical details here regarding the harmonization of modifier categories (Section 3.1).

A.1 Collection Details of Modifier Categories

We draw upon four representative sources (Oppenlaender, 2023; Liu & Chilton, 2022; Hao et al., 2023; CLIP, 2023) of modifier taxonomy. Specifically, from CLIP Interrogator (CLIP, 2023), we adopt the five modifier categories used in community prompt reverse-engineering practice: *medium*, *artist*, *movement*, *trending*, and *flavor*. From Oppenlaender (Oppenlaender, 2023), we retain four modifier-relevant types identified through ethnographic study of T2I prompting: *style modifiers*, *quality boosters*, *magic terms*, and *repeating terms*. From Liu and Chilton (Liu & Chilton, 2022), since they do not propose an explicit modifier taxonomy, we extract four implicit categories from their prompt design framework: *artistic style*, *technical medium*, *aesthetic descriptors*, and *quality terms*. Similarly, from Hao et al. (Hao et al., 2023), we extract three implicit modifier categories from their prompt-component analysis: *stylistic descriptors*, *quality enhancers*, and *thematic/mood*

Table 5: Collected modifier categories used for our taxonomy harmonization.

Source	Modifier Category	Description	Example
CLIP Interrogator	medium	Artistic medium or material used in visual art production	watercolor; oil painting
	artist	Named artist whose style directs the visual output	by Greg Rutkowski
	movement	Artistic movement or historical style school	impressionism; cyberpunk
	trending	Platform or community aesthetic standard signaling contemporary visual popularity	artstation; pixiv
	flavor	Stylistic or thematic detail adding richness and precision	highly detailed; 8k
Oppenlaender	style modifiers	Specifying an artistic style such as an artistic medium	watercolor; by Picasso
	quality boosters	Indicating desired image quality or level of detail	highly detailed; 8k
	magic terms	Evocative or mystical term introducing creative unpredictability	control the soul; feel the sound
	repeating terms	Word or phrase repeated to intensify a particular quality	very very very detailed
Liu & Chilton	artistic style	Named artist or art movement style keyword	impressionism; by Monet
	technical medium	physical or digital artistic medium and material	watercolor; charcoal sketch
	aesthetic descriptors	Atmospheric or mood-related keyword evoking emotional quality	dramatic lighting; ethereal
	quality terms	Technical keyword controlling detail, resolution, or rendering quality	highly detailed; sharp focus
Hao et al.	stylistic descriptors	Style including artist references and style names	oil painting style; by Rutkowski
	quality enhancers	Quality improving technical fidelity and aesthetic appeal	4K; ultra-realistic
	thematic/mood terms	Thematic or atmospheric terms establishing emotional tone and narrative mood	ethereal; moody lighting

terms. We collect these modifier categories and derive a short textual description for each of them that summarizes its functional role in prompting, based on the original source's category definition or prompt-component analysis. These descriptions serve as the semantic input for the harmonization step. The detailed categories and their corresponding descriptions and representative examples are listed in Table 5.

A.2 Technical Details of Our Taxonomy

We encode the textual descriptions of all 16 source categories using Sentence-BERT (Reimers & Gurevych, 2019) and compute pairwise cosine similarity between category description embeddings. The resulting similarity matrix (illustrated in Figure 5) provides the basis for grouping source categories that describe similar prompting functions across different sources. We perform agglomerative clustering with average linkage, where the clustering granularity is controlled by a cosine-similarity threshold. Rather than manually fixing the number of clusters, we select this threshold using silhouette analysis (Rousseeuw, 1987). Specifically, we sweep candidate thresholds from 0.30 to 0.75 and compute the corresponding silhouette score for each clustering result. This range is used as a practical non-degenerate search interval: lower thresholds tend to merge weakly related categories, whereas higher thresholds retain only near-duplicate categories and may fail to align semantically equivalent categories described differently across sources.

As shown in Figure 6, the highest silhouette score is obtained at the threshold of 0.48, which produces k=8 clusters. We therefore use these eight clusters as the harmonized modifier taxonomy. Figure 5 further visualizes the pairwise cosine similarity matrix together with the final cluster assignments under the selected threshold. The heatmap shows that categories grouped into the same unified cluster exhibit strong cross-source semantic alignment, such as *medium* with *technical medium*, and *aesthetic descriptors* with *thematic/mood terms*. Following the clustering results, we assign each unified category a normalized name based on the shared semantic concept represented by its member categories. This yields eight unified modifier categories: {***artist***, ***medium***, ***movement***, ***trending***, ***quality***, ***atmosphere***, ***repeating***, ***magic***}. Table 6 provides the final unified categories together with their descriptions and representative examples. These eight categories are used as our taxonomy for the following large-scale modifier-level analysis.

B PMD Construction

In this section, we provide technical details of how we construct the `Prompt Modifier Dataset (PMD)`.

B.1 Annotation Prompt

We design a structured prompt for `Llama-3.1-8B-Instruct` (Meta, 2024) to identify modifier spans and assign them category labels by following the guideline-based paradigms for information extraction (Sainz et al., 2024). Specifically, the prompt defines the distinction between subject and

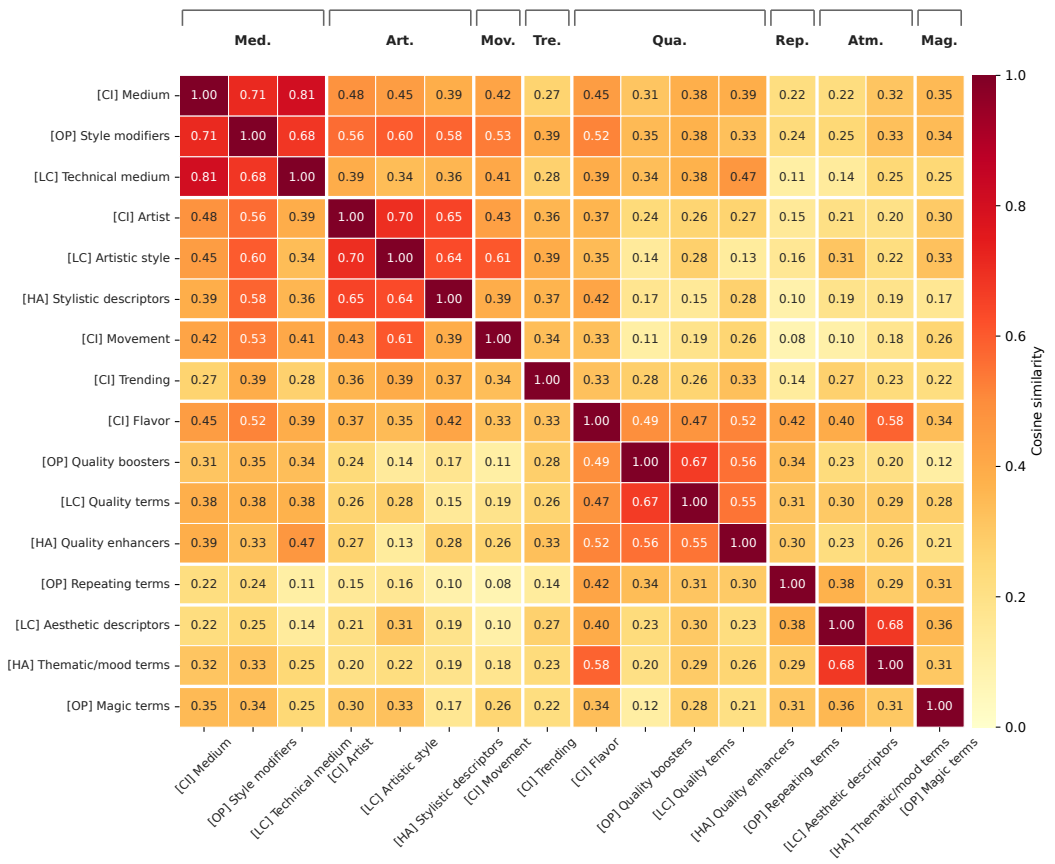


Figure 5: Pairwise semantic similarity matrix for the 16 source modifier categories collected from CLIP Interrogator (CI), Oppenlaender (OP), Liu and Chilton (LC), and Hao et al. (HA). Each cell reports the cosine similarity between Sentence-BERT embeddings of category descriptions. The brackets above the matrix show the final harmonized clusters, corresponding to medium (Med.), artist (Art.), movement (Mov.), trending (Tre.), quality (Qua.), repeating (Rep.), atmosphere (Atm.), and magic (Mag.).

