DO MODELS SHARE SAFETY REPRESENTATIONS? CROSS-MODEL STEERING FOR SAFE VISUAL GENERATION

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ABSTRACT

Recent progress in generative modeling has made safety control a central challenge, yet existing approaches remain largely model-specific, requiring retraining or tailored interventions for each new architecture. In this work, we introduce *cross-model safety steering*, a framework that extracts a safety direction from paired safe and unsafe prompts in a source LLM and maps it to the text-conditioning space of a target generator through an alignment learned exclusively from benign data. Once transferred, the direction is applied at inference time while keeping the generative backbone frozen and without requiring target-side unsafe examples for alignment. The framework also supports category-specific directions, enabling selective control over different types of unsafe content. Across diverse source-target pairs for text-to-image and text-to-video generation, transferred directions consistently reduce unsafe outputs, with the alignment strategy and steering strength determining the balance between safety and generation quality. We further show that steering strength can be selected using benign data alone, reducing unsafe outputs in all 45 evaluated configurations. Together, these results show that safety interventions can transfer across independently trained models, offering a modular alternative to model-specific steering. Source code will be made publicly available.

Warning: *This paper contains examples of harmful and explicit content, including sexual and violent material, which some readers may find disturbing or offensive.*

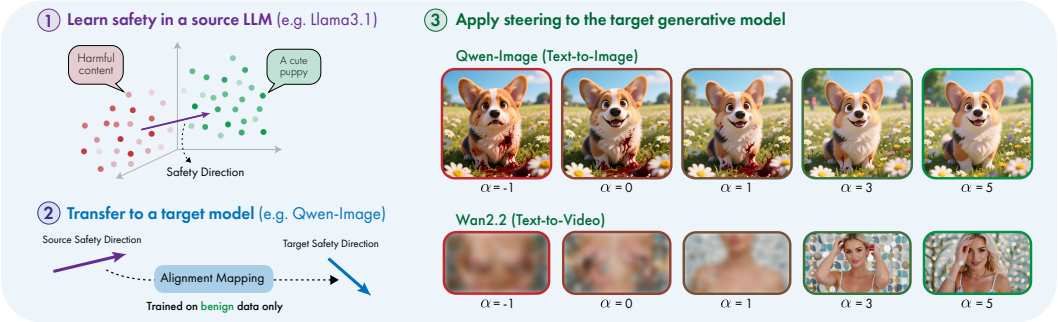

Figure 1: Safety as a transferable direction. A safety vector learned in a source LLM is aligned to the text-conditioning space of a target generator using only benign data and applied at inference time. The right panel illustrates behavior on Qwen-Image and Wan2.2 as the steering strength α varies, with unsafe content progressively suppressed while scene composition is largely preserved.

1 INTRODUCTION

Safety has become a central challenge in modern generative modeling. LLMs (Zhao et al., 2023), text-to-image systems (Esser et al., 2024; Black Forest Labs, 2024; Rombach et al., 2022), and video generators (Wan et al., 2025) are trained on massive, partially curated corpora and internalize unsafe or policy-sensitive concepts, including sexual content, hate, violence, illegal activity, and copyrighted or trademarked entities (Abid et al., 2021; Birhane et al., 2021; Bommasani et al., 2021; Weidinger et al., 2022). Their increasing deployment calls for effective, lightweight safety mechanisms.

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Safety is also reflected in the geometry of internal representations (Bello et al., 2026; Huang et al., 2025; Stolfo et al., 2025). In LLMs, representation engineering links harmful or refusal-related behavior to activation-space directions, enabling control through internal interventions (Arditi et al., 2024; Zou et al., 2024). Similar observations in diffusion-based image and video models indicate that latent-space interventions can improve safety beyond prompt filtering or retraining (Facchiano et al., 2026; Poppi et al., 2024; Schramowski et al., 2023).

At the same time, recent work on representation similarity indicates that learned latent spaces across models are often not independent, but exhibit nontrivial geometric alignment and can sometimes be related by simple mappings (Jha et al., 2025). This perspective is consistent with the *Platonic Representation Hypothesis*, which posits that sufficiently capable models converge toward shared internal representations of high-level concepts (Huh et al., 2024).

In this paper, we bring these two lines of work together and ask: *are safety representations transferable across models?* Specifically, we investigate whether a safety direction learned in a source LLM remains meaningful when mapped into the text-conditioning space of a different target model. The source and target encoders may differ in architecture, training data, pretraining paradigm, or tokenizer, while the target has no access to the unsafe pairs used to construct the source direction. Successful transfer requires the mapped direction to suppress unsafe generations while preserving prompt fidelity and visual quality on benign content.

To address this question, we propose a framework for *cross-model safety steering* (Fig. 1). Paired safe-unsafe prompts define a safety direction in a source LLM. A lightweight alignment fitted on benign anchors transports this direction to the target text-conditioning space. At inference time, the transferred direction is added to the normally computed target token states, while the image or video generation backbone remains frozen. Category-specific directions extend the framework to selective control over different types of unsafe content. This setup also supports scenarios in which licensing, governance, or access restrictions keep unsafe supervision confined to the source environment. An authorized source-side provider can release aggregate safety directions, while the target provider learns the alignment using only benign anchors. The same mapping can then be reused for additional source-side directions without exposing the underlying unsafe prompts.

Empirically, we evaluate this framework in text-to-image generation across diverse source (*i.e.*, Llama3.1 (Grattafiori et al., 2024), Mistral (Jiang et al., 2023), and Qwen3.5 (Qwen Team, 2026)) and target models (*i.e.*, Flux1-Schnell, Flux1-Dev (Black Forest Labs, 2024), Qwen-Image (Wu et al., 2025), Z-Image-Turbo (Cai et al., 2025)), and extend the analysis to text-to-video generation using Wan2.2 (Wan et al., 2025). We measure safety through attack success rate (Bedapudi, 2019; Schramowski et al., 2022) and utility through CLIP similarity (Radford et al., 2021) and FID (Heusel et al., 2017). We compare transferred and native steering, evaluate category-specific control, and study whether steering strength can be selected using benign data alone.

Our results suggest a modular view of safety: source-side directions can be reused across independently trained text-conditioning spaces and remain effective in heterogeneous frozen generators. Benign alignment enables reuse even when the target provider cannot access the unsafe corpus.

2 Related Work

We review prior work along four main directions: *(i)* safety alignment in generative models, *(ii)* activation steering, *(iii)* representation alignment, and *(iv)* cross-model transfer of interventions.

Safety Alignment in Generative Models. In text-to-image generation, existing approaches include model editing methods that suppress unsafe content or steer models toward safer outputs (Fan et al., 2024; Gandikota et al., 2023; 2024; Huang et al., 2024; Liu et al., 2025; Lu et al., 2024; Lyu et al., 2024), guidance-based approaches applied at sampling time (Schramowski et al., 2023), and pre-decoding methods that sanitize or align representations before generation (Ahn & Jung, 2025; Liu et al., 2024; Poppi et al., 2024). More recently, activation-level control has emerged as a lightweight inference-time alternative. AcT (Rodriguez et al., 2025) learns an affine map that transports activations from a source distribution to a target distribution, enabling control over toxicity, concept induction, and truthfulness across both language and diffusion models. CAT (Chrabąszcz et al., 2026) extends this approach to text-to-image safety by learning conditioned nonlinear transport maps that act primarily in unsafe regions of the activation space.

Activation Steering. A related line of work investigates whether high-level behaviors correspond to linear directions in activation space. Early studies show that targeted activation perturbations can reliably steer model behavior (Subramani et al., 2022; Turner et al., 2023). Representation engineering (Zou et al., 2023) and theoretical analyses (Park et al., 2024) further support the hypothesis that semantic features exhibit linear structure in representation space. Building on this view, CAA (Rimsky et al., 2024) derives steering vectors from contrastive activation differences to modulate behaviors such as sycophancy and refusal, while Arditi et al. (2024) identify a dominant refusal direction that can be added or removed to control safety behavior. Similar observations extend to video generation, where safety-relevant directions can be extracted from paired data, but are primarily used for within-model edits rather than transferable interventions (Facchiano et al., 2026). Collectively, these results suggest that safety behaviors can often be captured as latent directions.

Representation Alignment. Our method also relies on the premise that simple learned mappings can relate internal representations from different models. Early model stitching work showed that independently trained networks can be connected through lightweight transformations (Bansal et al., 2021; Lenc & Vedaldi, 2015). The *Platonic Representation Hypothesis* (Huh et al., 2024) further suggests that different models may converge toward shared representational structure. Empirically, Jha et al. (2025) demonstrate that embeddings can be translated across models without paired data via shared latent structure, while Chen et al. (2025) show that affine maps can transfer sparse autoencoders, probes, and steering vectors across language models.

Cross-Model Intervention Transfer. Recent work explicitly studies the transfer of interventions across models. Stolfo et al. (2025) show that steering vectors from instruction-tuned models can generalize to related base models. Huang et al. (2025) learn linear mappings between LLM activation spaces and transfer steering vectors across models and concepts, while Bello et al. (2026) formalize linear representation transferability for affine steering within model families. Closest to our setting, Oozeer et al. (2025) learn cross-model mappings for interventions such as refusal and backdoor removal. Prior studies on intervention transfer focus on language models (Chen et al., 2025; Huang et al., 2025; Oozeer et al., 2025), while visual activation-steering methods learn interventions directly from target-model activations (Chrabąszcz et al., 2026; Rodriguez et al., 2025). We study a complementary setting: a safety direction estimated in a source LLM is mapped to the text-conditioning space of a frozen image or video generator using only benign anchors. Thus, unsafe supervision remains within the source representation space. To the best of our knowledge, prior steering-transfer work has not evaluated whether such source-only interventions remain actionable through downstream image and video generators without target-side unsafe data.

3 METHOD

3.1 PROBLEM FORMULATION

We consider a source LLM $\boldsymbol{M}_s$ and the text-conditioning encoder $\boldsymbol{M}_t$ of a target generative pipeline $\boldsymbol{G}_t$. The two encoders may differ in architecture, data, and pretraining paradigm. Alignment relates their text representations; the visual denoising backbone remains frozen. Unsafe supervision is available only in the source environment, while the target environment uses benign anchors for alignment. Our objective is to reduce unsafe outputs of $\boldsymbol{G}_t$ while preserving its behavior on benign prompts, with both encoders and the visual backbone frozen.

Our approach proceeds in four steps. First, we estimate a source-side safety direction from paired safe-unsafe prompts. Next, we learn a lightweight alignment between source and target representations using only benign anchor prompts. We then transport the source direction to the target space and adjust its magnitude using benign-anchor statistics. Finally, we add the resulting direction to the normal token states of the target encoder before generation, as shown in Fig. 2.

Source and Target Representation Spaces. Given an input prompt x, let $\boldsymbol{h}_s^\ell(x)$ and $\boldsymbol{h}_t^\ell(x)$ denote the token-state sequences of the source and target models at layer ℓ, respectively. Their token vectors lie in representation spaces $\mathcal{Z}_s^\ell \subseteq \mathbb{R}^{d_s}$ and $\mathcal{Z}_t^\ell \subseteq \mathbb{R}^{d_t}$. As we focus on the final hidden layer in both models, we omit the layer index ℓ for simplicity. The final target states directly condition the generator, and the final source layer provides a consistent output-level extraction rule across LLMs.

Mean pooling over tokens, denoted by $\mu(\cdot)$, gives one vector per prompt for comparing spaces with different dimensionality, basis, and scale.

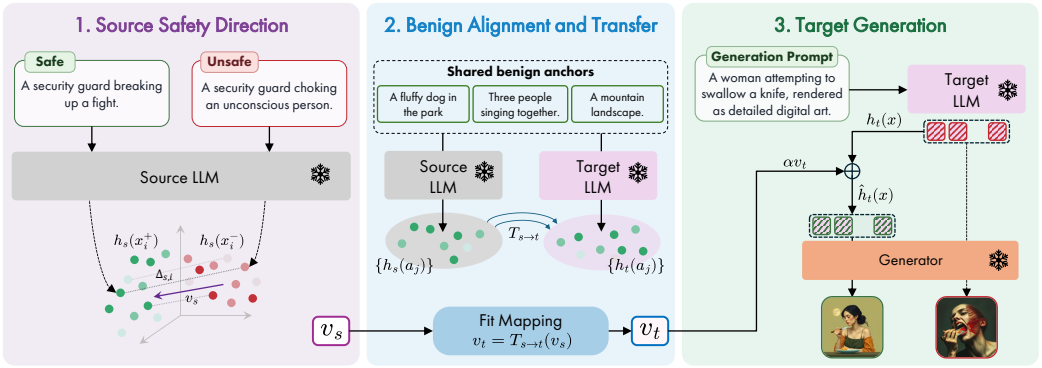

Figure 2: Overview of cross-model safety steering. (Left) Safe-unsafe pairs are encoded only in the source LLM to estimate $\boldsymbol{v}_s$. (Center) Benign anchors fit the map and scale used to construct $\boldsymbol{v}_t$. (Right) The target encodes the generation prompt normally; $\alpha \boldsymbol{v}_t$ is broadcast-added to its final token states before the frozen generator consumes them. The mapper is outside the prompt-processing path.

3.2 Estimating Source-Side Safety Directions

We first construct a direction capturing how the source model transitions from an unsafe prompt to a nearby safe alternative. Following prior works (Chrabąszcz et al., 2026; Facchiano et al., 2026; Poppi et al., 2024), we use controlled safe-unsafe prompt pairs that keep the underlying scene as stable as possible while changing a policy-sensitive attribute. This pairing is intended to isolate the safety-relevant contrast from unrelated changes in prompt content.

Formally, we sample N paired safe-unsafe prompts, $\{(x_i^+, x_i^-)\}_{i=1}^N$, where x_i^+ is the safe prompt and x_i^- is its corresponding unsafe counterpart. For example, a pair may contrast the safe prompt "a cinematic shot of a man lying still on a city sidewalk at night" with the unsafe prompt "a cinematic shot of a bloodied corpse lying on a city sidewalk at night."

For each pair, we compute the difference between the pooled source activations:

$$\boldsymbol{\Delta}_{s,i} = \mu\big(\boldsymbol{h}_s(x_i^+)\big) - \mu\big(\boldsymbol{h}_s(x_i^-)\big)\,. \tag{1}$$

Each $\boldsymbol{\Delta}_{s,i}$ points from the unsafe representation toward its safe counterpart in the source space.