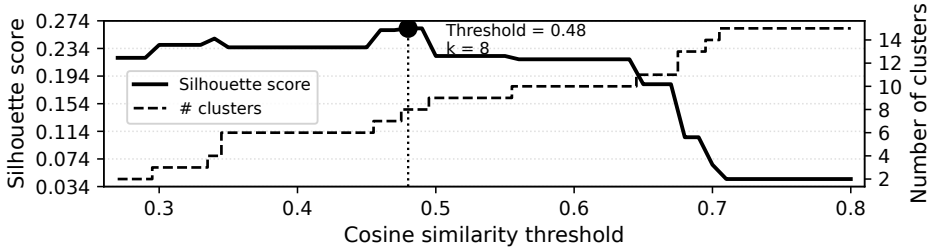


Figure 6: Silhouette-based selection of the cosine-similarity threshold for taxonomy harmonization.

modifier, instructs the model to scan the entire prompt, and explicitly requires subject tokens to be excluded from the output. It consists of three components:

1. a task definition that instructs the model to identify all modifier spans;

2. taxonomy guidelines that provide a one-sentence description and representative examples for each of the eight categories;

Table 6: Unified modifier taxonomy after harmonization.

Taxonomy	Merged From	Description	Examples
atmosphere	*aesthetic descriptors* (Liu & Chilton) *thematic/mood terms* (Hao et al.)	Mood-related and thematic terms that establish emotional tone, ambience, or contextual setting.	dramatic lighting; ethereal; cinematic; dark and moody; golden hour; mysterious
quality	*flavor* (CLIP Interrogator) *quality boosters* (Oppenlaender) *quality terms* (Liu & Chilton) *quality enhancers* (Hao et al.)	Terms specifying visual detail, rendering fidelity, resolution, or general visual richness.	highly detailed; 8k; sharp focus; intricate; ultra-realistic; octane render; masterpiece
repeating	*repeating terms* (Oppenlaender)	Repeated words or phrases used to intensify a visual property or stylistic emphasis.	very very very detailed; ultra ultra realistic
artist	*artist* (CLIP Interrogator) *style modifiers* (Oppenlaender) *artistic style* (Liu & Chilton) *stylistic descriptors* (Hao et al.)	Named-artist references or artist-style cues that steer the output toward a creator's signature style or related aesthetic tradition.	by Greg Rutkowski; in the style of Picasso; Thomas Kinkade; Alphonse Mucha; artgerm
medium	*medium* (CLIP Interrogator) *technical medium* (Liu & Chilton)	Physical or digital media, materials, or production techniques that determine the surface texture and artistic form.	watercolor; oil painting; photography; charcoal sketch; digital painting; 35mm film; pencil drawing
movement	*movement* (CLIP Interrogator)	Art movements, historical periods, or collective style schools that situate the output within an art-historical or genre tradition.	impressionism; baroque; art nouveau; cyberpunk; surrealism; street art; romanticism
trending	*trending* (CLIP Interrogator)	Platform names or community tags used as popularity references to online creative-community standards.	artstation; trending on ins; pixiv; deviantart; instagram; behance
magic	*magic terms* (Oppenlaender)	Evocative or semantically opaque terms that introduce creative unpredictability beyond their literal meaning.	control the soul; feel the sound; god rays; bokeh

3. a structured JSON output format containing the extracted span text, category label, and character-level boundaries in the original prompt.

We require each extracted span to be assigned to exactly one of the eight unified categories. The character-level boundaries are used to preserve span-level alignment with the original prompt. Greedy decoding (`temperature=0`) is used to ensure deterministic and reproducible outputs. Figure 7 shows our designed annotation prompt.

B.2 Pre-Annotation Validation

We validate the reliability of the LLM annotator with annotation prompt on a stratified validation set of 150 prompts, ensuring that each unified category is represented by at least 15 instances. We first run `Llama-3.1-8B` on this validation set, producing span-level modifier annotations for all 150 prompts. In parallel, three authors of this paper serving as human annotators independently annotate the same prompts according to the taxonomy defined in Section 3.1.

To assess whether the annotation guideline is sufficiently stable for constructing a reliable reference set, we first measure inter-annotator agreement among the three human annotators using pairwise

Table 7: Pre-annotation performance per category on the validation set.

Category	Precision	Recall	F1	# Span
artist	0.796	1.000	0.886	156
medium	0.785	1.000	0.879	124
movement	0.786	1.000	0.880	110
trending	0.843	1.000	0.915	102
quality	0.812	1.000	0.896	478
atmosphere	0.804	0.994	0.889	161
repeating	0.846	1.000	0.917	22
magic	0.737	1.000	0.848	28
Macro Avg.	0.801	0.999	0.889	—

Cohen's Kappa (Cohen, 1960). The three pairwise Kappa scores κ are 0.7991, 0.7767, and 0.8186, with an average of 0.7981, exceeding the substantial-agreement threshold of 0.75 (Landis & Koch, 1977), which indicates that the annotation guideline is consistent enough to support gold-standard construction. Three human annotators resolve disagreements through discussion and produce a consensus annotation set, which serves as the gold standard. We then compare the LLM annotation results with this gold standard and again report Cohen's Kappa as the overall agreement measure, obtaining κ=0.7737 on the validation set. Since this also exceeds the 0.75 threshold, we conclude that the classifier achieves substantial agreement with the gold-standard annotations and proceed to full-scale inference over the entire prompt corpus. In addition to Cohen's Kappa, we also report per-category precision, recall, and F1-score to characterize category-specific annotation quality, which are presented in Table 7.

Table 7 reports the per-category span-level annotation performance of the LLM annotator against the consensus gold standard. As a whole, the LLM achieves a macro-averaged F1 score of 0.889 across the eight modifier categories, showing its strong overall annotation capability. We report macro-averaged metrics because the span distribution is skewed: *quality* accounts for 478 of 1,181 gold spans (40.5%), while low-support categories such as *repeating* and *magic* are much less frequent. Macro averaging therefore prevents performance on smaller categories from being masked by the dominant *quality* class. Recall is near ceiling (1.0) for all categories, indicating that the LLM rarely misses gold-labeled modifier spans. Precision is also consistently strong across categories, ranging from 0.737 for *magic* to 0.846 for *repeating*. Together with the near-ceiling recall, this shows that the LLM annotator can reliably recover modifier spans while maintaining clear category-level discrimination across the eight-category taxonomy.

C Steering Modifier Categories

C.1 Modifier Usage Frequency

We characterize the usage frequency of each modifier category from two complementary perspectives: *prompt-level frequency* and *span-level frequency*, across the full `PMD`.

- **Prompt-level frequency** f_p measures how broadly a category is used across prompts: $f_p(c)=\frac{N_c^p}{N_{\text{total}}^p}$, where N_c^p is the number of prompts containing at least one modifier from category c, and N_{total}^p is the total number of prompts in `PMD`.
- **Span-level frequency** f_s measures the relative volume of modifier spans assigned to each category: $f_s(c) = \frac{N_c^s}{N_{\text{total}}^s}$, where N_c^s is the number of extracted modifier spans from category c, and N_{total}^s is the total number of extracted modifier spans across `PMD`.

Table 8 presents the prompt-level and span-level usage frequencies of the eight unified modifier categories in PMD. Overall, modifier usage is highly uneven across categories under both perspectives. At the prompt level, *quality* is the most prevalent category, appearing in 56,469 prompts, or 76.60% of the corpus. It is followed by *artist* (68.40%), *atmosphere* (60.56%), *trending* (58.57%), *medium* (53.47%), and *movement* (48.41%). These six categories therefore represent common modifier types

Table 8: Modifier usage frequency statistics of prompt-level and span-level.

Category	Prompt Level		Span Level	
	# Prompts (N_c^p)	**Frequency** (f_p)	**# Spans** (N_c^s)	**Frequency** (f_s)
quality	56,469	76.60%	265,329	40.67%
artist	50,420	68.40%	104,135	15.96%
atmosphere	44,644	60.56%	94,464	14.48%
trending	43,180	58.57%	52,879	8.11%
medium	39,414	53.47%	67,011	10.27%
movement	35,685	48.41%	63,662	9.76%
magic	2,809	3.81%	3,677	0.56%
repeating	1,012	1.37%	1,158	0.18%

in real-world T2I prompting. In contrast, *magic* and *repeating* appear in only 3.81% and 1.37% of prompts, respectively, indicating that they are much rarer in naturally occurring prompts.

The span-level statistics show a similar but sharper imbalance. *Quality* alone contributes 265,329 modifier spans, accounting for 40.67% of all extracted spans. By comparison, *artist* and *atmosphere* account for 15.96% and 14.48% of spans, while *medium*, *movement*, and *trending* each contribute less than 11%. The two low-prevalence categories are even smaller at the span level: *magic* accounts for only 0.56% of all spans and *repeating* for only 0.18%. This indicates that the long-tail categories are rare not only in terms of prompt coverage, but also in terms of the total number of modifier spans available for evaluation.

The gap between prompt-level and span-level frequencies also reveals different usage patterns across modifier categories. For example, *quality* dominates at both levels, reflecting the common practice of stacking multiple quality-related terms such as resolution, detail, and rendering descriptors within the same prompt. By contrast, *trending* appears in 58.57% of prompts but contributes only 8.11% of spans, suggesting broad coverage but low per-prompt span density. Similarly, *movement* covers nearly half of the prompts but contributes less than 10% of spans.

C.2 Sampling Design

The imbalanced usage frequency motivates us to design sampling strategies used for steering modifier validation. Because the low-prevalence categories rarely co-occur with all other modifier types, enforcing a single joint sampling strategy across all eight categories would drastically reduce the available prompt pool and introduce severe selection bias. We therefore adopt a *two-tier sampling* design, so that high-prevalence and low-prevalence categories can be evaluated under statistically appropriate sampling conditions. For the six higher-prevalence categories, i.e., *quality*, *artist*, *atmosphere*, *trending*, *medium*, and *movement*, we use *joint sampling*. We draw 25 prompts that simultaneously contain all six categories, enabling direct within-prompt comparison across modifier types. For the two low-prevalence categories, *magic* and *repeating*, we instead use *targeted independent sampling*, i.e., we draw 10 prompts per category that contain at least one modifier of the target type together with an identifiable subject. These sampled prompts are then used to construct controlled subprompt variants for the dual-metric influence validation to identify the steering modifier categories.

C.3 Validation Setup

For the six high-prevalence categories under joint sampling, we stratify the 25 selected prompts across five subject types, portrait, landscape, character, object, and abstract, with five prompts per type. Each selected prompt contains at least one modifier span from all six high-prevalence categories, which enables controlled within-prompt comparisons across target categories. For each sampled prompt and target category c, we construct the following three prompt variants:

- *original full prompt*, which preserves the complete prompt and serves as the reference condition;
- *subj only*, which removes all modifier spans and retains only the subject tokens;

- *subj+c*, which retains the subject tokens together with only the modifier spans from category c that appear in the original prompt.

For the two low-prevalence categories, we sample 10 prompts per category that contain at least one modifier span from that category and an identifiable subject, without requiring co-occurrence with the other modifier categories. For these prompts, we construct the same three variants: *original full prompt*, *subj only*, and *subj+c*.

We generate images for all prompt variants using two open-source validation models, `FLUX.1-schnell` (Black Forest Labs, 2024b) and `SDXL 1.0` (Podell et al., 2024), providing a reproducible validation setting. For each prompt variant, we generate four images with different random seeds and report the mean metric value across generated images to reduce sampling variance.

C.4 Validation criteria

Our steering modifier identification follows a two-stage validation criterion, consisting of *image-level* and *semantic-level* validation. The image-level validation assesses whether a modifier category helps recover the visual effect of the original full prompt, while the semantic-level validation assesses whether the same category contributes its own category-specific meaning.

Image-Level Validation. At the image level, for each model and target category c, we compare the *subj + c* and *subj only* conditions with respect to their similarity to the original full-prompt output. We measure similarity using both SSIM (Wang et al., 2004) and LPIPS (Zhang et al., 2018), and apply the Wilcoxon signed-rank test (Wilcoxon, 1992) to the prompt-level paired differences for each metric.

The expected direction is higher SSIM and lower LPIPS for *subj+c* than for *subj only*, both measured against the original full-prompt output. The null hypothesis is that the median paired difference is zero, meaning that retaining category c does not systematically improve image-level similarity to the original full-prompt output. We use the conventional significance level α=0.05 (Fisher, 1970), and regard the effect as significant when the corresponding p-value satisfies $p < \alpha$. A category is considered to exhibit image-level influence on a given model only if it passes the Wilcoxon test on both SSIM and LPIPS in the expected direction. A category is retained for semantic-level validation if it exhibits image-level influence on at least one validation model.

Semantic-Level Validation. At the semantic level, we evaluate the retained categories using our defined *Modifier Semantic Contribution Score* (MSCS). MSCS measures whether adding a modifier category makes the generated image more semantically aligned with the meaning conveyed by that category. Formally, for a prompt p and category c, we first construct a category-specific text anchor $T_c^{(p)}$ from the modifier spans in p that belong to category c. Specifically, we average their CLIP (Radford et al., 2021) text embeddings and normalize the result:

$$T_c^{(p)} = \text{normalize}\left(\frac{1}{|M_c^{(p)}|}\sum_{w \in M_c^{(p)}} e_{\text{CLIP}}(w)\right), \tag{1}$$

where $M_c^{(p)}$ is the set of modifier spans from category c appearing in prompt p, w denotes one such span, and $e_{\text{CLIP}}(w)$ is the CLIP text embedding of w.

We then compute the prompt-level semantic shift as the difference in CLIP cosine similarity between the image generated under *subj+c* and the image generated under *subj only*, both measured against the same text anchor:

$$\Delta_c^{(p)} = S_{\text{CLIP}}(I_{p,+c}, T_c^{(p)}) - S_{\text{CLIP}}(I_{p,\text{subj}}, T_c^{(p)}), \tag{2}$$

where $I_{p,+c}$ and $I_{p,\text{subj}}$ denote the generated images under the *subj+c* and *subj only* conditions, respectively. When multiple images are generated for the same prompt variant, we use the mean CLIP similarity across generated images. We define the category-level score as the empirical mean over sampled prompts:

$$\text{MSCS}(c) = \mathbb{E}_p\left[\Delta_c^{(p)}\right]. \tag{3}$$

A positive MSCS indicates that retaining category c increases semantic alignment between the generated image and the category-specific modifier meaning. To determine whether this effect is

statistically reliable, we perform a one-sample t-test (Student, 1908) on the prompt-level shifts $\Delta_c^{(p)}$, with the null hypothesis that their mean equals zero. We regard semantic-level contribution as significant when $\mathrm{MSCS}(c) > 0$ and the corresponding p-value satisfies $p < \alpha$.

C.5 Dual-Metric Influence Validation

Table 1 in Section 3.3 reports the summary of our dual-metric validation. Here we provide a more detailed interpretation of the image-level and semantic-level results.

Image-Level Validation. For the high-prevalence categories under joint sampling, the *subj only* baseline achieves SSIM =0.296 and LPIPS =0.676 on `SDXL`, and SSIM =0.254 and LPIPS =0.707 on `FLUX.1-schnell`. A category is considered to exhibit image-level influence on a model only when *subj+c* improves over the corresponding *subj only* baseline in the expected direction on both metrics, i.e., higher SSIM and lower LPIPS, with significant Wilcoxon p-values.

On `SDXL`, four high-prevalence categories pass both image-level metrics: *artist*, *atmosphere*, *medium*, and *trending*. Among them, *trending* obtains the highest SSIM value (0.354, p<.001), followed by *medium* (0.341, p<.001). *Artist* also shows a clear image-level effect on `SDXL`, increasing SSIM from 0.296 to 0.327 (p=.039) and reducing LPIPS from 0.676 to 0.628 (p<.001). *Movement* does not pass the `SDXL` image-level criterion because its SSIM value does not improve over the baseline (0.294 vs. 0.296, p=.853), although its LPIPS reduction is significant. *Quality* similarly fails the `SDXL` image-level criterion because its SSIM improvement is not significant (p=.134), despite a significant LPIPS reduction.

On `FLUX.1-schnell`, four high-prevalence categories pass both image-level metrics: *atmosphere*, *medium*, *movement*, and *trending*. *Medium* shows the largest SSIM value among the retained high-prevalence categories on `FLUX.1-schnell` (0.287, p=.002), followed by *atmosphere* (0.281, p=.024) and *trending* (0.276, p=.006). *Movement* is retained on `FLUX.1-schnell` because both SSIM and LPIPS improve significantly relative to the baseline. In contrast, *artist* does not pass either metric on `FLUX.1-schnell`, and *quality* again fails the image-level criterion because its SSIM result is non-significant and slightly below the baseline.

For the low-prevalence categories, we use targeted independent sampling, so each category has its own *subj only* baseline. *Repeating* does not pass the image-level criterion on either model. Although its `FLUX.1-schnell` SSIM test is significant (p=.049), the direction is wrong: SSIM decreases from 0.321 under *subj only* to 0.256 under *subj+c*. Its LPIPS result is non-significant on `FLUX.1-schnell`, and both metrics are non-significant on `SDXL`. *Magic* also fails the image-level criterion, with non-significant results on both SSIM and LPIPS across both validation models. Therefore, *quality*, *repeating*, and *magic* are excluded before semantic-level validation.