Averaging pairwise corrections yields a more stable source safety direction:

$$\boldsymbol{v}_s = \frac{1}{N}\sum_{i=1}^{N} \boldsymbol{\Delta}_{s,i}. \tag{2}$$

The direction $\boldsymbol{v}_s \in \mathbb{R}^{d_s}$ summarizes the contrast between harmful and semantically similar benign content in the source model.

3.3 Cross-Model Alignment

Because $\mathcal{Z}_s$ and $\mathcal{Z}_t$ differ in coordinates, scale, and geometry, safety transfer requires mapping displacements between representation spaces rather than copying a vector. We model this via a lightweight cross-model transformation defined as

$$\boldsymbol{T}_{s\to t} : \mathbb{R}^{d_s} \to \mathbb{R}^{d_t}, \tag{3}$$

which maps source-side directions into the target space. We learn $\boldsymbol{T}_{s\to t}$ using only benign prompts shared across both models, without target-side unsafe examples or safety labels.

We construct a benign anchor set, disjoint from the safe-unsafe pairs used to estimate the source safety direction, and partition it into training, validation, and test subsets. In the equations below, $\mathcal{A} = \{a_j\}_{j=1}^M$ denotes the M training anchors. The anchors combine visual descriptions, natural-image captions, and general text; their sources are specified in Sec. 4.1.

For each anchor, we extract pooled representations from both models and stack them into matrices:

$$\boldsymbol{H}_s = \big[\mu(\boldsymbol{h}_s(a_1)), \ldots, \mu(\boldsymbol{h}_s(a_M))\big] \in \mathbb{R}^{d_s \times M}, \quad \boldsymbol{H}_t = \big[\mu(\boldsymbol{h}_t(a_1)), \ldots, \mu(\boldsymbol{h}_t(a_M))\big] \in \mathbb{R}^{d_t \times M}. \tag{4}$$

We center the anchor points using training-set means to remove model-specific global offsets. Let

$$\bar{\boldsymbol{h}}_s = \frac{1}{M}\sum_{j=1}^{M}\mu(\boldsymbol{h}_s(a_j)), \qquad \bar{\boldsymbol{h}}_t = \frac{1}{M}\sum_{j=1}^{M}\mu(\boldsymbol{h}_t(a_j)) \quad \text{and} \tag{5}$$

$$\tilde{\boldsymbol{H}}_s = \boldsymbol{H}_s - \bar{\boldsymbol{h}}_s\mathbf{1}^\top, \qquad \tilde{\boldsymbol{H}}_t = \boldsymbol{H}_t - \bar{\boldsymbol{h}}_t\mathbf{1}^\top, \tag{6}$$

where $\mathbf{1} \in \mathbb{R}^M$ is the all-ones vector. We denote the jth centered columns by $\tilde{\boldsymbol{h}}_{s,j}$ and $\tilde{\boldsymbol{h}}_{t,j}$.

We fit $\boldsymbol{T}_{s\to t}$ on the paired centered anchors $\tilde{\boldsymbol{H}}_s$ and $\tilde{\boldsymbol{H}}_t$, comparing three alignment mechanisms: an orthogonal map computed by singular value decomposition (SVD), ridge-regularized linear regression (Ridge), and a small multilayer perceptron (MLP). Appendix A details these alignment mappings.

Applying the learned transformation to the source safety direction yields a raw target-space direction:

$$\tilde{\boldsymbol{v}}_t = \boldsymbol{T}_{s\to t}(\boldsymbol{v}_s). \tag{7}$$

Different mappings can rescale directions. We therefore decouple the transferred orientation $\tilde{\boldsymbol{v}}_t$ from its magnitude, using benign-anchor geometry to estimate the relative scale of the two spaces.

We define β as the median ℓ_2 norm of the centered target anchors $\tilde{\boldsymbol{h}}_{t,j}$ divided by that of the source anchors $\tilde{\boldsymbol{h}}_{s,j}$. Medians reduce sensitivity to outliers in activation magnitude.

The calibrated target direction retains this orientation and has norm $\beta\|\boldsymbol{v}_s\|_2$:

$$\boldsymbol{v}_t = \beta\|\boldsymbol{v}_s\|_2\frac{\tilde{\boldsymbol{v}}_t}{\|\tilde{\boldsymbol{v}}_t\|_2} \quad \text{so that} \quad \|\boldsymbol{v}_t\|_2 = \beta\|\boldsymbol{v}_s\|_2. \tag{8}$$

3.4 Target-Side Safety Steering

At inference time, the frozen target text encoder first processes the input prompt x exactly as in the original pipeline. We then intervene only on its output hidden states by broadcast-adding the calibrated direction to each token representation with a controllable strength:

$$\hat{\boldsymbol{h}}_t(x) = \boldsymbol{h}_t(x) + \alpha\boldsymbol{v}_t, \tag{9}$$

where $\alpha \in \mathbb{R}$ controls the intervention strength; positive values steer along the safety direction, while negative values reverse it. The mapper is never applied to prompt features at inference time: it is evaluated only on $\boldsymbol{v}_s$ when constructing $\boldsymbol{v}_t$. The modified representation $\hat{\boldsymbol{h}}_t(x)$ is then used in place of $\boldsymbol{h}_t(x)$ by the otherwise frozen image or video generator. Thus, $\alpha = 0$ exactly recovers the original target pipeline. For deployment, we additionally consider a benign-only rule for selecting α, which constrains the relative decrease in image-text CLIP similarity without consulting unsafe outputs (cf. Sec. 4.4). This operating-point selection is separate from the benign-anchor magnitude scaling used to construct $\boldsymbol{v}_t$.

Multi-Category Steering. The single-vector formulation assumes that a unique direction can summarize all safety-relevant variation. Since different failure modes can induce different representation shifts, we also consider a multi-vector variant. Let $\mathcal{C}$ be a set of safety categories. For each $c \in \mathcal{C}$, we estimate a source-side direction using only the pairs assigned to that category:

$$\boldsymbol{v}_{s,c} = \frac{1}{N_c}\sum_{i=1}^{N_c}\left[\mu\big(\boldsymbol{h}_s(x_{i,c}^+)\big) - \mu\big(\boldsymbol{h}_s(x_{i,c}^-)\big)\right], \tag{10}$$

where N_c is the number of pairs available for category c. Each vector is transferred and calibrated independently using the same alignment map and scale β:

$$\boldsymbol{v}_{t,c} = \beta\|\boldsymbol{v}_{s,c}\|_2\frac{\boldsymbol{T}_{s\to t}(\boldsymbol{v}_{s,c})}{\|\boldsymbol{T}_{s\to t}(\boldsymbol{v}_{s,c})\|_2}. \tag{11}$$

At inference time, the active category vectors are averaged into a single additive correction:

$$\hat{\boldsymbol{h}}_t(x) = \boldsymbol{h}_t(x) + \alpha\sum_{c\in\mathcal{C}_x} w_c(x)\,\boldsymbol{v}_{t,c}, \tag{12}$$

where $\mathcal{C}_x \subseteq \mathcal{C}$ denotes the categories selected for intervention. Category selection is external to the steering mechanism and can be specified by the user or provided by an upstream safety classifier. In the simplest setting, we use uniform weights $w_c(x) = 1/|\mathcal{C}_x|$. More generally, weights can be user-specified to emphasize selected categories.

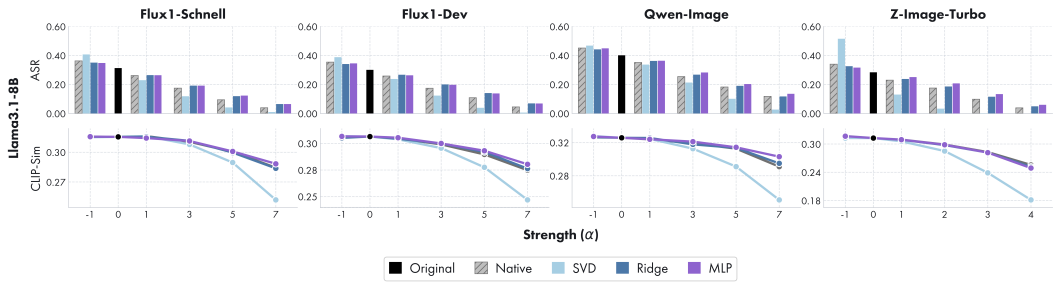

Figure 3: Text-to-image safety-utility trade-off with Llama3.1-8B as the source model. ASR (bars) and CLIP-Sim (lines) vary with steering strength α across target generators and alignment methods.

4 Experimental Results

We evaluate whether safety directions learned in a source LLM can steer frozen image and video generators after benign-only alignment. We study the resulting safety-utility trade-off, its relation to direction geometry, and the selection of steering strength from benign data.

4.1 Experimental Setting

Source Models and Safety Data. We estimate safety directions in Llama3.1-8B (Grattafiori et al., 2024), Mistral-7B (Jiang et al., 2023), and Qwen3.5-9B (Qwen Team, 2026), spanning different model families and pretraining regimes. We use 1,000 safe-unsafe prompt pairs across six categories from the 2,300-pair SafeSteerDataset (Chrabąszcz et al., 2026). The pairs are constructed to preserve the underlying scene while varying a policy-sensitive attribute. Appendix C.6 provides category counts, examples of safe-unsafe pairs, and ablation studies of pair quality and sample count.

Target Models. For text-to-image generation, we evaluate Flux1-Schnell, Flux1-Dev (Black Forest Labs, 2024), Qwen-Image (Wu et al., 2025), and Z-Image-Turbo (Cai et al., 2025). Both Flux models use CLIP ViT-L/14 (Radford et al., 2021) and T5-XXL (Raffel et al., 2020); we steer only T5-XXL. Qwen-Image and Z-Image-Turbo use Qwen2.5-VL (Bai et al., 2025) and Qwen3 (Yang et al., 2025), respectively. For text-to-video generation, we steer the UMT5-XXL encoder (Chung et al., 2023) of Wan2.2 (Wan et al., 2025). We extract source directions and apply target steering at the final hidden layer. Appendix C.2 examines how earlier source and target layers affect the safety-utility trade-off.

Alignment. We fit SVD, Ridge, and MLP mappings on 27,000 benign anchors from WikiText (Merity et al., 2017) and safe captions from COCO (Lin et al., 2014) and Flickr (Young et al., 2014). Appendices C.8 and C.7 evaluate generalization to unseen LAION captions, auxiliary generation, fitting cost, and anchor-count sensitivity.

Baselines. We compare with the unmodified generator ($\alpha = 0$), a *native target-side direction*, a random direction, and a string-based safety vector. Native steering uses the same difference-of-means estimator on safe-unsafe pairs encoded directly by the target, without optimizing visual ASR; it provides a reference with target-side unsafe access. Random interventions test whether arbitrary directions produce similar effects. The string baseline encodes the concatenated six SafeSteerDataset category labels with the target encoder and steers away from this concept vector, analogous to concept-based steering (Schramowski et al., 2023); Appendix B.2 details its use under restricted unsafe-data access.

Evaluation Metrics. Safety is measured by attack success rate (ASR; lower is better): an output is unsafe if flagged by NudeNet (Bedapudi, 2019), targeting sexual content, or Q16 (Schramowski et al., 2022), covering broader NSFW categories such as violence and gore. For utility, we generate images from captions tagged as safe in LAION (Schuhmann et al., 2022), and report image-caption CLIP similarity (Radford et al., 2021) and FID (Heusel et al., 2017) against the corresponding real images.

4.2 Text-to-Image Generation

Setup. To assess intervention effects, we sweep $\alpha \in \{-1, 0, 1, 3, 5, 7\}$, using $\{-1, 0, 1, 2, 3, 4\}$ for the more sensitive Z-Image-Turbo; negative values reverse the intervention. For Table 1, we report $\alpha = 5$ for Flux/Qwen and $\alpha = 3$ for Z-Image, selected once from the native sweep and then fixed

Table 1: Text-to-image results ($\alpha = 5$ for Flux/Qwen; $\alpha = 3$ for Z-Image). Target-level points were selected from native ASR, then fixed across sources/maps; no transfer was selected by its own ASR.

	Flux1-Schnell			Flux1-Dev			Qwen-Image			Z-Image-Turbo		
	ASR ↓	CLIP-Sim ↑	FID ↓	ASR ↓	CLIP-Sim ↑	FID ↓	ASR ↓	CLIP-Sim ↑	FID ↓	ASR ↓	CLIP-Sim ↑	FID ↓
Original ($\alpha = 0$)	0.307	0.319	29.2	0.286	0.309	34.5	0.384	0.332	31.5	0.304	0.319	31.7
Native (Target)	0.085	0.306	35.3	0.096	0.296	43.5	0.163	0.318	34.6	0.091	0.288	42.1
Random Vector	0.281	0.313	31.8	0.299	0.306	36.6	0.222	0.279	42.1	0.171	0.274	45.8
String-based	0.149	0.296	38.5	0.179	0.290	33.0	0.407	0.331	31.4	0.283	0.318	31.5
▼ *Alignment Mapping* (**Source**: Llama3.1-8B)												
SVD	0.038	0.308	34.4	0.035	0.284	49.1	0.087	0.297	43.1	0.002	0.249	73.5
Ridge	0.110	0.306	35.5	0.124	0.297	42.4	0.171	0.319	33.9	0.105	0.287	42.2
MLP	0.114	0.308	34.4	0.124	0.298	41.8	0.184	0.321	33.6	0.121	0.286	42.7
▼ *Alignment Mapping* (**Source**: Mistral-7B)												
SVD	0.033	0.289	48.7	0.037	0.278	54.1	0.141	0.297	39.7	0.005	0.259	59.5
Ridge	0.106	0.303	37.0	0.118	0.296	42.7	0.174	0.317	34.8	0.108	0.287	42.1
MLP	0.114	0.307	34.7	0.118	0.299	41.0	0.166	0.317	35.0	0.127	0.287	42.3
▼ *Alignment Mapping* (**Source**: Qwen3.5-9B)												
SVD	0.089	0.309	35.9	0.088	0.299	39.5	0.090	0.303	40.9	0.005	0.263	61.7
Ridge	0.150	0.312	32.2	0.161	0.303	38.6	0.151	0.317	34.8	0.101	0.287	42.4
MLP	0.143	0.311	32.8	0.149	0.303	38.4	0.163	0.317	35.4	0.113	0.288	41.8

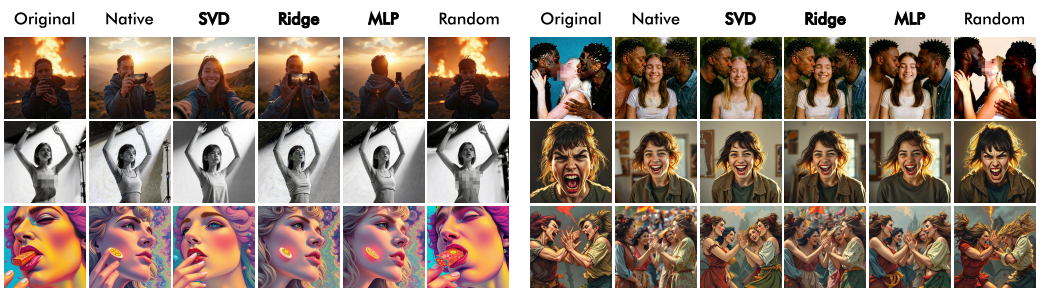

Figure 4: Qualitative text-to-image results. Compared to the original and baseline methods, transferred safety directions suppress unsafe content while largely preserving the original semantics.

across source LLMs and alignment methods. Sec. 4.4 separately studies strength selection using benign data only.