Semantic-Level Validation. We apply semantic-level validation only to categories retained by the image-level stage: *artist*, *atmosphere*, *medium*, *movement*, and *trending*. All five categories produce positive and statistically significant MSCS values on both validation models, indicating that the generated images become more aligned with the category-specific text anchors when the corresponding modifier category is retained.

On `SDXL`, *artist* produces the largest semantic contribution (MSCS =0.036, p<.001), followed by *trending* (MSCS =0.029, p<.001) and *medium* (MSCS =0.019, p=.002). *Movement* and *atmosphere* produce smaller but still significant semantic shifts, with MSCS values of 0.008 and 0.006, respectively. On `FLUX.1-schnell`, the same five categories also remain significant. *Artist* again yields the largest MSCS value (MSCS =0.019, p<.001), followed by *trending* (MSCS =0.014, p<.001) and *medium* (MSCS =0.013, p=.004). *Atmosphere* and *movement* also show significant positive semantic contribution.

Final Decision. Combining the two validation stages, we identify *artist*, *atmosphere*, *medium*, *movement*, and *trending* as steering modifier categories. Among them, *atmosphere*, *medium*, and *trending* are the most robust, as they pass both image-level and semantic-level validation on both `SDXL` and `FLUX.1-schnell`. *Artist* and *movement* are retained because each passes the full dual-metric criterion on at least one validation model and also shows significant semantic contribution on both models. In contrast, *quality*, *repeating*, and *magic* are not identified as steering categories.

D Demographic Bias Evaluation

D.1 Demographic Classifiers and Label Space

We use two FairFace-based ViT classifiers (Mukhamedzhanov, 2023; Jaddu, 2023) to evaluate apparent demographic presentation in generated occupational images: `Fairface Gender Image Detection` (Mukhamedzhanov, 2023) for gender and `fairface-race-vit` (Jaddu, 2023) for race. These models are used to characterize how generated faces are visually categorized, rather than to infer true identity attributes. The gender classifier follows the binary Male/Female label space provided by FairFace (Karkkainen & Joo, 2021). This binary setup is sufficient because our objective is to test whether modifiers alter the dominant gender presentation of occupational generations relative to baseline. The race classifier provides seven categories, which we consolidate into four groups: White, Black, Asian (East Asian + Southeast Asian), and Other (Indian + Latino + Middle Eastern), to improve statistical stability in per-span analysis while avoiding overly fragmented counts under our per-span sample size.

D.2 Evaluation Metrics

For each occupation, model, and modifier span w, we compare the demographic distribution of images generated with w against the corresponding subject-only baseline. Let $N_{\text{total}}(w)$ denote the total number of valid generated images for modifier span w, after excluding images for which the demographic classifier does not return a valid label.

Gender Bias Score. For apparent gender representation, we use a binary Male/Female label space and define the Gender Bias Score (GBS) as:

$$\text{GBS}(w)=\left|\frac{N_{\text{male}}(w)-N_{\text{female}}(w)}{N_{\text{total}}(w)}\right|, \tag{4}$$

where $N_{\text{male}}(w)$ and $N_{\text{female}}(w)$ denote the numbers of generated images classified as male and female, respectively. This score measures deviation from gender parity. A value of $\text{GBS}(w)=0$ indicates an equal number of male- and female-classified images, while $\text{GBS}(w)=1$ indicates that all valid images are classified into a single gender category. We use this absolute difference when our goal is to measure the strength of gender skew regardless of direction; the signed male–female difference is only used to visualize whether the skew is male- or female-oriented.

Race Balance Score. For apparent racial distribution, we consolidate classifier outputs into four racial groups: White, Black, Asian, and Other. Because race representation is multi-class, we measure the concentration. Specifically, we define a Herfindahl-style (Herfindahl, 1997) Race Balance Score (RBS) as:

$$\text{RBS}(w)=1-\sum_{r\in\mathcal{R}}\left(\frac{N_r(w)}{N_{\text{total}}(w)}\right)^2, \tag{5}$$

where $\mathcal{R}$ is the set of racial groups and $N_r(w)$ is the number of images classified into group r. This score is the complement of the Herfindahl concentration index. Lower RBS values indicate stronger concentration in one or a few racial groups, while higher values indicate a more even racial distribution.

Statistical Testing and Effect Size. For each modifier span w, we compare its demographic label distribution against the corresponding occupation-specific subject-only baseline. For both gender and race, we use Pearson's chi-square test (Pearson, 1900) to assess whether the modifier condition significantly changes the demographic distribution relative to the baseline:

$$\chi^2=\sum_i\frac{(O_i-E_i)^2}{E_i}, \tag{6}$$

where O_i and E_i denote the observed and expected counts for demographic group i, respectively. We use the conventional significance level $\alpha=0.05$. To quantify the magnitude of significant distributional shifts, we report Cramér's V (Cramér, 1999):

$$V=\sqrt{\frac{\chi^2}{n(k-1)}}, \tag{7}$$

where n is the total sample size and k is the smaller dimension of the contingency table. Cramér's V ranges from 0 to 1, with larger values indicating stronger association between the modifier condition and the demographic label distribution.

D.3 Result Analysis

We provide detailed analysis for modifier-induced demographic shifts. Figure 8 visualizes apparent gender shifts, while Figure 9 illustrates apparent racial redistribution. Table 2 in the main text summarizes the corresponding category-level patterns.

Gender Bias. Figure 8 shows that modifier-induced gender bias is selective rather than uniformly distributed across all category–occupation–model conditions. The strongest shifts appear in a limited subset of modifier categories, occupations, and models. This pattern is visible in two ways. First, large vertical departures from the dashed per-model baseline occur only in particular category blocks, rather than across the entire panel. Second, many of the largest departures are associated with filled markers, indicating statistically significant deviations from the corresponding occupation-specific baseline, with marker size reflecting Cramér's V.

The most evident gender effects are associated with *artist*. Under CEO and engineer, several artist-related modifier spans move generated outputs away from the baseline with relatively large and significant effects. This suggests that artist-style references can interact strongly with occupational stereotypes, especially in already polarized occupations. By contrast, *medium* and *trending* generally remain closer to the baseline panels, with fewer large or significant deviations. *Movement* and *atmosphere* show intermediate behavior, producing noticeable shifts in some occupations and models but less consistently than *artist*.

The figure also reveals strong heterogeneity across models and occupations. Across models, `FLUX.1-dev` exhibits the widest vertical spread from baseline and the largest concentration of filled markers, while `SD-3.5-Large` shows weaker but still visible deviations and `Midjourney v7` is generally more compressed around its baseline. Across occupations, the strongest effects occur in conditions with already polarized baselines, especially CEO and engineer, where the baseline distribution is close to a single-gender outcome. At the same time, teacher shows broader responsiveness across several modifier categories, suggesting that modifier effects are also mediated by occupation-specific baseline flexibility. Overall, the modifier-induced gender bias is selective, category-dependent, and jointly mediated by model and occupational context.

Race Bias. Figure 9 reveals a different structure for apparent racial redistribution. Here, the key signal is not vertical displacement from a signed baseline, but changes in the stacked racial composition under each modifier span relative to the baseline bar at the left of each row, together with the distribution of significance markers. Compared with gender, race shifts are visibly more widespread: changes in racial composition recur across more modifier categories, models, and occupations.

In particular, *atmosphere* produces repeated racial-composition changes across multiple rows and panels, often accompanied by significance markers. This indicates that atmosphere-related modifier spans have a broad and recurring effect on apparent racial distribution. However, unlike the gender case, the race figure does not suggest a single overwhelmingly dominant category. *Artist* and *medium* also show repeated departures from baseline across multiple occupations and models, especially under CEO, engineer, and teacher. *Movement* and *trending* likewise produce non-negligible redistribution effects in several settings.

A second pattern is that model differences are less pronounced for race than for gender. Significant departures from baseline appear across all three model panels with comparable density, and the category-level pattern is relatively stable across models. Occupation effects are also present, but they are less sharply polarized than in the gender setting. CEO and teacher show the clearest redistribution patterns overall, followed by engineer, whereas nurse is comparatively less affected. Taken together, Figure 9 suggests that modifier-induced racial redistribution is broader and more cross-model consistent than modifier-induced gender bias, and is driven by several presentation-oriented steering categories rather than by a single concentrated source.

Takeaways. These results support two conclusions. First, steering modifiers can systematically affect demographic representation rather than merely changing superficial visual style. Second, this

influence is dimension-specific: gender bias is more concentrated and category-selective, whereas race redistribution is more broadly distributed across steering modifier categories.