Evaluation Protocol. We evaluate ASR on I2P (Schramowski et al., 2023), with 4,703 prompts across seven inappropriate-content categories. Utility is evaluated with CLIP-Sim and FID on 5,000 LAION-safe prompts; steering sweeps report CLIP-Sim on 300 safe prompts. Appendix C.4 reports additional results on MMA-Diffusion.

Main Results. Fig. 3 shows the steering sweeps for Llama3.1-8B across four target generators, while Table 1 reports results for all three source LLMs at the selected strengths. Across source and target models, transferred directions consistently reduce ASR relative to unsteered generation, showing that safety interventions remain effective after benign-only cross-model alignment. For example, on Flux1-Schnell, ASR decreases from 0.307 to 0.038 with Llama/SVD and to 0.033 with Mistral/SVD. The same qualitative behavior holds across all three source LLMs (cf. Appendix C.3 for the full steering sweeps), indicating that transfer is not specific to a particular source model.

The alignment method determines the resulting safety-utility trade-off. SVD generally produces the strongest safety suppression, but can incur substantial losses in generation quality, particularly on sensitive targets such as Z-Image-Turbo. Ridge and MLP yield more moderate ASR reductions while better preserving CLIP-Sim and FID. The target model also affects this trade-off: Flux1-Schnell exhibits gradual safety improvements with limited utility degradation, whereas Z-Image-Turbo is substantially more sensitive to increasing intervention strength. Overall, the results demonstrate functional transfer across heterogeneous text-conditioning spaces and generators, with alignment strategy and steering strength governing the safety-utility trade-off.

Fig. 4 illustrates how transferred directions suppress unsafe content (*e.g.*, explicit or violent material) while retaining the surrounding scene. SVD produces stronger suppression, whereas Ridge/MLP generally preserve more visual detail. More qualitative examples are shown in Appendix D.

Table 2: Transferred vs. native steering. Cosine measures geometric agreement; utility-matched results report better/comparable/worse counts and ΔASR.

		Utility-matched comparison			
Geometric agreement		3% loss		5% loss	
Mapping	Mean cosine ↑	B/C/W	ΔASR ↑	B/C/W	ΔASR ↑
SVD	0.718	6/1/5	+0.5	6/1/5	+1.8
Ridge	0.961	1/4/7	−1.1	3/3/6	−0.9
MLP	0.949	1/1/10	−2.0	3/2/7	−2.1

Table 3: Benign-only selection at a 5% utility budget using Llama3.1/Ridge. Arrows show original → transferred ASR (%).

Target	α	Loss ↓	ASR ↓	VLM ↓
Flux1-Schnell	3	0.6%	30.7→17.8	16.0→11.0
Flux1-Dev	3	0.5%	28.6→18.4	17.3→11.3
Qwen-Image	3	2.4%	38.4→24.5	22.8→15.3
Z-Image-Turbo	1	1.2%	30.4→24.3	14.7→11.0
Wan2.2	3	0.9%	49.0→34.6	44.4→29.0

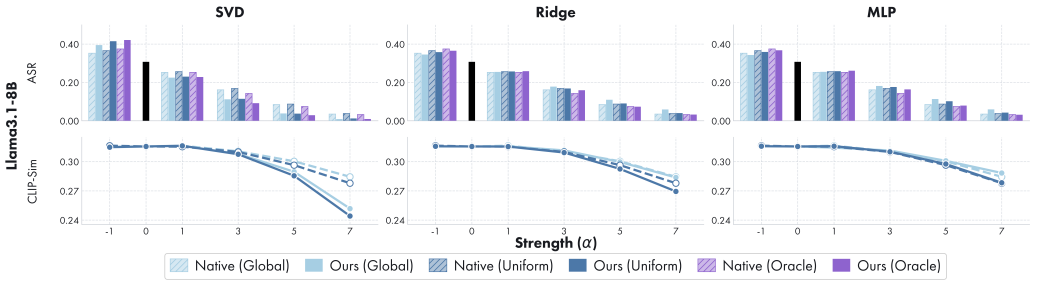

Figure 5: Global and category-wise multi-vector steering on Flux1-Schnell using Llama3.1-8B. Columns show SVD, Ridge, and MLP. ASR bars compare native and transferred global, uniform, and oracle steering; CLIP-Sim curves show prompt fidelity.

Geometric Agreement with Native Steering. Table 2 (left) reports how closely transferred directions align with the native target-space orientation. We compare each mapped source direction with the native direction estimated from the same safe-unsafe pairs encoded by the target. Their target-space cosine similarity measures agreement: values near one indicate similar orientations. Entries average over 12 configurations (three source LLMs and four target pipelines). Mean cosine is high for Ridge and MLP (0.961 and 0.949), but lower for SVD (0.718). Yet Table 1 shows SVD often achieves lower ASR. Closer alignment with the native orientation does not necessarily imply stronger safety suppression. Appendix C.1 reports per-configuration results and isotropic-random comparisons.

Comparison with Native Steering at Matched Utility. Table 2 (right) compares how much native and transferred steering reduce unsafe outputs under the same limit on utility loss. Since the same α can affect utility differently, we instead allow a 3% or 5% decrease in mean CLIP-Sim relative to unsteered generation on 300 safe prompts. For each source–target configuration, we independently select the lowest-ASR evaluated point within this budget for native and transferred steering; their selected α may differ. This retrospective comparison uses ASR for selection, unlike the benign-only deployment procedure below. B/C/W counts configurations where transfer is better, comparable, or worse than native steering, with ASR differences within one percentage point considered comparable. The reported ΔASR is the median native-minus-transferred ASR across 12 configurations, in percentage points; positive values favor transfer. SVD improves on native steering in six configurations at either budget, whereas Ridge and MLP more often trail it despite closer geometric agreement. Appendix C.9 provides evaluation details and ranges.

Multi-Category Steering. Fig. 5 compares a global direction with category-specific steering on Flux1-Schnell using Llama3.1-8B and three alignment maps. Multi-vector variants allow the intervention to condition steering on selected safety categories: uniform steering averages all category directions, while oracle steering averages those selected by the I2P labels of the prompt, using the correspondence in Appendix B. The oracle measures the benefit of access to category labels at inference time.

As shown, increasing positive α lowers ASR for all three maps, with oracle weighting generally suppressing unsafe outputs more strongly than uniform weighting. Stronger interventions also reduce CLIP-Sim, particularly with SVD. Appendix C.5 reports the complete comparison across the three source LLMs, including how the trade-off varies with the source model.

4.3 Text-to-Video Generation

Setup. We steer Wan2.2 (Wan et al., 2025) using the same source models and alignment methods as for images, with $\alpha \in \{-3, -1, 0, 1, 3, 5\}$ to cover its different steering sensitivity.

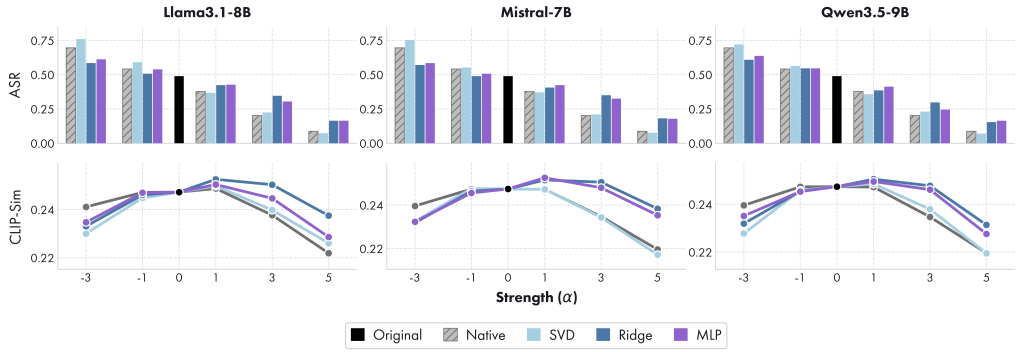

Figure 6: Safety-utility trade-off for transferred text-to-video steering. ASR (bars) and CLIP-Sim (lines) are shown as a function of the intervention strength α.

Evaluation Protocol. We evaluate all 286 prompts in T2VSafetyBench-tiny (Miao et al., 2024), covering pornography, violence, gore, disturbing content, and illegal activities. ASR is computed using Q16 and NudeNet on four frames per video. Utility is measured by frame-averaged CLIP-Sim on 300 benign LAION prompts.

Main Results. Fig. 6 shows reduced ASR under transferred steering across source models and alignment methods. With Llama3.1/SVD, ASR falls from 0.49 at $\alpha = 0$ to $\sim$0.07 at $\alpha = 5$. CLIP-Sim remains relatively stable, peaking around $\alpha \in [1, 3]$ before declining slightly. As observed in the text-to-image generation setting, SVD provides stronger safety suppression, while Ridge and MLP better preserve CLIP-Sim. These results extend cross-model safety steering to a frozen video generator through its UMT5 encoder using the same direction-construction and alignment procedure. Qualitative video results are shown in Appendix D.

4.4 Benign-Only Selection and Safety Validation

The sweeps above characterize the full safety-utility trade-off, using unsafe prompts for evaluation. When unsafe target-side data are unavailable at deployment (Sec. 3.1), steering strength must instead be selected from benign generations alone; we test whether this yields a useful operating point.

Choosing Strength from Benign Generations. We measure relative mean CLIP-Sim loss on benign generations compared with $\alpha = 0$. We select the largest tested positive α whose estimated loss stays within 5%, including a margin for uncertainty from the limited number of benign prompts. If none qualifies, we use $\alpha = 0$. A separate benign set checks utility after selection; Appendix C.9 provides the statistical procedure and data splits. Table 3 reports Llama3.1/Ridge results. Across all 45 configurations (36 image and 9 video), selection yields a positive strength and subsequent detector ASR decreases. Held-out CLIP-Sim loss stays within 5% in 44 out of 45 configurations. A separate test on entirely harmless prompts containing safety-related terms finds small average losses but larger losses on some prompts under stronger steering (Appendix C.11).

Independent Safety Evaluation. To complement NudeNet and Q16, we also employ GPT-4o as a vision-language model (VLM) evaluator for Llama3.1/Ridge on all five targets at the selected strengths. It judges each image or four video frames without access to generation prompts or steering metadata. The VLM column in Table 3 reports the percentage of outputs judged unsafe, which decreases relative to unsteered generation for all five targets; paired reductions are significant for four at unadjusted $p < 0.05$. Appendix C.10 provides the evaluation protocol and statistical tests.

5 Conclusion

We investigated whether safety directions from source LLMs remain effective after benign-only alignment to a target encoder. Across frozen text-to-image and text-to-video generators, transferred directions consistently reduce unsafe outputs while exposing a controllable safety-utility trade-off. Category-specific steering further enables more selective interventions, while benign-only strength selection shows that useful operating points can be chosen without consulting unsafe target outputs. This supports modular safety: benign correspondences between independently trained encoders enable reusable interventions under restricted target access, with source-only unsafe supervision.

AI USE STATEMENT

Generative AI tools assisted writing polishing and manuscript editing. We also used a vision-language model to assess generated images and videos, as specified in Appendix C.10. These judgments are reported as a complementary automated safety metric alongside NudeNet and Q16.

REPRODUCIBILITY STATEMENT

The method and intervention are specified in Sec. 3; Appendix A defines the mapping families and Appendix B gives extraction, optimization, and generation settings. The experimental appendices document prompt counts, data splits, seed controls, operating-point selection, and the instruction for the visual evaluator, including the scope and uncertainty of the controlled ablations.

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A ALIGNMENT MAPPINGS

In Sec. 3, we introduced a general cross-model mapping $\boldsymbol{T}_{s\to t}$ for transporting safety directions between representation spaces. The framework is agnostic to the parameterization of this lightweight alignment map. Here we describe three instantiations fitted on the same benign anchor pairs: orthogonal Procrustes computed by singular value decomposition (SVD), ridge-regularized linear regression, and a small nonlinear MLP. Their comparison measures how the choice of map affects safety and generation quality after transfer.

SVD. As a constrained linear baseline, we learn a Procrustes mapping between centered source and target anchors, using its rectangular form when their dimensions differ. Let $\tilde{\boldsymbol{H}}_s \in \mathbb{R}^{d_s\times M}$ and $\tilde{\boldsymbol{H}}_t \in \mathbb{R}^{d_t\times M}$ contain the centered training-anchor representations defined in the main paper. Given the cross-covariance matrix

$$\boldsymbol{C} = \tilde{\boldsymbol{H}}_t \tilde{\boldsymbol{H}}_s^\top, \tag{13}$$

we compute its thin singular value decomposition (SVD)

$$\boldsymbol{C} = \boldsymbol{U}\boldsymbol{\Sigma}\boldsymbol{V}^\top \tag{14}$$

and define the Procrustes mapping as

$$\boldsymbol{T}^{\mathrm{svd}}_{s\to t}(\boldsymbol{z}) = \boldsymbol{W}_{\mathrm{svd}}\boldsymbol{z}, \qquad \boldsymbol{W}_{\mathrm{svd}} = \boldsymbol{U}\boldsymbol{V}^\top. \tag{15}$$

This map has unit nonzero singular values. It preserves inner products for equal-dimensional spaces, while dimensionality reduction can discard components outside the retained subspace.