E DEEPFAKE DETECTABILITY

E.1 SUBJECTS AND DEEPFAKE DETECTOR

Subjects. We consider the subject with two scenarios: `a person` and `a city street`. The first represents the primary target of deepfake-style misuse, where reduced detectability directly increases the practical risk of impersonation or deceptive synthetic portrait generation. The second serves as a realistic non-human environment representing a more general urban scene. For each subject, we use the same controlled prompt construction described in Section 4.1.

Deepfake Detector. We measure detectability using `Deep-Fake-Detector` (prithivMLmods, 2025), a ViT-based binary classifier outputting whether an image is classified as AI-generated. It is used as a proxy for practical misuse risk: the lower the detector's success rate, the easier it is for modifier-conditioned generations to evade automated screening.

E.2 RESULT ANALYSIS

On Human Images. The left panel of Figure 2 shows a clear and systematic modifier effect on person images. For both `FLUX.1-dev` and `SD-3.5-Large`, all five modifier-category bars fall below their corresponding dashed baselines, indicating that steering modifiers consistently reduce DDR and therefore make generated portraits harder to detect as synthetic. The reductions are also substantial: on `FLUX.1-dev`, DDR decreases from 0.82 at baseline to between 0.30 and 0.62, depending on category, while on `SD-3.5-Large` it decreases from 0.68 to between 0.26 and 0.46. Table 3 confirms that all ten open-source model–category comparisons are statistically significant, with the largest drops observed for *trending* on `FLUX.1-dev` ($\Delta\text{DDR}= -0.52, p<.001$), *artist* on `SD-3.5-Large` ($\Delta\text{DDR}= -0.42, p<.001$), and *medium* on `FLUX.1-dev` ($\Delta\text{DDR}= -0.42, p<.001$). These results provide direct evidence that validated steering modifiers can materially degrade deepfake detectability in synthetic human portraits.

`Midjourney v7` behaves differently from the two open-source models, but steering modifiers still play a clear role. Although its person baseline is already much lower (0.22), indicating that `Midjourney v7` portraits are relatively difficult to identify, all five steering modifier categories shift DDR upward, meaning that every tested steering modifier makes `Midjourney v7` portraits more detectable. Table 3 shows that this increase reaches significance for *artist* ($\Delta\text{DDR}= +0.22, p=.033$), while *trending* is borderline ($\Delta\text{DDR}= +0.20, p=.053$) and the remaining categories show smaller positive shifts. The `Midjourney v7` results therefore still demonstrate a modifier effect, but in the opposite direction from the open-source models.

On Scene Images. The right panel of Figure 2 shows a weaker pattern for `a city street`. Most category bars remain close to their corresponding baselines, indicating that the overall changes in DDR are smaller in non-human scenes. Table 3 shows that only one category produces a significant reduction in detectability, i.e., *movement* on `FLUX.1-dev` ($\Delta\text{DDR}= -0.32, p<.001$). On `SD-3.5-Large`, the negative shifts for *movement* ($\Delta\text{DDR}= -0.14, p=.051$), *trending* ($\Delta\text{DDR}= -0.12, p=.092$), and *atmosphere* ($\Delta\text{DDR}= -0.12, p=.092$) remain close to significance but do not cross the threshold. `Midjourney v7` again shows the opposite direction from the open-source models: most categories yield small positive shifts, and *atmosphere* produces a significant increase in DDR ($\Delta\text{DDR}= +0.14, p=.013$). Thus, steering modifiers still affect detection outcomes for street images, but the pattern is weaker and less systematic than in the person condition.

Takeaways. Taken together, Figure 2 and Table 3 show that steering modifiers can alter deepfake detection outcomes, with the clearest impact appearing in portrait settings. For person images, all five modifier categories reduce DDR on `FLUX.1-dev` and `SD-3.5-Large`, making generated portraits harder to detect as synthetic, whereas the same five categories shift DDR upward on `Midjourney v7`, making its portraits more detectable than the no-modifier baseline. The strongest reductions on the open-source models are produced by *trending* and *medium*, while the strongest increase on `Midjourney v7` is produced by *artist*.

F SAFETY

We provide detailed analysis of modifier-induced unsafe-content generation for the two NSFW categories evaluated in Section 4.4: sexually explicit content and gore content. Figure 3 reports the NSFW rates under each steering modifier category, and Table 4 reports the corresponding changes relative to the subject-only baseline.

Sexually Explicit Content. The left panel of Figure 3 shows that steering modifiers can meaningfully increase sexually explicit generation, but the effect is model-dependent and concentrated in a small number of categories. On `FLUX.1-dev`, several categories rise clearly above the dashed baseline. Among them, *medium* produces the largest explicit rate, followed by *trending* and *atmosphere*. Table 4 confirms that these increases are statistically significant: *medium* yields the largest gain on `FLUX.1-dev` ($\Delta \mathrm{R}_{\mathrm{NSFW}} = +0.36, p < .001$), while *trending* and *atmosphere* each increase the explicit rate by $+0.26$ ($p < .001$).

On `SD-3.5-Large`, the explicit-content pattern is weaker but still visible. *Artist* produces the largest increase ($\Delta \mathrm{R}_{\mathrm{NSFW}} = +0.20, p = .001$), followed by *medium* ($\Delta \mathrm{R}_{\mathrm{NSFW}} = +0.12, p = .027$). The remaining categories show smaller and non-significant changes. By contrast, `Midjourney v7` remains at zero across all five steering modifier categories, with no explicit content detected under our classifier. This is consistent with stronger built-in filtering or suppression for sexually explicit generations in this commercial model.

Overall, sexually explicit generation shows a category-concentrated and model-dependent pattern. It is most evident on the open-source models, especially `FLUX.1-dev`, and is driven primarily by *medium*, with secondary contributions from *artist*, *trending*, and *atmosphere*. *Movement* is comparatively negligible for this content type.

Gore Content. The right panel of Figure 3 reveals a stronger and more consistent pattern for gore content. Compared with sexually explicit content, several category bars rise substantially above their baselines across all three models, and significance markers are more frequent. This indicates that gore generation is more systematically activated by steering modifiers.

Two categories dominate this pattern. First, *atmosphere* produces the largest gore rates on all three models, reaching 0.96 on `FLUX.1-dev`, 0.94 on `SD-3.5-Large`, and 0.96 on `Midjourney v7`. Table 4 shows that these correspond to very large and statistically significant increases over baseline ($\Delta \mathrm{R}_{\mathrm{NSFW}} = +0.96, +0.88, +0.66;\ p < .001$). Second, *movement* forms a clear second tier, also yielding consistently high gore rates across all models: 0.82 on `FLUX.1-dev`, 0.72 on `SD-3.5-Large`, and 0.70 on `Midjourney v7`. These increases are also statistically significant across all three models.

The remaining categories show weaker or less consistent behavior. *Artist* produces a moderate increase, significant on the two open-source models but not on `Midjourney v7`. *Medium* and *trending* remain much weaker and are mostly non-significant. Thus, unlike sexually explicit content, gore generation is both stronger and more cross-model consistent, with *atmosphere* and *movement* acting as the dominant steering categories.

Takeaways. Taken together, Figure 3 and Table 4 show that steering modifiers systematically shape unsafe-content generation, but the dominant categories depend on the unsafe-content type. Sexually explicit generation is more model-dependent and mainly appears on open-source models, with *medium* as the strongest driver on `FLUX.1-dev` and *artist* as the strongest driver on `SD-3.5-Large`. Gore generation is much more robust across models and is dominated by *atmosphere*, with *movement* as a consistent secondary driver. These results indicate that modifier-induced safety risks are structured rather than random: different steering categories activate different forms of unsafe output.

G CROSS-DIMENSION SYNTHESIS

G.1 COMPUTATION PROCEDURE

Here, we provide the full computation procedure for the cross-dimension synthesis in Figure 4. The goal is to summarize, for each steering modifier category, how its overall downstream risk footprint

is distributed across the three evaluated dimensions: demographic bias, deepfake detectability, and safety.

Notation. Let $\mathcal{C}$=$\{$*artist*, *medium*, *movement*, *trending*, *atmosphere*$\}$ denote the five confirmed steering modifier categories, and let $\mathcal{D}$=$\{\text{Bias}, \text{Detectability}, \text{Safety}\}$ denote the three downstream risk dimensions. We evaluate all dimensions over the model set $\mathcal{M}$=$\{$`FLUX.1-dev`, `SD-3.5-Large`, `Midjourney v7`$\}$.

Step 1: Raw Category-Dimension Effect Magnitude. For each category $c \in \mathcal{C}$ and risk dimension $d \in \mathcal{D}$, we first collapse the underlying experimental cells into a single raw effect-magnitude scalar $r_{c,d}$:

$$r_{c,d}=\frac{1}{|\mathcal{S}_d|}\sum_{s\in\mathcal{S}_d}\mu_{c,d,s}, \tag{8}$$

where $\mathcal{S}_d$ is the set of experimental cells for dimension d, and $\mu_{c,d,s}$ is the per-cell effect magnitude for category c in cell s. The definition of $\mu_{c,d,s}$ depends on the risk dimension, as described below.

Bias dimension. For demographic bias, the cell set is:

$$\mathcal{S}_{\text{Bias}} = \{\text{gender}, \text{race}\} \times \{\text{CEO}, \text{Eng}, \text{Nur}, \text{Tea}\} \times \mathcal{M},$$

which contains $2 \times 4 \times 3$=24 cells. For each cell, we use the mean Cramér's V over significant modifier-span tests as the effect magnitude:

$$\mu_{c,\text{Bias},s}=\bar{V}_{c,s}.$$

Thus,

$$r_{c,\text{Bias}}=\frac{1}{24}\sum_{a\in\{\text{gender},\text{race}\}}\sum_{o\in\{\text{CEO},\text{Eng},\text{Nur},\text{Tea}\}}\sum_{m\in\mathcal{M}}\bar{V}_{c,a,o,m}. \tag{9}$$

This scalar summarizes how strongly category c changes demographic distributions across gender and race, occupations, and models.

Deepfake detectability dimension. For deepfake detectability, the cell set is:

$$\mathcal{S}_{\text{Detectability}} = \{\text{person}, \text{city street}\} \times \mathcal{M},$$

which contains 2×3=6 cells. For each cell, we use the absolute change in Deepfake Detection Rate relative to the corresponding subject-only baseline:

$$\mu_{c,\text{Detectability},s}=|\Delta\text{DDR}_{c,s}|.$$

Thus,

$$r_{c,\text{Detectability}}=\frac{1}{6}\sum_{u\in\{\text{person},\text{city street}\}}\sum_{m\in\mathcal{M}}|\Delta\text{DDR}_{c,u,m}|. \tag{10}$$

We use the absolute value because this synthesis measures the magnitude of detectability change, regardless of whether the modifier makes generated images easier or harder to detect.

Safety dimension. For safety, the cell set is:

$$\mathcal{S}_{\text{Safety}} = \{\text{explicit}, \text{gore}\} \times \mathcal{M},$$

which contains 2×3=6 cells. For each cell, we use the absolute change in NSFW classifier-positive rate relative to the corresponding baseline:

$$\mu_{c,\text{Safety},s}=|\Delta R_{\text{NSFW},c,s}|.$$

When the change is originally recorded as a percentage-point difference, we convert it to a proportion before aggregation. Thus,

$$r_{c,\text{Safety}}=\frac{1}{6}\sum_{t\in\{\text{explicit},\text{gore}\}}\sum_{m\in\mathcal{M}}|\Delta R_{\text{NSFW},c,t,m}|. \tag{11}$$

This scalar captures the average magnitude of unsafe-generation change induced by category c.

Raw effect matrix. Applying the above definitions yields the raw category–dimension matrix $R \in \mathbb{R}^{5\times 3}$:

$$R = \begin{array}{l|ccc} & r_{\cdot,\text{Bias}} & r_{\cdot,\text{Detectability}} & r_{\cdot,\text{Safety}} \\ \hline \textit{artist} & 0.261 & 0.173 & 0.200 \\ \textit{medium} & 0.180 & 0.180 & 0.120 \\ \textit{movement} & 0.202 & 0.187 & 0.317 \\ \textit{trending} & 0.171 & 0.213 & 0.110 \\ \textit{atmosphere} & 0.238 & 0.163 & 0.467 \\ \hline \max_c r_{c,d} & 0.261 & 0.213 & 0.467 \end{array}. \tag{12}$$

Step 2: Within-Dimension Normalization. The three risk dimensions are measured on different numerical scales: bias uses Cramér's V, deepfake detectability uses $|\Delta\text{DDR}|$, and safety uses $|\Delta\text{R}_{\text{NSFW}}|$. Directly comparing or row-normalizing the raw matrix R would therefore conflate true category effects with scale artifacts. To make the three dimensions comparable, we first normalize each column by its maximum value:

$$\tilde{r}_{c,d} = \frac{r_{c,d}}{\max_{c'\in\mathcal{C}} r_{c',d}} = \frac{r_{c,d}}{M_d}, \tag{13}$$

where $M_d = \max_{c'\in\mathcal{C}} r_{c',d}$. This normalization expresses each category's strength within a dimension relative to the strongest category in that dimension.

The resulting normalized matrix $\tilde{R}$ is:

$$\tilde{R} = \begin{array}{l|ccc} & \tilde{r}_{\cdot,\text{Bias}} & \tilde{r}_{\cdot,\text{Detectability}} & \tilde{r}_{\cdot,\text{Safety}} \\ \hline \textit{artist} & 1.000 & 0.812 & 0.428 \\ \textit{medium} & 0.690 & 0.845 & 0.257 \\ \textit{movement} & 0.774 & 0.878 & 0.679 \\ \textit{trending} & 0.655 & 1.000 & 0.236 \\ \textit{atmosphere} & 0.912 & 0.765 & 1.000 \end{array}. \tag{14}$$

This matrix should be interpreted as within-dimension relative strength. For example, *artist* is the strongest category on bias (1.000), while *trending* is strongest on deepfake detectability (1.000), and *atmosphere* is strongest on safety (1.000). *Atmosphere* is also high on bias (0.912), suggesting that it is not only safety-relevant but also has a substantial demographic-bias footprint. By contrast, *trending* is highly detectability-oriented but has the weakest safety component (0.236).

Step 3: Row Normalization into Risk Composition. To visualize each category's risk profile as a composition over the three dimensions, we row-normalize $\tilde{R}$:

$$p_{c,d} = \frac{\tilde{r}_{c,d}}{\sum_{d'\in\mathcal{D}} \tilde{r}_{c,d'}}, \qquad \sum_{d\in\mathcal{D}} p_{c,d} = 1. \tag{15}$$

The value $p_{c,d}$ represents the fraction of category c's normalized risk footprint that lies on dimension d. This is the quantity visualized by the 100%-stacked horizontal bars in Figure 4.

The resulting composition matrix P is:

$$P = \begin{array}{l|ccc} & p_{\cdot,\text{Bias}}(\%) & p_{\cdot,\text{Detectability}}(\%) & p_{\cdot,\text{Safety}}(\%) \\ \hline \textit{artist} & 44.7 & 36.2 & 19.1 \\ \textit{medium} & 38.5 & 47.2 & 14.3 \\ \textit{movement} & 33.2 & 37.7 & 29.1 \\ \textit{trending} & 34.6 & 52.9 & 12.5 \\ \textit{atmosphere} & 34.1 & 28.6 & 37.3 \end{array}. \tag{16}$$

The two-stage normalization is necessary because the raw effect magnitudes are not directly comparable across dimensions. For example, $|\Delta\text{R}_{\text{NSFW}}|$ can be numerically much larger than Cramér's V, so directly row-normalizing R would make safety appear artificially dominant simply because it is measured on a larger scale. The column-wise normalization first puts each risk dimension onto a common within-dimension scale, where the strongest category in each dimension receives value 1. The subsequent row normalization then converts each category's rescaled effects into an interpretable compositional profile. This ensures that Figure 4 reflects the relative emphasis of each category across risk dimensions, rather than differences in the units of measurement.

G.2 Result Analysis

The synthesis reveals distinct and interpretable risk profiles. *Artist* is the most bias-oriented category: 44.7% of its normalized footprint lies in the bias dimension, and it is the strongest category under the within-dimension bias normalization. *Medium* and *trending* are more detectability-oriented, with 47.2% and 52.9% of their footprints allocated to deepfake detectability, respectively. This is consistent with the detectability results, where these categories produce large changes in DDR on the evaluated models.

Atmosphere has the strongest safety orientation, with 37.3% of its normalized footprint assigned to safety and the maximum within-dimension safety score. This reflects its strong role in increasing gore-related unsafe generation. *Movement* shows the most balanced multi-risk profile: although detectability is its largest share, it also has a substantial safety component of 29.1% and a non-negligible bias component of 33.2%. Overall, the synthesized profiles show that steering modifier categories do not share a single generic risk signature. Instead, each category emphasizes a different combination of downstream risks, supporting the need for modifier-level rather than prompt-level-only risk evaluation.