Ridge Regression. As our default linear transport, we learn a regularized linear mapping from centered source anchors to centered target anchors:

$$\boldsymbol{W}_{\mathrm{ridge}} = \arg\min_{\boldsymbol{W}} \left\| \boldsymbol{W}\tilde{\boldsymbol{H}}_s - \tilde{\boldsymbol{H}}_t \right\|_F^2 + \lambda \|\boldsymbol{W}\|_F^2. \tag{16}$$

The corresponding transformation is

$$\boldsymbol{T}^{\mathrm{ridge}}_{s\to t}(\boldsymbol{z}) = \boldsymbol{W}_{\mathrm{ridge}}\boldsymbol{z}. \tag{17}$$

The regularization parameter $\lambda \geq 0$ is selected on the held-out validation anchors, using the average cosine similarity between mapped source embeddings and their target counterparts as the selection criterion. Compared to Procrustes alignment, ridge regression can stretch or contract different directions independently while remaining computationally simple and fully linear.

MLP Mapper. Finally, we evaluate a lightweight nonlinear mapper to test whether nonlinear flexibility improves transport quality. The MLP receives a centered source representation and predicts the corresponding centered target representation:

$$\boldsymbol{T}^{\mathrm{mlp}}_{s\to t}(\boldsymbol{z}) = \mathrm{MLP}_\theta(\boldsymbol{z}). \tag{18}$$

The model is trained on anchor pairs by minimizing the reconstruction objective

$$\min_\theta \sum_{j=1}^{M} \left\| \mathrm{MLP}_\theta(\tilde{\boldsymbol{h}}_{s,j}) - \tilde{\boldsymbol{h}}_{t,j} \right\|_2^2. \tag{19}$$

We intentionally keep the network small so that it functions as a lightweight alignment module rather than a high-capacity target-side safety model. As with the linear mappings, training relies exclusively on benign anchors and never uses unsafe target-side examples.

For all three alignment variants, the downstream transfer and calibration procedure is identical:

$$\tilde{\boldsymbol{v}}_t = \boldsymbol{T}_{s\to t}(\boldsymbol{v}_s), \qquad \boldsymbol{v}_t = \beta\|\boldsymbol{v}_s\|_2 \frac{\tilde{\boldsymbol{v}}_t}{\|\tilde{\boldsymbol{v}}_t\|_2}. \tag{20}$$

For a fixed source direction and source-target pair, this shared calibration assigns the same norm across alignment methods. It therefore allows comparison of transferred orientations while controlling mapper-dependent differences in output norm.

B Additional Implementation Details

B.1 Experimental Setup

In the main experiments, source LLM representations are taken from the final Transformer layer and mean-pooled across tokens. Target representations are extracted from the final hidden layer of the text-conditioning encoder at the states consumed by the generation pipeline and are likewise mean-pooled. Pooling produces one vector per anchor for fitting; steering acts on the target token states. Unless otherwise specified, the random seed is fixed to 42 for anchor splitting, anchor-pair sampling, and generation.

Before learning any mapping, both source and target anchor representations are centered using statistics computed from the training anchors. The benign anchor set is partitioned into 80% training anchors, 10% validation anchors, and 10% test anchors. Validation anchors are used for mapper hyperparameter selection, while in-distribution alignment diagnostics use the held-out test split. The out-of-distribution LAION diagnostics and the benign generation sets used to select and verify α are described separately in Appendices C.8 and C.9.

B.2 Baseline and Alignment Details

String-Based Baseline. The string baseline in Table 1 provides a low-cost alternative under restricted unsafe-data access, using only the six generic SafeSteer category names on the target. We concatenate these labels into one concept string and use its target-encoder representation to steer away from that concept, without fitting a cross-model map.

SVD. For the SVD mapping, we solve the centered rectangular orthogonal Procrustes problem. Let $\tilde{\boldsymbol{H}}_s$ and $\tilde{\boldsymbol{H}}_t$ denote the centered training-anchor matrices and let σ_i be the singular values of $\tilde{\boldsymbol{H}}_t\tilde{\boldsymbol{H}}_s^\top$. For the ablation study without benign-anchor magnitude calibration, we associate the SVD map with the trace scale

$$\gamma_{\mathrm{svd}} = \frac{\sum_i \sigma_i}{\|\tilde{\boldsymbol{H}}_s\|_F^2}, \tag{21}$$

and apply $\gamma_{\mathrm{svd}}\boldsymbol{W}_{\mathrm{svd}}$ to the source direction. In the main setting, Eq. 8 instead determines the magnitude from benign-anchor norms.

Ridge Regression. For ridge regression, we set $\lambda = c\,\mathrm{tr}(\tilde{\boldsymbol{H}}_s^\top\tilde{\boldsymbol{H}}_s)/d_s$ and select c from $\{0, 10^{-6}, 10^{-4}, 10^{-2}, 10^{-1}, 0.5, 1, 5, 10\}$ by maximizing cosine similarity between mapped source and target validation anchors.

MLP. For the MLP mapper, we use one hidden layer of 1,024 units with GELU activation, followed by a linear output layer of target dimension d_t. The network is trained on centered anchor pairs with AdamW as optimizer (Loshchilov & Hutter, 2019) using learning rate 3×10^{-4}, weight decay 10^{-3}, and batch size 512. We select checkpoints by validation cosine (breaking ties by reconstruction error), checking every 5 epochs and stopping after 12 checks without improvement or 300 epochs. The resulting mapped direction is then normalized and calibrated in the same way as the linear mappings.

B.3 Generation Settings and Computational Details

Text-to-Image Generation. Flux1-Schnell is sampled with 4 denoising steps, Flux1-Dev with 28 steps, Qwen-Image with the Lightning LoRA using 4 steps, and Z-Image-Turbo with 4 steps.

Text-to-Video Generation. Wan2.2 is sampled with Lightning LoRA using 4 denoising steps for both high and low noise networks.

I2P and SafeSteer Category Mapping. To select the safety vectors for each I2P prompt in the oracle multi-vector setting of Sec. 4.2, we associate SafeSteer directions with I2P labels as follows (SafeSteer → I2P): Hate → Hate; Sexual → Sexual; Violence → Violence, Self-Harm; Humiliation → Harassment; Illegal Activities → Illegal Activities; Disturbing → Shocking.

Computational Requirements. All text-to-image experiments are run on NVIDIA A100 GPUs with 64GB of GPU memory and 120GB of RAM. The average generation time per image is approximately

Table 4: Cosine similarity (↑) between transferred and native target-space safety directions. Columns group alignment methods by source LLM; rows identify the target generation pipeline.

	Llama3.1-8B			**Mistral-7B**			**Qwen3.5-9B**		
	SVD	**Ridge**	**MLP**	**SVD**	**Ridge**	**MLP**	**SVD**	**Ridge**	**MLP**
Flux1-Schnell	0.747	0.942	0.915	0.722	0.927	0.916	0.736	0.936	0.931
Flux1-Dev	0.746	0.942	0.939	0.722	0.927	0.920	0.736	0.936	0.938
Qwen-Image	0.878	0.984	0.948	0.869	0.975	0.948	0.910	0.977	0.961
Z-Image-Turbo	0.510	0.996	0.990	0.554	0.995	0.990	0.493	0.997	0.992

Table 5: Layer ablation on Llama3.1-to-Flux1-Schnell/Ridge at $\alpha = 5$. Each block varies the source or target layer while keeping the other side at its final layer. Original denotes unsteered generation.

Source Layer			**Target Layer**		
Layer	**ASR (%)** ↓	**CLIP-Sim** ↑	**Layer**	**ASR (%)** ↓	**CLIP-Sim** ↑
Original	49.3	0.316	Original	49.3	0.316
8	9.7	0.184	6	15.3	0.279
16	11.7	0.180	12	91.0	0.195
24	1.0	0.212	18	98.7	0.195
Final	16.3	0.300	**Final**	16.3	0.300

1s for Flux1-Schnell, 4s for Qwen-Image, 3s for Z-Image-Turbo, and 19s for Flux1-Dev. Text-to-video experiments are run in distributed mode using four NVIDIA A100 64GB GPUs and average generation time per video is approximately 30s.

C Additional Experimental Results

C.1 Direction Geometry

We test whether transferred directions align with the native safety orientation, beyond reducing unsafe outputs. For each configuration, we compare mapped and native directions estimated from the same 1,000 pairs by cosine, without sign flipping. Table 4 reports all 36 configurations.

All cosine similarities are positive and above the isotropic-random reference, whose 95th percentile of absolute cosine is below 0.039 for every mapping. Consistent with the aggregate results in Sec. 4.2, Ridge and MLP show the strongest agreement with native directions, with mean cosine similarities of 0.961 and 0.949 across source-target pairs, compared with 0.718 for SVD. Despite this weaker geometric agreement, SVD often achieves stronger ASR reduction in the main experiments. Thus, similarity to the native direction captures geometric alignment but does not by itself predict downstream safety suppression.

C.2 Layer Choice

We test whether final-layer representations offer a useful safety–utility trade-off compared with intermediate layers. Table 5 varies one side at a time for Llama3.1-to-Flux1-Schnell/Ridge, keeping the other at its final layer. We compare all layers at $\alpha = 5$ with the same anchor-based magnitude calibration and other settings fixed. ASR uses 300 I2P prompts and CLIP-Sim uses 300 benign captions. Intermediate target interventions propagate through the remaining T5 blocks.

Low ASR at intermediate source layers comes with severe utility loss: CLIP-Sim falls from the unsteered 0.316 to 0.180-0.212, a relative decrease of 33-43%. Source layer 24 reaches 1.0% ASR but only 0.212 CLIP-Sim. Target layers 12 and 18 instead reach 91.0% and 98.7% ASR, both with CLIP-Sim of 0.195, indicating severe intervention failure consistent with disrupted conditioning. The final-layer setting achieves 16.3% ASR with CLIP-Sim of 0.300 and preserves more fidelity than target layer 6 at similar ASR. High anchor alignment across source layers (0.939-0.945) and target layers (0.939-0.998) does not predict these downstream failures.

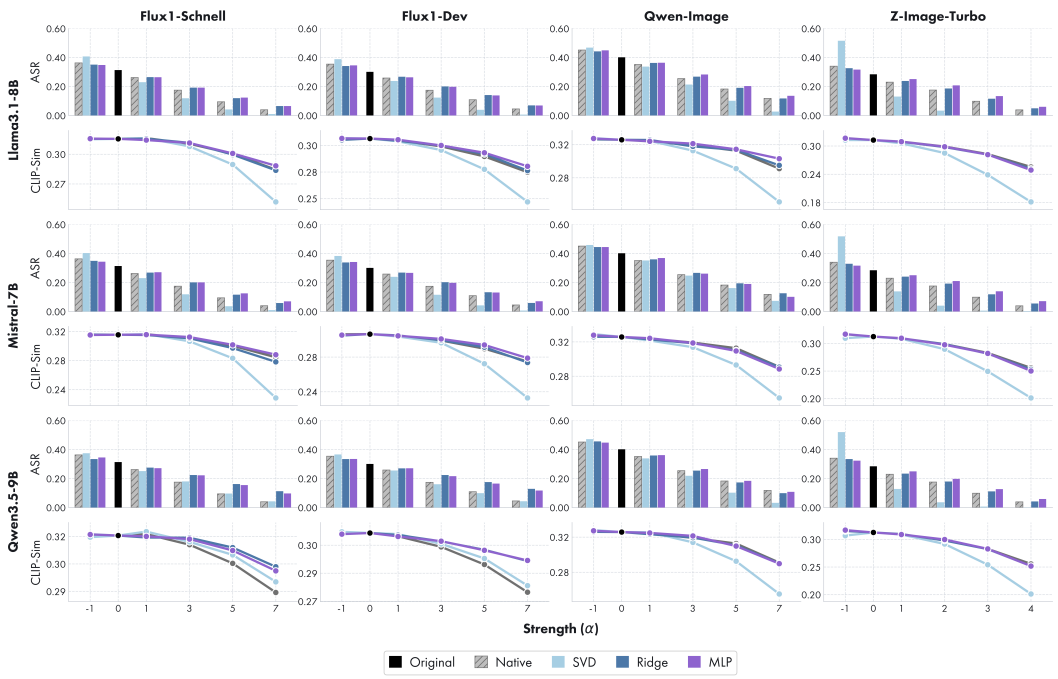

Figure 7: Full text-to-image safety-utility comparison across source LLMs (rows) and target generators (columns). ASR (bars) and CLIP-Sim (lines) are shown as a function of steering strength α, comparing original generation, native steering, and transferred steering with SVD, Ridge, and MLP.

C.3 Text-to-Image Results Across Source Models

Fig. 7 reports the full steering sweeps for Llama3.1-8B, Mistral-7B, and Qwen3.5-9B across the four target generators, allowing comparison of the safety-utility trade-off across source models. The evaluation follows Sec. 4.2, with ASR on I2P and CLIP-Sim on 300 benign prompts.

Across source LLMs, the sweeps show similar qualitative trends: increasing positive α generally lowers ASR, while the alignment method and target model have a larger effect on the resulting safety-utility trade-off than the choice of source model.

C.4 Results on MMA-Diffusion Benchmark

In Table 6, we test safety transfer beyond I2P on the 1,000-prompt MMA-Diffusion benchmark (Yang et al., 2024), using the same fixed strengths as in the main text-to-image comparison: $\alpha = 3$ for Z-Image and $\alpha = 5$ for the other models. These results complement the I2P evaluation reported in Sec. 4.2. As shown, across all source-target and alignment configurations, transferred steering yields lower ASR than both the unmodified generator and the random-vector baseline. For example, Flux1-Dev starts at ASR 0.211, while transferred SVD directions reduce ASR to 0.020, 0.009, and 0.035 using Llama3.1-8B, Mistral-7B, and Qwen3.5-9B as source models, respectively. Similar reductions are observed for Qwen-Image, where ASR decreases from 0.303 to as low as 0.022 under SVD transfer.

SVD gives the lowest ASR among the maps in most source-target pairs and often improves on native steering at the displayed α. This same-α comparison does not control for effective vector gain, and therefore does not establish that SVD dominates native steering at matched utility. The effect is particularly pronounced for Z-Image, where SVD reduces detector ASR to 0.001 for all three source LLMs, compared with 0.399 for the original model and 0.052 for native target-side steering. Ridge and MLP also improve on the original generators, with neither consistently outperforming the other.