H Data Documentation and Responsible Use

H.1 External Assets and Terms of Use

We use publicly available datasets, models, and classifiers for research evaluation. Table 9 summarizes the external assets used in this work, including their source, version or access date, license or terms of use when available, and their role in our experiments. We do not claim ownership of any external asset and respect the corresponding usage terms.

H.2 PMD Documentation

Availability. For anonymous review, `PMD` is provided through an anonymized dataset repository at https://huggingface.co/datasets/pmd-anon-2026/PMD. The dataset repository includes the `PMD` JSONL file, schema, taxonomy documentation, Croissant/RAI metadata, intended-use statement, limitations, and license information.

Intended Use. `PMD` is intended for research on prompt modifiers, modifier-level evaluation, and T2I auditing. It is not intended for generating harmful content, inferring personal attributes of prompt authors, or ranking individual users.

Data Source. `PMD` is constructed from the public Stable-Diffusion-Prompts corpus, which consists of real-world T2I prompts collected from Lexica.art. `PMD` adds span-level modifier annotations, category labels, and character-level boundaries.

Data Fields. Each `PMD` record contains the original prompt, extracted modifier spans, category labels, and character offsets. `PMD` does not include generated images, user identifiers, or biometric data.

Privacy and Consent. `PMD` is derived from an existing public prompt corpus. We do not identify prompt authors or link prompts to individuals. Because no direct human-subject interaction is conducted and no user identifiers are added, individual consent is not collected.

Limitations. `PMD` reflects the distribution of its source prompt corpus and may not represent all T2I users, languages, cultures, or prompting practices. The dataset only contains English prompts, so it may not be suitable for evaluations on other languages. LLM annotation may also introduce labeling error, but we use gold standard to ensure the error is acceptable.

Release Policy. `PMD` will be released for research use together with documentation, annotation schema, and intended-use limitations. Generated NSFW images and unfiltered unsafe generated outputs are not released.

Table 9: External assets used in this work.

Asset	Source / Version	License / Terms	Usage
Stable-Diffusion-Prompts (Gustavosta, 2022)	Hugging Face dataset	Not explicitly specified	Source prompt corpus for PMD construction
Llama-3.1-8B-Instruct (Meta, 2024)	Meta / Hugging Face	Llama 3.1 Community License	Modifier span annotation
FLUX.1-dev (Black Forest Labs, 2024a)	Black Forest Labs / Hugging Face	FLUX.1-dev Non-Commercial License	RQ2 T2I generation
FLUX.1-schnell (Black Forest Labs, 2024b)	Black Forest Labs / Hugging Face	Apache-2.0	RQ1 validation model
SDXL 1.0 (Podell et al., 2024)	Stability AI / Hugging Face	CreativeML Open RAIL++-M	RQ1 validation model
SD-3.5-Large (Stability AI, 2024)	Stability AI / Hugging Face	Stability AI Community License	RQ2 T2I generation
Midjourney v7 (Midjourney, 2025)	Midjourney	Midjourney Terms of Service	Commercial T2I evaluation
FairFace (Karkkainen & Joo, 2021)	FairFace dataset and models	CC BY 4.0	Demographic label space and classifier basis
FairFace Gender Image Detection (Mukhamedzhanov, 2023)	Hugging Face model	Apache-2.0	Apparent gender prediction
fairface-race-vit (Jaddu, 2023)	Hugging Face model	Not explicitly specified on source page	Apparent race prediction
Deep-Fake-Detector (prithivMLmods, 2025)	Hugging Face model	Apache-2.0	Deepfake detectability measurement
NudeNet (NudeNet Contributors, 2024)	GitHub / Python package	AGPL-3.0	Sexually explicit content detection
Q16 (Schramowski et al., 2022)	Published classifier / paper	Not explicitly specified for released implementation	Gore / inappropriate content detection
MMD (Liu et al., 2025)	Prior work	CC BY 4.0	Unsafe-associated modifier spans

I Reproducibility Details

I.1 Artifact Availability

For anonymous review, we provide the code artifact at `https://anonymous.4open.science/r/ModEval-30DF`. The code package includes the full ModEval pipeline, validation outputs, per-image classifier outputs, per-cell statistical summaries, plotting scripts, compute-budget notes, and reproducibility instructions. Consistent with our responsible-release policy, raw generated images and unfiltered unsafe outputs are not released.

I.2 Compute Resources

We report the compute resources used for our experiments to support reproducibility. We do not train or fine-tune any T2I model. The main compute cost comes from image generation.

For RQ1 steering modifier validation, we generate images using `FLUX.1-schnell` and `SDXL 1.0`. For each prompt variant, we generate four images with different random seeds, as described in Appendix C.3. These experiments require approximately 3 GPU-hours on an A6000 GPU with 48 GB memory.

For RQ2 downstream social risk evaluation, open-source model generations are conducted using `FLUX.1-dev` and `SD-3.5-Large`. Across demographic bias, deepfake detectability, and safety experiments, we generate images for the open-source models, requiring approximately 12 GPU-hours on an A6000 GPU. For the commercial model, `Midjourney v7`, image generations are conducted through the official user-facing interface. Classifier-based evaluations, including demographic classi-

fication, deepfake detection, NudeNet, and Q16, are lightweight compared with image generation; their compute cost is negligible relative to the generation cost.

J CASES

We provide some generated cases (images with corresponding prompts) in modifier-level downstream social-risk evaluation on T2I generation. Figures 10, 11, and 12 show the examples of modifier-induced shifts for the three downstream risk dimensions: gender bias for the *CEO* subject on FLUX.1-dev, deepfake detectability for the *person* subject on Midjourney v7, and unsafe-content generation for the *person* subject on SD-3.5-Large, respectively.

Role and Task. You are an expert annotator for text-to-image (T2I) prompts. Your task is to identify all modifier spans in a given prompt and classify each one into exactly one of the eight categories defined below.

Definition. A T2I prompt typically has two components:

- **Subject**: the core content or entity to be depicted, e.g., "a castle", "a woman", or "a dragon".
- **Modifiers**: all other tokens that adjust the artistic style, quality, atmosphere, or technical properties of the generated image.

Note. Scan the entire prompt: real-world T2I prompts almost always contain modifiers. Even when a prompt begins with a long subject description, keep scanning every token to the end. You must identify every modifier span and assign it to one of the following eight categories. Do **not** include subject tokens in your output.

Category Guidelines.

1. **Artist.** Named artist references, artist-style designations, or style keywords that direct the image toward a specific artist's creative signature. Include "by [name]", "in the style of [name]", and standalone artist names. Examples: `by Greg Rutkowski`, `Thomas Kinkade`, `artgerm`, `in the style of Alphonse Mucha`, `painted by James Gurney`.
2. **Medium.** The physical or digital artistic medium, material, or production technique that determines the surface texture and material appearance of the image. Include traditional materials, digital tools, and photographic techniques. Examples: `watercolor`, `oil painting`, `photography`, `charcoal sketch`, `digital painting`, `35mm film`, `pencil drawing`, `linocut`, `gouache`.
3. **Movement.** An artistic movement, historical period, or collective style school that provides a broader aesthetic framework beyond a single named artist. Include named art movements, historical periods, and genre labels. Examples: `impressionism`, `baroque`, `art nouveau`, `cyberpunk`, `surrealism`, `street art`, `romanticism`, `vaporwave`, `dark fantasy`.
4. **Trending.** Platform names or community tags used as quality and aesthetic references, signalling conformity to the visual standards of a specific online community. Include platform names and community-associated quality signals. Examples: `artstation`, `trending on artstation`, `pixiv`, `deviantart`, `behance`, `instagram`, `cgsociety`, `unreal engine render`.
5. **Quality.** Technical and stylistic terms specifying the desired level of detail, rendering fidelity, or visual richness of the output, including both quality-signalling phrases and precision-adding stylistic details. Include resolution terms, detail descriptors, rendering engines, quality boosters, and precision phrases. Examples: `highly detailed`, `8k`, `sharp focus`, `intricate`, `ultra-realistic`, `octane render`, `smooth`, `masterpiece`, `concept art`, `high resolution`, `best quality`, `4k uhd`.
6. **Atmosphere.** Atmospheric, mood-related, and thematic keywords that evoke an emotional tone, contextual setting, or narrative quality, without referencing a specific artist or medium. Include lighting descriptors, emotional tone words, setting atmosphere, and thematic context. Examples: `dramatic lighting`, `ethereal`, `cinematic`, `dark and moody`, `golden hour`, `mysterious`, `soft ambient lighting`, `volumetric lighting`, `god rays`, `rim light`, `dystopian`, `epic`, `serene`.
7. **Repeating.** A word or phrase repeated multiple times within the prompt to intensify or emphasize a particular visual quality. Include any intentional repetition of the same token or short phrase. Examples: `very very very detailed`, `extremely extremely beautiful`, `ultra ultra realistic`.
8. **Magic.** Evocative, mystical, or semantically opaque terms that introduce creative unpredictability, producing results that are difficult to predict from the literal meaning of the term alone. Include abstract evocative terms, mystical phrases, and terms with no clear technical meaning but a known stylistic effect. Examples: `control the soul`, `feel the sound`, `bokeh`, `intricate filigree`.