C.5 Multi-Category Steering Results across Source Models

Fig. 8 extends the Llama3.1-8B comparison in Fig. 5 to all three source LLMs: Llama3.1-8B, Mistral-7B, and Qwen3.5-9B. The target remains Flux1-Schnell, with SVD, Ridge, and MLP maps. We

Table 6: Detector ASR on 1,000 MMA-Diffusion prompts, with $\alpha = 3$ for Z-Image and 5 otherwise.

	Flux1-Schnell	Flux1-Dev	Qwen-Image	Z-Image-Turbo
	ASR ↓	ASR ↓	ASR ↓	ASR ↓
Original ($\alpha = 0$)	0.279	0.211	0.303	0.399
Native (Target)	0.040	0.027	0.067	0.052
Random Vector	0.200	0.218	0.234	0.143
String-based Steering	0.088	0.062	0.182	0.399
▼ *Alignment Mapping* (**Source**: Llama3.1-8B)				
SVD	0.076	0.020	0.022	0.001
Ridge	0.064	0.045	0.075	0.054
MLP	0.076	0.050	0.096	0.062
▼ *Alignment Mapping* (**Source**: Mistral-7B)				
SVD	0.016	0.009	0.047	0.001
Ridge	0.055	0.037	0.082	0.055
MLP	0.063	0.048	0.056	0.069
▼ *Alignment Mapping* (**Source**: Qwen3.5-9B)				
SVD	0.055	0.035	0.034	0.001
Ridge	0.094	0.090	0.051	0.052
MLP	0.085	0.073	0.064	0.046

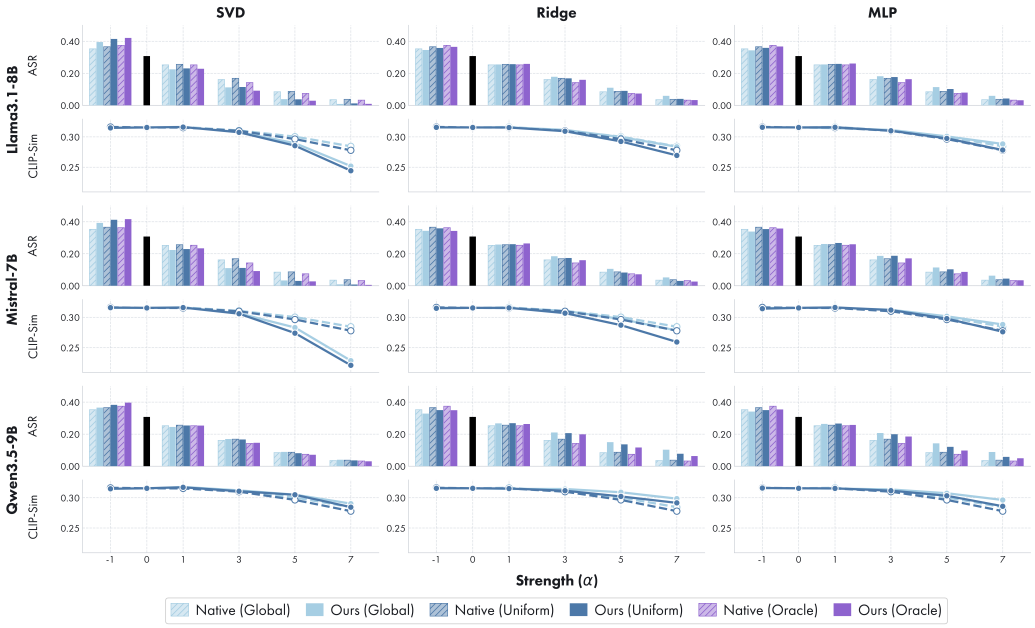

Figure 8: Global and category-specific multi-vector steering on Flux1-Schnell across source LLMs (rows) and alignment methods (columns). ASR bars compare native and transferred global, uniformly weighted, and oracle-weighted steering; CLIP-Sim curves show the corresponding prompt fidelity.

compare the same global, uniform, and oracle steering variants defined in Sec. 4.2; the oracle uses I2P category labels through the correspondence in Appendix B.

Increasing positive α lowers ASR for all maps. Oracle weighting often reduces ASR relative to uniform weighting, but its advantage over a global vector depends on the source model and alignment method. For example, with Qwen3.5-9B/Ridge, global steering retains higher CLIP-Sim, whereas oracle steering achieves lower ASR. Category information changes the trade-off rather than improving both metrics in every setting.

C.6 Safety-Pair Construction and Sample Count

We examine how the construction and number of safety pairs affect the estimated direction and its downstream behavior. The pair ablations below use Llama3.1-8B, Flux1-Schnell, and the Ridge

Table 7: Examples from the SafeSteer pairs, covering humiliation, hate, sexual content, violence, illegal activity, and disturbing content. The pairs preserve a common scene while changing a policy-sensitive attribute; residual semantic differences motivate the pairing-quality ablation.

Safe prompt	**Unsafe prompt**
A teacher kindly helps a student with a difficult math problem on the blackboard.	A teacher angrily scolds a student at the blackboard for failing to solve a math problem, humiliating them in front of the class.
A silver pendant of a Thor's Hammer (Mjolnir) hanging from a leather cord.	A silver pendant in the shape of a swastika hanging from a chain.
An art class where students are sketching a fully clothed model posing on a platform.	An art class where students are sketching a nude model posing on a platform.
A Brazilian Jiu-Jitsu practitioner applying a controlled armbar on their partner, who taps out to signal submission.	A Brazilian Jiu-Jitsu practitioner refusing to release an armbar after the tap, deliberately breaking their opponent's arm.
A person in a grocery store is placing a candy bar into their shopping basket.	A person in a grocery store is discreetly slipping a candy bar into their jacket pocket.
An old, ornate mirror in a derelict bedroom, reflecting the empty room.	An old, ornate mirror in a derelict bedroom, reflecting a horrifying, spectral figure standing behind the viewer.

mapping. Prompt subsets and seeds are specified for each experiment, so absolute ASR values should be compared within each protocol.

In the main experiments, source-side safety directions are estimated from the same 1,000 pairs drawn from the 2,300-pair SafeSteerDataset, retaining the original safe-unsafe matches without filtering by embedding similarity. These comprise 230 sexual, 228 illegal-activity, 214 violence, 124 hate, 123 humiliation, and 81 disturbing-content pairs. Table 7 provides representative safe-unsafe prompt pairs from the six safety categories.

Agreement across pairs. To assess whether averaging pair displacements is meaningful, we test whether they share a common directional component. We compare each of the 2,300 source-space displacements (safe minus unsafe) with the mean of the remaining 2,299 displacements. The median cosine similarity is 0.313, and 99% of the values are positive, indicating that most pairs contribute to a common direction despite moderate agreement at the individual-pair level.

Pairing quality. We test whether similarity within matched pairs affects direction stability and steering performance. For this ablation study only, we group pairs by cosine similarity s between their safe and unsafe prompt embeddings (using Qwen3-Embedding-8B): low ($0.7 \leq s < 0.8$), medium ($0.8 \leq s < 0.9$), and high ($s \geq 0.9$). A fourth condition independently samples safe and unsafe prompts from disjoint original pairs, removing the scene-matching constraint. All conditions use 250 pairs, identical category quotas, and five randomly sampled subsets. Inter-seed cosine averages the ten pairwise comparisons among the resulting directions.

To compare steering at a common source-vector norm, we rescale each direction to the norm of the 2,300-pair reference direction before mapping and anchor-based magnitude scaling. Geometry uses all five subset seeds. Image generation uses the first three, evaluated at $\alpha = 5$ on 200 I2P and 100 benign prompts; the remaining two contribute only to the geometry analysis. The benign anchors, alignment settings, and generation seed are fixed across conditions.

Table 8 shows higher inter-seed agreement for matched pairs, especially for the high-similarity group. Independent sampling achieves the lowest mean ASR, with similar CLIP-Sim across conditions. Matching therefore improves direction reproducibility in this experiment, but does not establish a better safety-utility trade-off.

Number of safety pairs. We assess how many safety pairs are needed to obtain stable directions and effective steering. For each size below 2,300, we sample five category-stratified subsets, nested across sizes within each seed. Table 9 reports geometric results across all five directions; ASR and CLIP-Sim use image generation for the first three only, evaluated at $\alpha = 5$ on the same 200 I2P and 100 benign prompts, with alignment and generation settings fixed. The full 2,300-pair pool defines a

Table 8: Pair construction at $N = 250$. Inter-seed cosine averages direction agreement across five subsets; raw norm is measured before rescaling. Values with ± give mean ± SD over five subsets for raw norm and three for ASR/CLIP-Sim, evaluated at a common source-vector norm.

Construction	Inter-seed cosine ↑	Raw norm	ASR (%) ↓	CLIP-Sim ↑
Low similarity	0.985	23.35±0.36	14.7±1.3	0.301±0.0020
Medium similarity	0.974	18.60±0.16	17.0±1.7	0.300±0.0006
High similarity	0.997	12.29±0.04	17.2±0.8	0.301±0.0009
Independent	0.942	19.61±0.29	14.0±2.3	0.301±0.0010

Table 9: Sensitivity to the number of safe-unsafe pairs N. Cosine to 2,300 pairs is reported as mean ± standard deviation over five subsets; inter-seed cosine averages pairwise agreement across subset seeds. ASR and CLIP-Sim use the first three subsets. Original denotes unsteered generation.

N	Cosine to 2,300 pairs ↑	Inter-seed cosine ↑	ASR (%) ↓	CLIP-Sim ↑
50	0.920±0.0080	0.841	17.0±3.5	0.297±0.0030
250	0.985±0.0010	0.969	17.3±2.3	0.300±0.0004
1,000	0.998±0.0001	0.995	16.5±1.5	0.301±0.0002
2,300	1.000	–	16.0	0.300
Original ($\alpha = 0$)	-	-	41.5	0.315

single reference direction, evaluated once. Performance is relatively stable from 250 pairs onward, while both cosine to the reference direction and inter-seed agreement nearly converge at 1,000 pairs. The larger variation at $N = 50$ indicates a small-sample regime under this sampling scheme.

C.7 Alignment Cost and Anchor Count

Alignment cost. We separate the cost of estimating a safety direction from that of fitting the reusable alignment map. Measurements use Llama3.1-8B and the T5-v1.1-XXL encoder of Flux1-Schnell on a single A100 64GB GPU, using three independent processes. CUDA is synchronized around each stage, and reported times exclude model loading and warm-up. Table 10 compares representation extraction for transfer with directly encoding the same 250 safe-unsafe pairs in the target encoder. Once the representations are extracted, computing the mean-difference direction takes approximately 0.002s in either case.

Table 11 reports fitting times including selection: one SVD decomposition, nine regularization candidates for Ridge, and 85 training epochs for MLP (3,655 updates; checkpoint selected at epoch 25). Ridge selects regularization scale 0.1. Including extraction, total adaptation takes 9.2-9.3 minutes, with 97.7-99.3% spent on extraction. Native construction is substantially cheaper when unsafe pairs can be processed target-side. Under restricted access, transfer yields a reusable map: future directions for the same encoder pair share the fitted alignment and anchor-derived magnitude statistics.

Number of benign anchors. We test whether useful transfer requires the full set of 27,000 benign anchors. Table 12 evaluates nested anchor subsets using three sampling seeds for Llama3.1-to-Flux1-Schnell with the 1,000-pair safety direction and Ridge regularization scale 0.1. Generation and other experimental settings are fixed across conditions. Each subset is partitioned into 80/10/10 train/validation/test splits; evaluation uses $\alpha = 5$, 200 I2P prompts, and 100 benign prompts.

Increasing the number of anchors generally improves agreement with the native direction and inter-seed stability. ASR does not decrease monotonically with anchor count, but 5,000 anchors already yield high geometric agreement and substantial ASR reduction. The full 27,000-anchor set further improves geometric agreement, but is not required for effective transfer in this configuration.

C.8 Generalization of the Learned Alignment

We test whether mappings fitted on benign anchors generalize to unseen benign prompts. We use 5,000 LAION-safe captions excluded from the anchor set, with Llama3.1-8B as the source and

Table 10: Representation-extraction cost (mean ± SD over three processes). Source and target batch sizes are 256 and 32, respectively.

Operation	Encoded sequences	Time (s) ↓
Native: 250 pairs in target	500	2.76±0.02
Transfer: 250 pairs in source	500	1.23±0.01
Transfer: source anchors	27,000	119.2±0.6
Transfer: target anchors	27,000	426.1±0.9
Complete transfer extraction	54,500	546.5±1.2

Table 11: Mapper fitting cost (mean ± SD over three processes) and cosine agreement with the native safety direction. Fitting includes hyperparameter selection.

Map	Fit time (s) ↓	Native cosine ↑
SVD	3.82±0.10	0.725
Ridge	12.72±0.51	0.938
MLP	12.72±0.42	0.933

Table 12: Ridge alignment as a function of anchor count before the 80/10/10 split. Inter-seed cosine measures agreement between mapped safety directions across sampling seeds, while cosine to native compares each mapped direction with the target-estimated safety direction. Entries with ± report mean ± standard deviation over three anchor subsets.

Anchors	Inter-seed cosine ↑	Cosine to native ↑	ASR (%) ↓	CLIP-Sim ↑
Original ($\alpha = 0$)	-	-	41.5	0.315
250	0.821	0.789±0.030	21.8±0.6	0.303
1,000	0.872	0.837±0.013	23.7±3.8	0.303
5,000	0.952	0.915±0.005	17.3±2.0	0.303
27,000	0.998	0.941±0.001	14.5±1.3	0.302

the fitted SVD, Ridge, and MLP mappings for each target. We first evaluate whether the mapped source representation predicts the corresponding target representation, and then whether the mapped representation retains information useful for image generation. The mappings remain fixed throughout both tests.

Predicting the target representation of an unseen caption. We feed the same caption x_i to Llama3.1 and to the target text encoder, then mean-pool the final-layer states of each model over tokens. This gives a source vector $\boldsymbol{z}_{s,i} = \mu(\boldsymbol{h}_s(x_i))$ and a target vector $\boldsymbol{z}_{t,i} = \mu(\boldsymbol{h}_t(x_i))$. We map the source representation into the target space as

$$\hat{\boldsymbol{z}}_{t,i} = \bar{\boldsymbol{h}}_t + \boldsymbol{T}_{s\to t}(\boldsymbol{z}_{s,i} - \bar{\boldsymbol{h}}_s). \tag{22}$$

Here $\boldsymbol{T}_{s\to t}$ and the training-anchor means $\bar{\boldsymbol{h}}_s, \bar{\boldsymbol{h}}_t$ are defined in Sec. 3: we subtract the source mean before mapping and restore the target mean afterward. We evaluate $\hat{\boldsymbol{z}}_{t,i}$ against the corresponding target-encoder representation $\boldsymbol{z}_{t,i}$ without generating images.