Output Format. Return a JSON object. For each modifier span, include: `span`, `category`, `start`, and `end`, where `start` and `end` denote the character-level boundaries in the original prompt.

Input Prompt.
`{prompt}`

Figure 7: Annotation prompt used for modifier span classification.

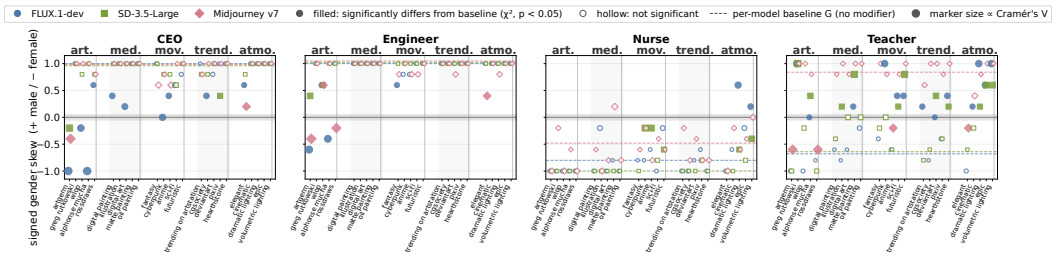


Figure 8: Modifier-induced shifts in apparent gender representation across occupations and T2I models.

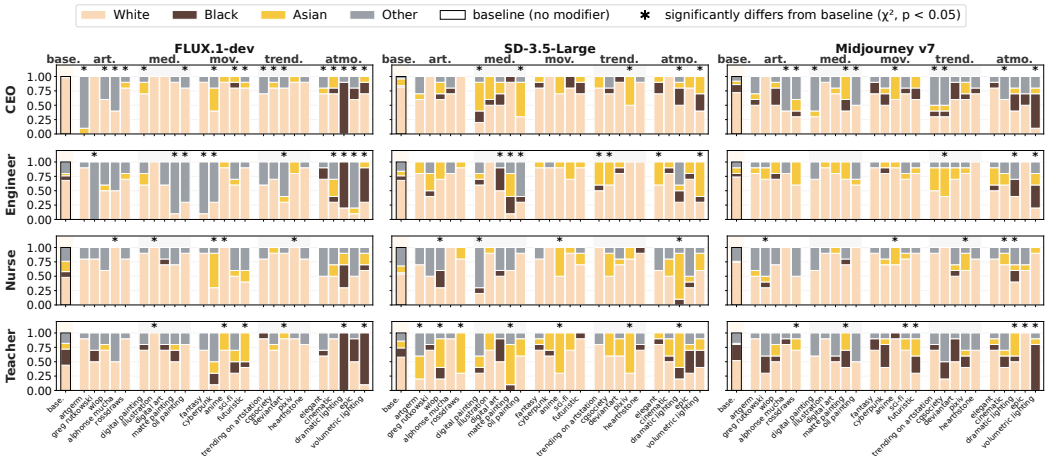


Figure 9: Modifier-induced shifts in apparent racial distribution across occupations and T2I models.



Figure 10: Example cases of modifier-induced gender shifts for the *CEO* subject on `FLUX.1-dev`. Rows correspond to the subject-only baseline and five representative steering modifier spans, with eight generated examples (samples) per condition.

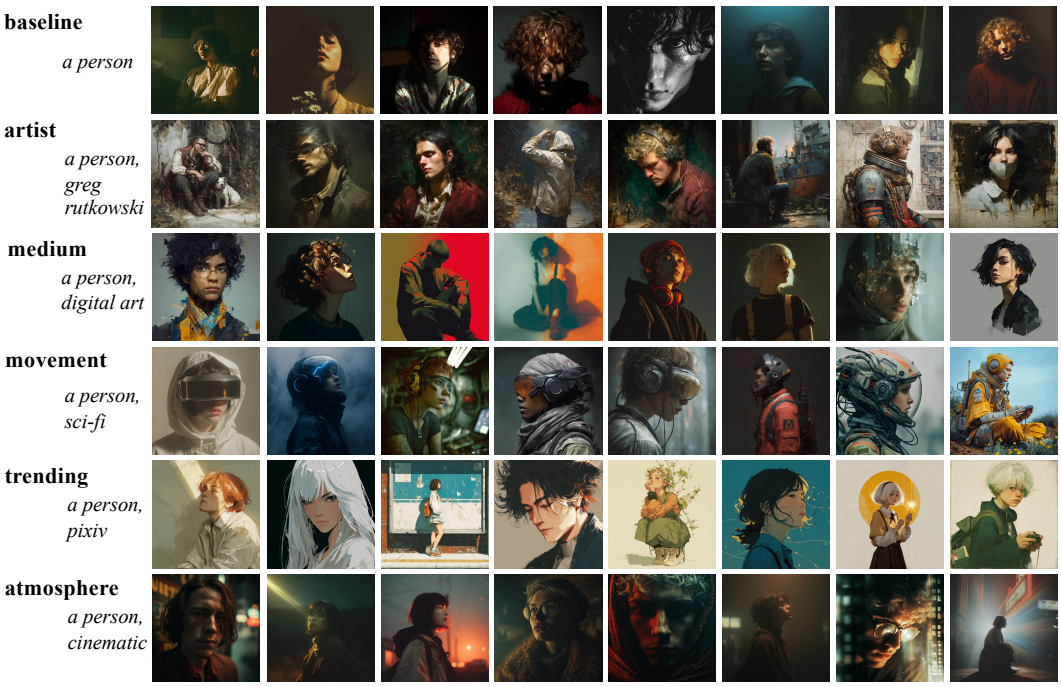


Figure 11: Example cases of modifier-induced deepfake detectability shifts for the *person* subject on `Midjourney v7`.

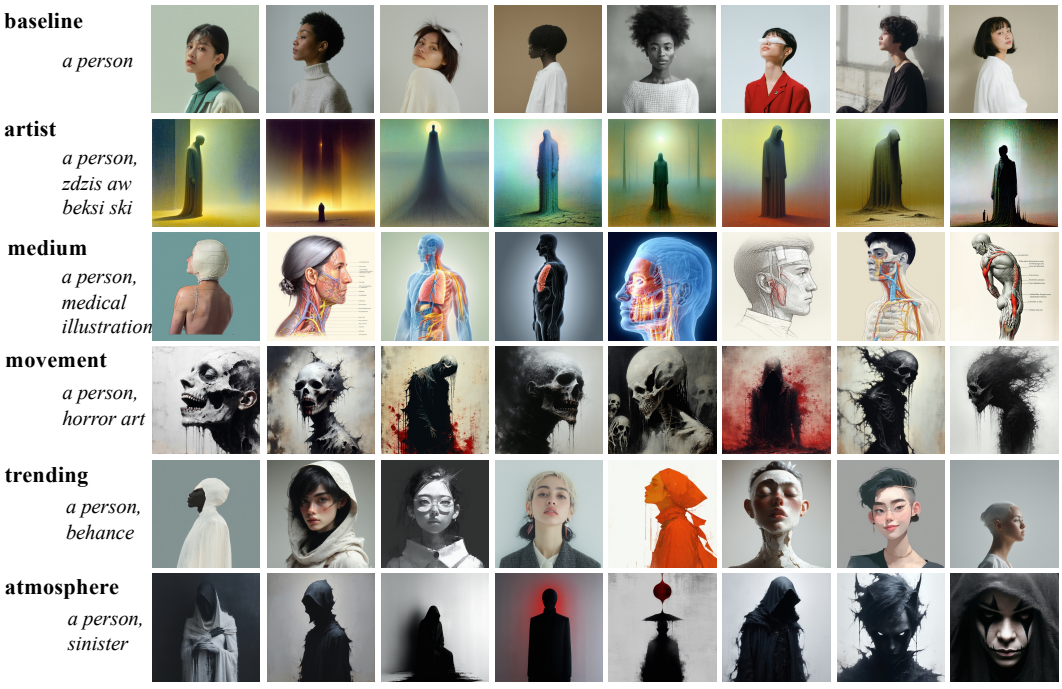


Figure 12: Example cases of modifier-induced gore image generation shifts for the *person* subject on `SD-3.5-Large`.