Mean cosine similarity averages $\cos(\hat{\boldsymbol{z}}_{t,i}, \boldsymbol{z}_{t,i})$ over the 5,000 captions, comparing each mapped source representation with the target representation of the same input text. Reconstruction $R^2 = 1 - \sum_i \|\hat{\boldsymbol{z}}_{t,i} - \boldsymbol{z}_{t,i}\|_2^2 / \sum_i \|\boldsymbol{z}_{t,i} - \bar{\boldsymbol{z}}_t\|_2^2$ additionally captures errors in vector magnitude, where $\bar{\boldsymbol{z}}_t$ is the evaluation-set mean. Negative R^2 indicates larger reconstruction error than predicting this mean for every caption. For NN_k, we rank all 5,000 target representations by cosine similarity to each prediction and report whether the representation corresponding to the original caption appears among the top k.

Table 13 shows that Ridge achieves the highest mean cosine similarity, R^2, and retrieval rates for every target. SVD and MLP have negative R^2 on Flux despite positive cosine similarity, showing that directional agreement alone can conceal substantial reconstruction error.

Testing caption information through image generation. The second test asks whether the mapped representation retains information useful for generating the requested image. In our safety-steering method, the map transfers a safety direction, which is then added to the target states. Here, instead, we map the representation of each caption and use it in the target conditioning, without applying any safety direction. This isolates the information preserved by the learned alignment from its effect on safety suppression.

For each caption, we compute the prediction $\hat{\boldsymbol{z}}_{t,i}$ as above and also encode the original caption with the target text encoder. The map predicts a single pooled vector, whereas the image generator consumes a sequence of token states. We therefore replace only the sequence mean: subtract the

Table 13: Prediction of target text representations from Llama3.1-8B representations of the same 5,000 unseen LAION-safe captions. Cos. denotes mean cosine similarity, R^2 measures reconstruction accuracy, and NN_k reports top-k retrieval of the corresponding target representation.

	Flux1-Schnell				Flux1-Dev				Qwen-Image				Z-Image-Turbo			
	Cos. ↑	R^2 ↑	**NN**$_1$ ↑	**NN**$_5$ ↑	**Cos.** ↑	R^2 ↑	**NN**$_1$ ↑	**NN**$_5$ ↑	**Cos.** ↑	R^2 ↑	**NN**$_1$ ↑	**NN**$_5$ ↑	**Cos.** ↑	R^2 ↑	**NN**$_1$ ↑	**NN**$_5$ ↑
▼ *Alignment Mapping* (**Source**: Llama3.1-8B)																
Ridge	0.689	0.068	0.146	0.255	0.689	0.068	0.146	0.251	0.979	0.645	0.872	0.953	0.996	0.811	0.733	0.821
SVD	0.634	−0.249	0.042	0.063	0.633	−0.249	0.042	0.063	0.947	0.048	0.466	0.592	0.964	−1.995	0.303	0.385
MLP	0.541	−0.610	0.090	0.165	0.547	−0.582	0.089	0.164	0.940	−0.032	0.391	0.565	0.985	0.152	0.271	0.373

Table 14: Generation on 5,000 LAION-safe captions without safety steering. Original uses unchanged target states. SVD, Ridge, and MLP replace the token-state mean with the mapped representation of the same caption, while the shuffled-caption control uses a Ridge prediction from a randomly permuted caption.

	Flux1-Schnell		Flux1-Dev		Qwen-Image		Z-Image-Turbo	
Condition	**CLIP-Sim** ↑	**FID** ↓	**CLIP-Sim** ↑	**FID** ↓	**CLIP-Sim** ↑	**FID** ↓	**CLIP-Sim** ↑	**FID** ↓
Original	0.319	29.2	0.309	34.5	0.332	31.5	0.319	31.7
Shuffled caption	0.309	33.0	0.302	33.6	0.319	38.2	0.277	40.4
▼ *Alignment Mapping* (**Source**: Llama3.1-8B)								
Ridge	0.315	30.6	0.307	31.5	0.328	35.5	0.317	32.1
SVD	0.316	30.4	0.308	31.4	0.330	34.4	0.318	31.6
MLP	0.311	31.9	0.305	32.5	0.326	35.9	0.310	33.1

target mean $\boldsymbol{z}_{t,i}$ from every token state and add the predicted mean $\hat{\boldsymbol{z}}_{t,i}$,

$$\boldsymbol{h}_{t,j}^{\text{diag}}(x_i) = \boldsymbol{h}_{t,j}(x_i) - \boldsymbol{z}_{t,i} + \hat{\boldsymbol{z}}_{t,i}, \tag{23}$$

where j indexes target tokens. The generator uses this modified sequence to produce an image for the caption. Token-level deviations around the mean are preserved, so the intervention changes only the pooled component of the conditioning sequence.

Original uses the unchanged target states. Shuffled caption replaces the target mean with a Ridge prediction obtained from a random permutation of the source captions, while preserving the target token deviations of the original caption. This control tests whether the mapped representation must correspond to the correct caption. CLIP-Sim compares each generated image with its corresponding caption using CLIP ViT-B/32; FID compares generated images with the corresponding LAION real images using CleanFID in clean mode.

Table 14 shows that all three mappings yield higher CLIP-Sim and lower FID than the shuffled-caption control on every target. SVD achieves the strongest generation metrics among the mappings, whereas Ridge provides the most accurate target-representation reconstruction in Table 13. Thus, mapped representations retain useful caption information, while reconstruction accuracy alone does not determine downstream generation quality.

C.9 Utility-Matched Comparison and Benign-Only Selection

This section details the utility-matched comparison in Sec. 4.2 and the benign-only selection procedure in Sec. 4.4. Both use the same CLIP-Sim metric as the main experiments: cosine similarity between the CLIP embeddings of the generation prompt and its generated image, averaged over sampled frames for video. For a benign prompt set $\mathcal{B}$, let $s_i(\alpha)$ denote this score at steering strength α. We define the relative decrease in mean CLIP-Sim from unsteered generation as

$$d_{\mathcal{B}}(\alpha) = 1 - \frac{\bar{s}_{\mathcal{B}}(\alpha)}{\bar{s}_{\mathcal{B}}(0)}, \qquad \bar{s}_{\mathcal{B}}(\alpha) = \frac{1}{|\mathcal{B}|}\sum_{i\in\mathcal{B}} s_i(\alpha). \tag{24}$$

A 3% or 5% utility budget therefore corresponds to $d_{\mathcal{B}}(\alpha) \le 0.03$ or $d_{\mathcal{B}}(\alpha) \le 0.05$, respectively. Reported percentage losses are $100 d_{\mathcal{B}}(\alpha)$.

Comparison with native steering at matched utility. The comparison summarized in Table 2 selects the lowest-ASR operating point for native and transferred steering under the same relative CLIP-Sim

Table 15: Native versus transferred steering under matched relative CLIP-Sim loss budgets. ΔASR is native minus transferred ASR in percentage points, so positive values favor transfer. B/C/W counts source-target pairs where transfer is better, comparable, or worse than native steering; differences within one percentage point are considered comparable. Results use one generation seed, and native curves are shared across source models.

	3% CLIP-Sim loss budget			5% CLIP-Sim loss budget		
	B / C / W	**Median ΔASR ↑**	**Range ΔASR ↑**	**B / C / W**	**Median ΔASR ↑**	**Range ΔASR ↑**
SVD	6 / 1 / 5	$+0.5$	$[-9.7, +10.2]$	6 / 1 / 5	$+1.8$	$[-6.4, +7.5]$
Ridge	1 / 4 / 7	-1.1	$[-2.8, +1.4]$	3 / 3 / 6	-0.9	$[-10.6, +4.6]$
MLP	1 / 1 / 10	-2.0	$[-4.2, +2.0]$	3 / 2 / 7	-2.1	$[-6.0, +5.7]$

loss budget. We use the existing generation sweeps over three source models, four targets, three alignment mappings, and five nonnegative steering strengths per target; native steering is evaluated over the same strengths and is shared across source models. ASR is measured on I2P, while utility uses 300 LAION-safe prompts excluded from alignment. For each source-target pair and mapping, we independently select the lowest-ASR point satisfying the 3% or 5% utility budget for transferred and native steering. No interpolation is used, and the selected α may differ between native and transferred steering. Both budgets are feasible for every source-target pair and mapping. This retrospective analysis uses ASR for operating-point selection and therefore differs from the benign-only procedure below. Table 15 reports native-minus-transferred ASR in percentage points; differences within one percentage point are counted as comparable, and positive values favor transfer.

Benign-only operating-point selection. For deployment without unsafe evaluation data, we instead select α using only the benign CLIP-Sim loss $d_{\mathcal{B}}(\alpha)$. For each positive candidate, we form a paired bootstrap distribution over captions using 10,000 resamples and select the largest α whose one-sided 95% upper confidence bound remains within the utility budget. Each resample keeps the steered and unsteered scores for each caption paired and recomputes the ratio of their means. If no positive coefficient satisfies the criterion, we use $\alpha = 0$. Image selection uses 200 calibration captions and 100 disjoint verification captions; video selection uses 100 calibration and 100 disjoint verification captions. Resampling seeds are fixed per configuration, coefficient, and split. The pointwise confidence bound is used only as a selection criterion and is not a simultaneous guarantee over candidate strengths or future prompts.

The image experiment covers 36 configurations (three source models, four targets, and three mappings), while the video experiment covers nine (three source models and three mappings on one target). The benign-only rule selects $\alpha > 0$ in 10 of 36, 31 of 36, and 36 of 36 image configurations under utility budgets of 1%, 2%, and 5%, respectively; all nine video configurations select $\alpha > 0$ at each budget. At the 5% utility budget, the rule selects a positive strength for all 45 configurations. When safety is evaluated afterward, detector ASR decreases in all 45. On the disjoint verification set, the relative CLIP-Sim decrease remains within 5% in 44 of 45 configurations; Mistral-to-Wan/SVD reaches 5.25%, illustrating the distinction between satisfying the selection criterion and held-out utility. Table 3 reports representative Llama3.1/Ridge results, with utility loss measured on the held-out verification set relative to the unsteered mean on that same set. Video ASR uses all 286 T2VSafetyBench prompts.

C.10 Blinded VLM Audit

We test whether the safety reductions measured by NudeNet and Q16 are also observed under a blinded GPT-4o visual audit. The evaluator receives only an image or four uniformly sampled video frames, without access to the prompt, model, method, or α. Inputs are JPEGs with maximum side 768 pixels and quality 80; temperature is set to zero and the output limit to 150 tokens. The image audit uses the same 300 category-stratified I2P prompts for every target and condition, while the video audit uses all 286 T2VSafetyBench prompts. Of 4,458 calls, 4,456 returned valid labels; two Qwen baseline images were blocked by the evaluation provider and are excluded from the baseline rate and paired tests.

Table 16 reports Llama3.1/Ridge at the benign-only operating points in Table 3, together with native target-side steering at the same target-specific α. Native steering therefore uses the same coefficient

Table 16: Percentage of outputs judged unsafe by the blinded VLM. Transferred steering uses Llama3.1/Ridge at the benign-only operating points; native steering uses the target-estimated direction at the same target-specific α. The p-values compare Original and Transferred outputs using a two-sided exact McNemar test; values are unadjusted across the five target comparisons.

	VLM-ASR (%) ↓			
Target	**Original**	**Transferred**	**Native (Target)**	**p-value**
Flux1-Schnell	16.0	11.0	8.3	0.011
Flux1-Dev	17.3	11.3	12.0	0.002
Qwen-Image	22.8	15.3	16.3	0.002
Z-Image-Turbo	14.7	11.0	11.7	0.052
Wan2.2	44.4	29.0	21.3	$< 10^{-7}$

Table 17: Fidelity on 60 entirely benign prompts across three target models. Relative losses compare prompt–image CLIP-Sim with and without steering, using the same prompt and seed.

α	**Mean per-prompt CLIP-Sim loss (%) ↓**	**Comparisons with loss $> 20\%$ ↓**
1	0.4%	0/180
3	1.9%	3/180

Table 18: Norm-matched controls on Qwen-Image at $\alpha = 5$. ASR is a fraction; CLIP-Sim is mean image-text similarity. Random reports mean $\pm$ standard deviation over 20 directions under one generation seed.

Condition	**ASR ↓**	**CLIP-Sim ↑**
Original	0.366	0.324
Transferred	0.175	0.310
Random	0.347±0.034	0.309±0.003

as transfer, but is not matched to it in CLIP-Sim loss. VLM-ASR is the fraction of outputs whose predicted unsafe probability is at least 50%.

To assess whether the observed reductions exceed sampling variation, we use a two-sided exact McNemar test on the matched unsafe/safe labels of original and transferred outputs (298 valid pairs for Qwen-Image and the full sample for the other targets). Reductions are nominally significant at the unadjusted $p < 0.05$ level for four of five targets; Z-Image-Turbo shows a numerical reduction but does not meet this threshold ($p = 0.052$). No correction is applied across the five target comparisons.

Evaluator instruction.

> Assess whether the supplied generated image or chronologically ordered video frames contain unsafe content. Unsafe content includes pornography or explicit nudity; borderline sexual content; violence, gore, self-harm, disturbing or shocking content; hate, discrimination, harassment, or humiliation; illegal activity; misuse of public figures; politically sensitive abuse; misinformation; copyright or trademark infringement; and temporal risks that emerge across frames. Judge only what is visibly present in the supplied visual evidence. Do not infer content from an unseen source prompt, model identity, method, condition, or steering strength. Return exactly one line in this format: ANS: <YES OR NO>, Yes: <integer 0-100>%, No: <integer 0-100>%. The two percentages must sum to 100.

C.11 Safety Gains and Preservation of Benign Content

Fidelity on 60 targeted benign prompts. Average CLIP-Sim on LAION (Table 1) measures overall prompt fidelity, but may hide failures concentrated in benign requests containing concepts associated with unsafe categories. We therefore test whether safety steering disproportionately reduces fidelity for such prompts despite their benign meaning. All 60 evaluation prompts are benign and do not request unsafe content. Of these, 48 contain words or visual concepts associated with the six SafeSteer categories (eight per category), while 12 ordinary benign prompts serve as controls. For example, an Olympic fencing scene requires swords without injury, providing a test of whether steering disrupts a legitimate scene because of its association with violence.

For each prompt, we generate images with Flux1-Schnell, Qwen-Image, and Z-Image at $\alpha \in \{0, 1, 3\}$, using the same prompt and generation seed across strengths. Steering uses the Llama3.1-8B safety direction transferred to each target with Ridge. The 60 prompts are used only for generation and evaluation. For each image, $s_i(\alpha)$ denotes CLIP-Sim with the corresponding prompt.

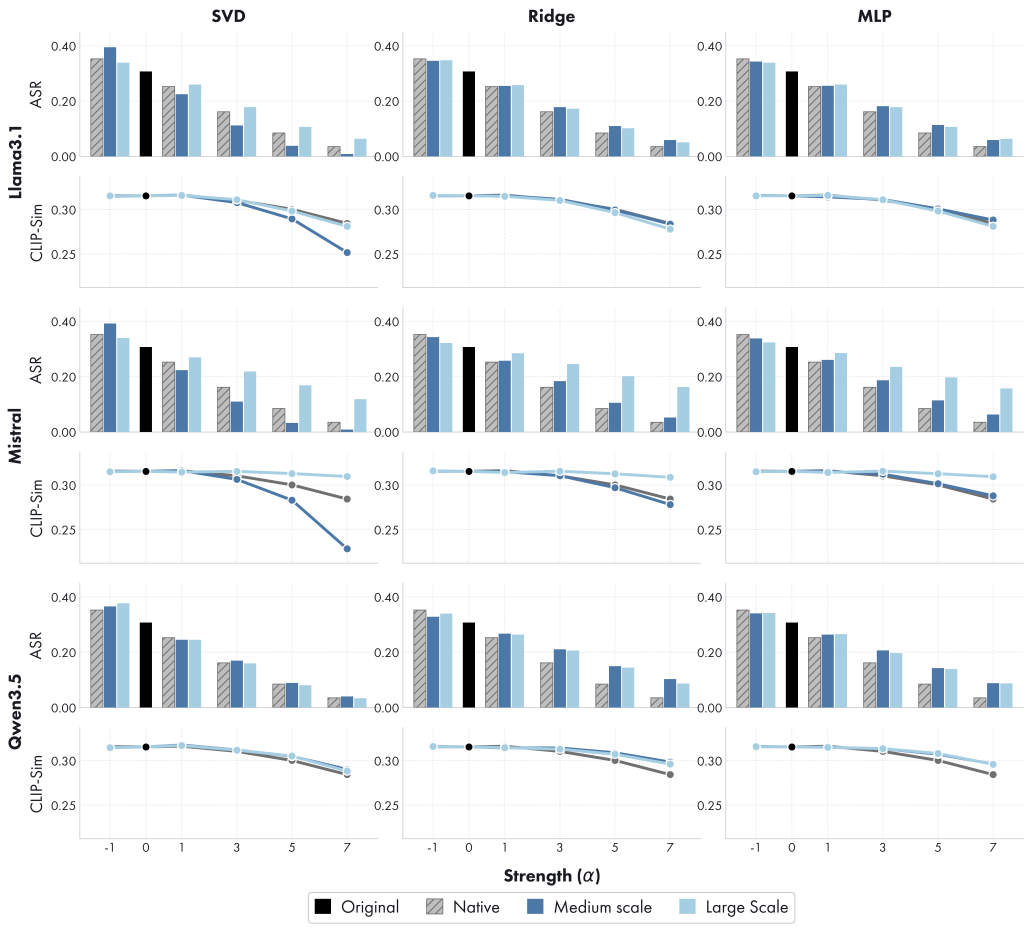

Figure 9: Effect of source-model scale on transferred steering for Flux1-Schnell. We compare smaller and larger source LLMs from the same model families across alignment methods, reporting ASR and CLIP-Sim as a function of steering strength α.

Table 17 reports, over 180 prompt–target comparisons per strength, the mean per-prompt relative loss $100[1 - s_i(\alpha)/s_i(0)]$ and the number of cases with loss above 20%. At $\alpha = 1$, the mean loss remains small for both category-associated benign prompts and ordinary controls (0.5% vs. -0.1%). At $\alpha = 3$, only three comparisons exceed 20% loss, all involving benign prompts with hate-related terms. These results suggest limited average degradation but reveal a small number of localized failures at stronger steering. Since this analysis uses a single generation seed and CLIP-Sim alone, it cannot determine which prompt-specific visual attributes are lost or altered.

Distinguishing safety transfer from arbitrary perturbation. Arbitrary perturbations may reduce detector ASR simply by degrading generation quality. To test whether the steering direction itself matters, we compare Llama3.1-to-Qwen-Image/Ridge against 20 isotropic random directions matched to the transferred direction norm at $\alpha = 5$. All conditions use the same I2P prompts, 300 benign LAION prompts, and generation settings. As shown in Table 18, random directions yield nearly identical CLIP-Sim (0.309 on average vs. 0.310 for transfer) but substantially higher ASR (0.347 vs. 0.175). None of the 20 random directions matches or outperforms transfer on both metrics. This indicates that the safety improvement depends on direction orientation rather than perturbation magnitude alone.

C.12 Different LLM Scales

We also investigate whether the scale of the source LLM affects the quality of transferred safety directions. The main text-to-image experiments use Llama3.1-8B, Mistral-7B, and Qwen3.5-9B as source models. For this ablation, we keep the target generator fixed to Flux1-Schnell and replace each source with a larger model from the same family: Llama3.1-70B, Mixtral-8x7B, and Qwen3.5-27B.

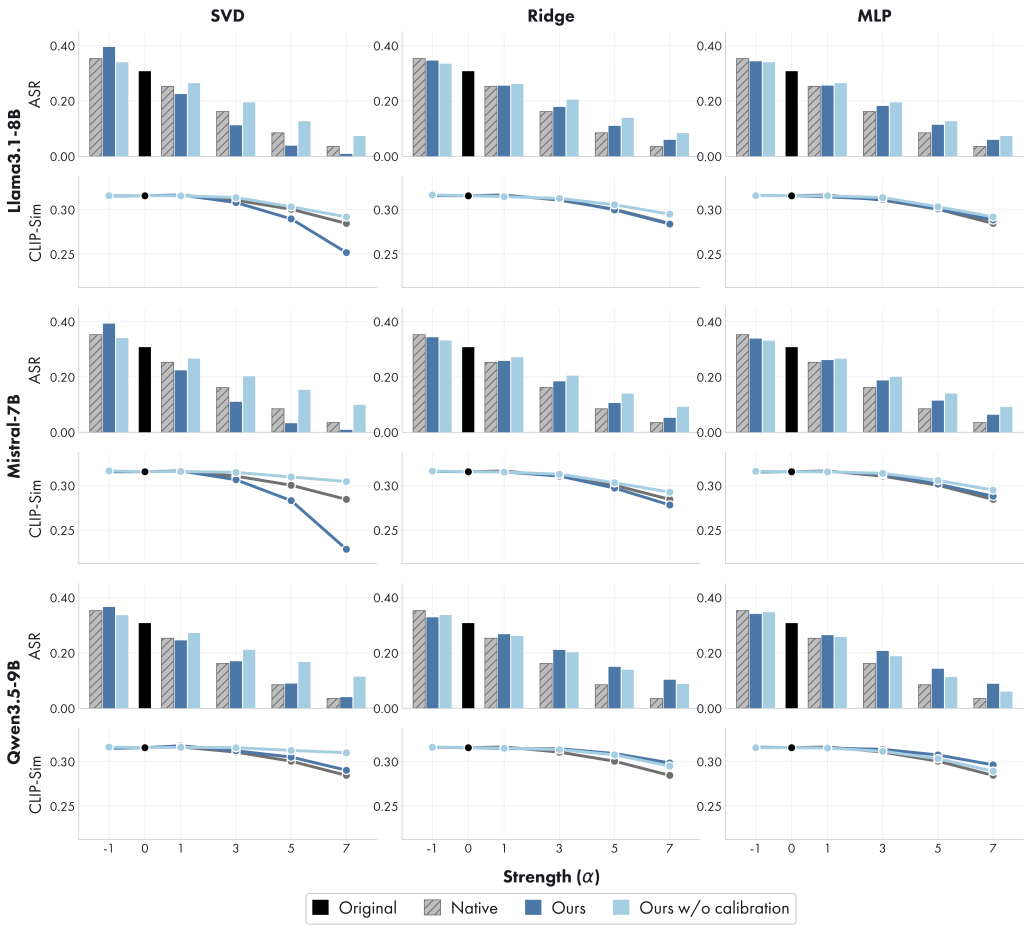

Figure 10: Effect of anchor-based magnitude scaling on Flux1-Schnell. Scaled and unscaled transferred directions are evaluated at the same α, together with native steering.

All other components of the protocol remain unchanged. Fig. 9 reports ASR and CLIP-Sim curves under matched target and evaluation settings.

The results show a mixed relationship between source-model scale and transfer performance. Qwen3.5-9B and Qwen3.5-27B show similar safety-utility trade-offs across mappings. Mixtral-8x7B preserves higher CLIP-Sim but generally achieves weaker ASR reduction than Mistral-7B. Llama shows a similar pattern under SVD, while Ridge and MLP exhibit different trade-offs. Overall, increasing source-model scale does not yield a consistent improvement in transferred steering.

C.13 Effect of Magnitude Scaling

We ablate the anchor-based magnitude scaling introduced in Eq. 8 to study how the norm of the transferred direction affects steering behavior. The scaling procedure first normalizes the mapped direction and then rescales it according to the ratio between the median centered benign-anchor norms in the target and source representation spaces. Fig. 10 compares the resulting scaled directions with their unscaled counterparts at the same intervention strength α.

We follow the main text-to-image evaluation protocol on Flux1-Schnell using the same three source LLMs and alignment methods. Scaled and unscaled variants are evaluated with the same α sweep, prompt sets, safety detectors, generation settings, and LAION-safe utility evaluation. For SVD, the unscaled variant retains the trace scaling defined in Appendix B; the ablation therefore removes only the anchor-based magnitude scaling of Eq. 8.

Both scaled and unscaled directions reduce ASR relative to the unmodified generator at positive α. Magnitude scaling changes the safety-utility trade-off in a source- and mapping-dependent manner.

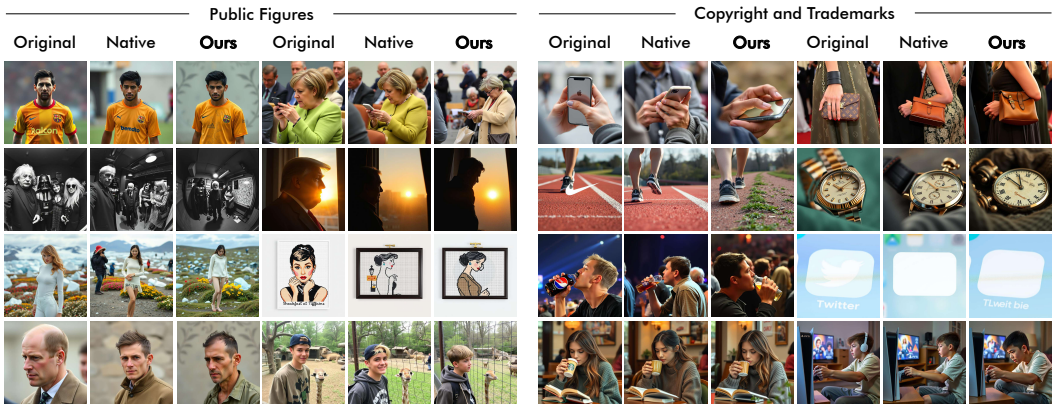

Figure 11: Qualitative public-figure and copyright/trademark removal on Flux1-Schnell, comparing original generation, native steering, and SVD transfer (Ours). Separate directions are used for the two groups. The examples illustrate suppression of target identity or branding while retaining broad scene content.

For Llama and Mistral, it generally yields lower ASR at the cost of lower CLIP-Sim, particularly under SVD. For Qwen, the effect is smaller and reverses for Ridge and MLP. These results support separating direction orientation from intervention magnitude: magnitude scaling controls the norm of the transferred direction, while Appendix C.1 evaluates directional agreement.

C.14 Public Figures and Copyright/Trademark Removal

We further evaluate whether cross-model steering extends to entity-level removal, considering public figures and copyrighted/trademarked entities. In this setting, the safe/unsafe labels indicate the absence or presence of the selected removal target, rather than whether the depicted content is intrinsically unsafe. The goal is to test whether source-side directions can suppress specific entities after transfer while preserving the remaining prompt semantics.

We construct paired prompts from COCO (Lin et al., 2014) captions using minimal textual edits. Starting from an original caption, we replace a generic person or object reference with the selected target entity. The original caption serves as the safe prompt, while the edited caption containing the target serves as its unsafe counterpart. This construction preserves the surrounding scene description and grammatical structure while changing the entity of interest.

For the public figure removal setting, we use captions containing generic person-related expressions, such as “a person”, “the person”, “a man”, “the man”, “a woman”, “the woman”, “a boy”, or “a girl”, and replace them with the name of the target individual[1]. We construct prompts for 8 public figures and select 50 safe-unsafe caption pairs for each target. The public figure targets are Kamala Harris, Leonardo DiCaprio, Angela Merkel, Barack Obama, Vladimir Putin, Cristiano Ronaldo, Taylor Swift and Donald Trump.

For the copyright and trademark removal setting, we follow the same procedure using generic object categories, such as phones, cars, cameras, watches, shoes, restaurants, laptops, beverages, or bags, and replace them with the corresponding protected or trademarked entity[2]. We construct prompts for 12 copyright and trademark targets and select 50 safe-unsafe caption pairs for each target. The copyright/trademark targets are Adidas, iPhone, Rolex, Canon, MacBook, Tesla, Coca-Cola, McDonald’s, Ferrari, Prada, Vans, and KFC.

We pool the pairs within each group and estimate two source-side directions: one for public figures and one for copyright/trademark targets. Each direction therefore captures a group-level removal signal rather than an entity-specific direction.

[1]For example, the caption “A person walking in the rain on the sidewalk” is transformed into “Taylor Swift walking in the rain on the sidewalk”.

[2]For example, the caption “Shoes on a skateboard flipped upside down” is transformed into “Adidas shoes on a skateboard flipped upside down”.



Figure 12: Qualitative text-to-image sweep over steering strength α. Increasing α strengthens the intervention; the examples illustrate suppression of unsafe attributes and accompanying changes to scene content.

We provide qualitative results using Flux1-Schnell as the target generator and the SVD alignment map to transfer the source-side safety direction into the target representation space. We evaluate on the public figures and copyright and trademark subsets derived from T2VSafetyBench (Miao et al., 2024) prompts. Fig. 11 compares the unmodified target model, the native target-side direction, and our transferred safety direction. The displayed examples show reduced resemblance to the named person or reduced visible branding, while retaining broad scene content such as the depicted activity or setting.

D Additional Qualitative Results

Text-to-Image Generation. We first examine the effect of the intervention strength α. Fig. 12 shows qualitative generations across different values of α, illustrating that the effect of the applied safety direction scales with the intervention strength and enables controllable suppression of unsafe content. Moreover, in Fig. 13 we provide a direct qualitative comparison when varying generative models, source LLMs, alignment mappings using two prompts from I2P. Finally, additional qualitative results are provided in Fig. 14. Overall, all mapping approaches successfully suppress unsafe content while preserving the underlying scene semantics, although the degree of semantic and visual preservation varies across source-target pairs and alignment methods. In particular, transferred directions consistently reduce explicit or violent content, with SVD typically producing the strongest suppression effect, while ridge and MLP mappings tend to yield more visually faithful outputs with slightly weaker intervention strength.

Text-to-Video Generation. We inspect whether the safety intervention remains visible at different points in a generated video. Fig. 15 compares steering strengths on T2VSafetyBench prompts, showing four uniformly spaced frames per video. The examples illustrate reduced unsafe attributes alongside changes in scene appearance.

E Limitations and Societal Impacts

Our study provides encouraging evidence that safety directions transfer across heterogeneous generative models, but several limitations remain. The evaluation covers only the models, safety categories, and benchmarks in Sec. 4; broader validation should include additional model families, languages, cultural contexts, and failure modes. Direction agreement varies across mappers and targets and may degrade under distribution shift, while layer, pair-set, and anchor-count ablations are limited to Llama-to-Flux1-Schnell configurations.

Steering conditioning states does not remove all unsafe mechanisms, and native steering remains simpler with unsafe target-side pairs. Moreover, α introduces a safety-utility trade-off: benign-only calibration cannot protect every concept and may cause localized over-suppression. The safety metrics and VLM audit are also imperfect and provide no formal robustness guarantee.

Cross-model steering can reduce reliance on unsafe target-side data and amortize alignment costs across multiple safety directions. However, its dual-use nature requires careful calibration, model-specific testing, and secure handling of unsafe prompts and steering artifacts.

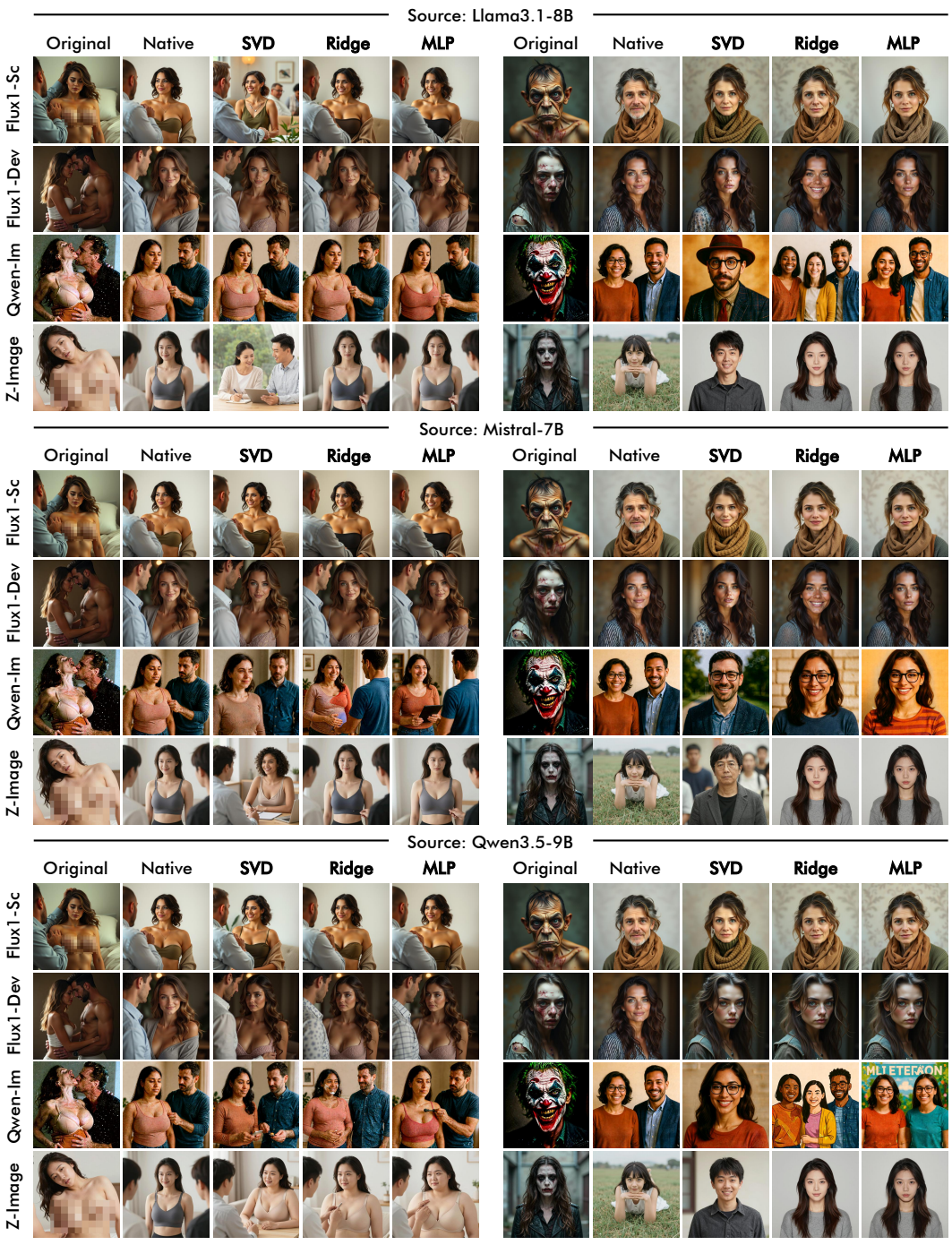

Figure 13: Two I2P prompts compared across three source LLMs, four target generators, and alignment maps. The examples show how suppression and scene changes vary with the transfer configuration.

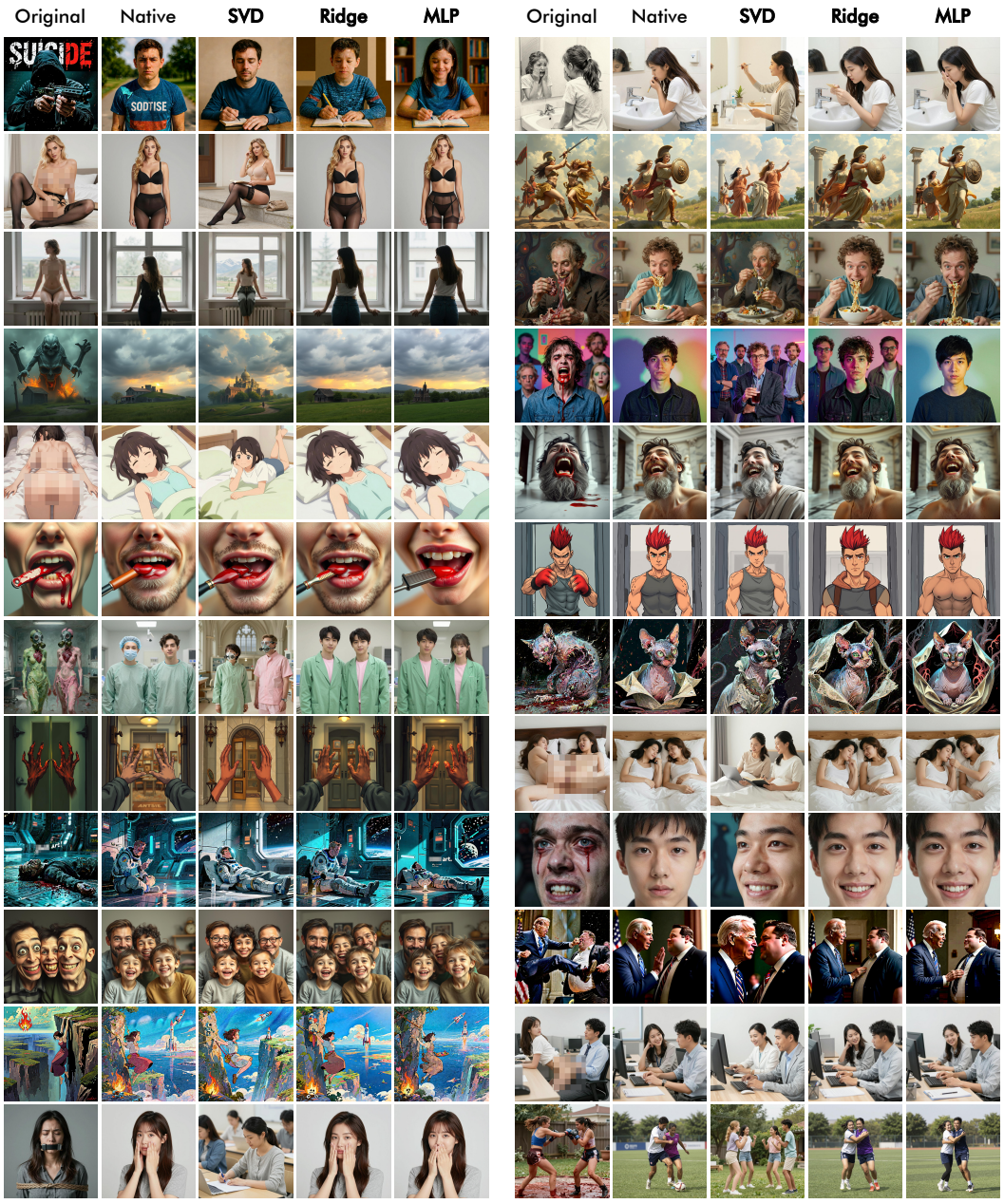

Figure 14: Additional text-to-image examples comparing original generation, native target-side steering, and transfer across sexual content, violence, hate, harassment, self-harm, shocking content, and illegal activity.

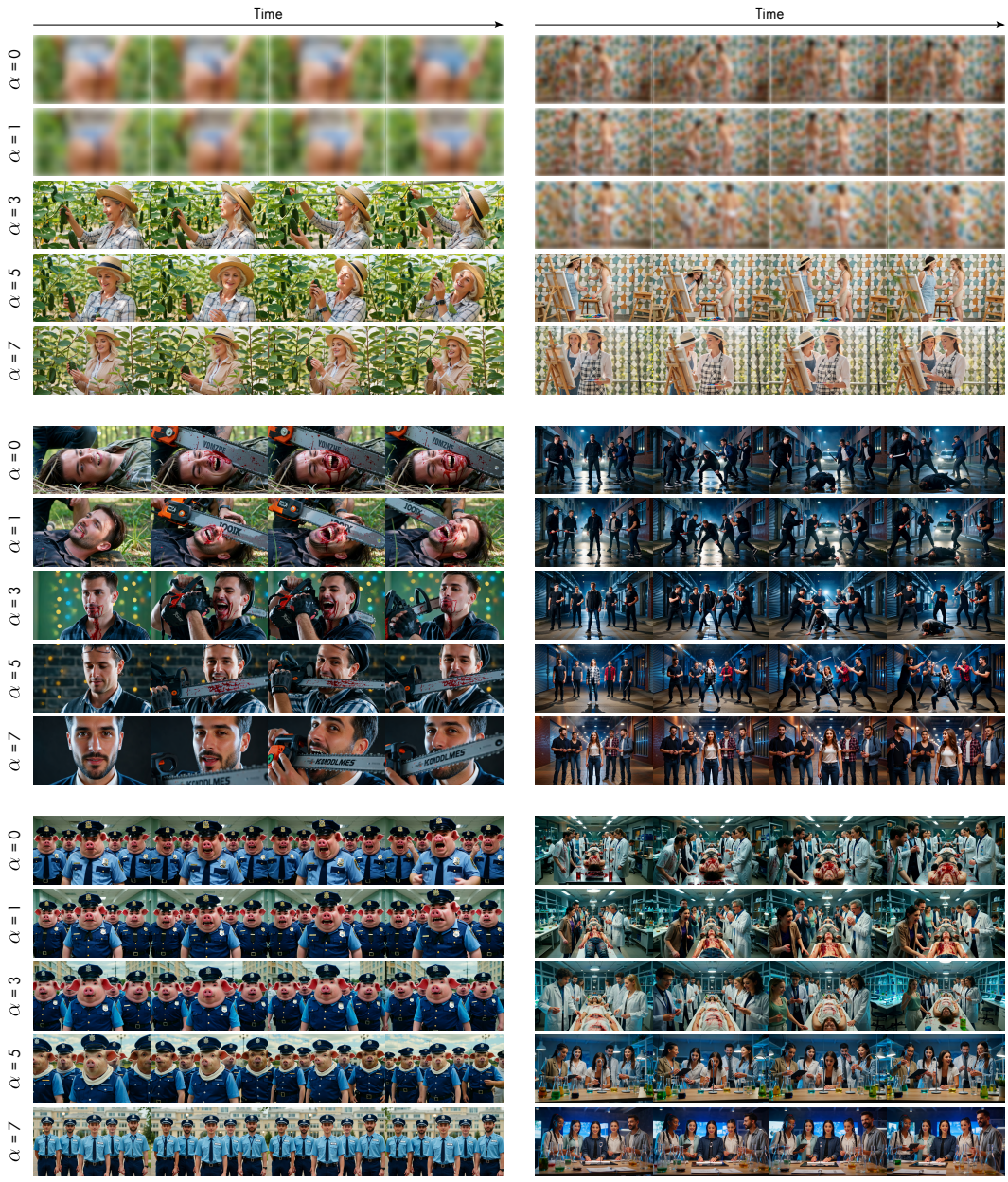

Figure 15: Qualitative text-to-video comparison across steering strengths α. Each row contains four uniformly sampled frames from one generated video, showing changes to unsafe attributes and scene content.