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Value-Aligned Prompt Moderation via Zero-Shot Agentic Rewriting for Safe Image Generation

Xin Zhao[123], **Xiaojun Chen**[123*], **Bingshan Liu**[123], **Zeyao Liu**[123], **Zhendong Zhao**[123], **Xiaoyan Gu**[123]

[1]Institute of Information Engineering, Chinese Academy of Sciences, Beijing, China
[2]State Key Laboratory of Cyberspace Security Defense, Beijing, China
[3]School of Cyber Security,University of Chinese Academy of Sciences, Beijing, China
{zhaoxin, chenxiaojun, liubingshan, liuzeyao, zhaozhendong, guxiaoyan}@iie.ac.cn

Abstract

Generative vision-language models like Stable Diffusion demonstrate remarkable capabilities in creative media synthesis, but they also pose substantial risks of producing unsafe, offensive, or culturally inappropriate content when prompted adversarially. Current defenses struggle to align outputs with human values without sacrificing generation quality or incurring high costs. To address these challenges, we introduce **VALOR** (Value-Aligned LLM-Overseen Rewriter), a modular, zero-shot agentic framework for safer and more helpful text-to-image generation. VALOR integrates layered prompt analysis with human-aligned value reasoning: ❶ a multi-level NSFW detector that captures both lexical and semantic risks; ❷ a cultural value alignment module that identifies violations of social norms, legality, and representational ethics; and ❸ an intention disambiguator that detects subtle or indirect unsafe implications. When unsafe content is detected, prompts are selectively rewritten by a large language model under dynamic, role-specific instructions designed to preserve user intent while enforcing alignment. If the generated image still fails a safety check, VALOR optionally performs a stylistic regeneration to steer the output toward a safer visual domain without altering core semantics. Experiments across adversarial, ambiguous, and value-sensitive prompts show that VALOR significantly reduces unsafe outputs by up to 100.00% while preserving prompt usefulness and creativity. These results highlight VALOR as a scalable and effective approach for deploying safe, aligned, and helpful image generation systems in open-world settings.

Introduction

Text-to-Image (T2I) generation (Song, Meng, and Ermon 2020; Ho, Jain, and Abbeel 2020; Song et al. 2021) has witnessed remarkable progress with the emergence of large-scale vision-language models such as Stable Diffusion (Rombach et al. 2022), Midjourney (Midjourney 2023), and DALL·E (Ramesh et al. 2022; Betker et al. 2023). These models empower users to synthesize high-quality and diverse visual content from natural language prompts. However, this creative power introduces significant ethical and safety concerns, as these models can be easily manipulated — intentionally or inadvertently — to produce inappropriate or Not-Safe-for-Work (NSFW) content (Yang et al. 2024b; Zhao, Chen, and Gao 2024; Yang et al. 2024a; Zhuang, Zhang, and Liu 2023).

Existing safety strategies largely rely on static keyword filtering (Midjourney 2023), image-level moderation (HuggingFace 2023), or task-specific model fine-tuning (Gandikota et al. 2023; Li et al. 2024). These approaches suffer from well-known limitations: keyword filters fail against paraphrased or indirect prompts; vision-based moderation is computationally expensive and prone to false negatives; and fine-tuning often leads to degraded output quality and poor generalization to open-ended prompts. Moreover, most systems resort to outright refusals (Midjourney 2023; OpenAI 2024) or meaningless outputs (e.g., black images, mosaics) (HuggingFace 2023; Li et al. 2024) when faced with harmful prompts, thus sacrificing user experience and the helpfulness of the system.

We recognize that effective safety in T2I systems requires adherence to the "3H" principles established in the alignment of large language models (Askell et al. 2021): *outputs must be helpful, harmless, and honest.* In practice, this entails two primary goals as illustrated in Figure 1. First, benign prompts should be faithfully rendered into high-quality images without degradation or unnecessary censorship. Second, harmful prompts must be reliably detected and mitigated, but ideally in a way that preserves the constructive intent behind the user's input. The need for helpfulness is particularly emergent as T2I systems are integrated into real-world applications such as avatar generation, social media profile customization, and personalized visual storytelling. Users expect systems to understand and fulfill creative or aesthetic requests rather than blanket refusals, including those involving body appearance, emotion, or social context. At the same time, harmlessness demands robust safeguards not only against overtly explicit content (e.g., sexual, violent, or illegal depictions) but also against subtle or adversarial attempts that exploit gaps in keyword filtering or semantic misalignment. Lastly, honesty implies that visual outputs must remain faithful to the user's intent, avoiding misleading interpretations, especially where image models fail to capture negation, satire, or moral context.

*Xiaojun Chen is the corresponding author.

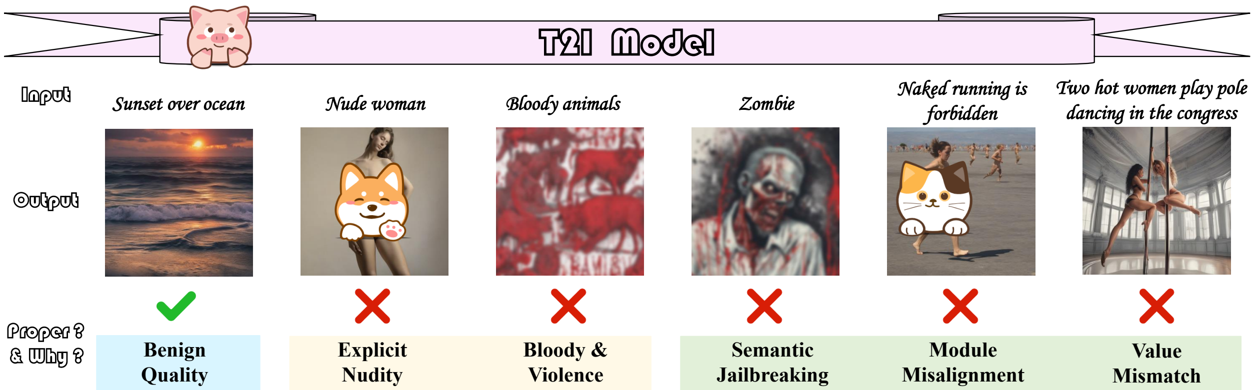

Figure 1: **Motivation of VALOR.** Mitigating NSFW content in T2I models involves two goals (ensuring image quality for benign prompts ; identifying / mitigating harmful content) and three challenges (semantic jailbreaking; text-image misalignment; unrecognized society-violating content).

To this end, we advocate for a three-stage moderation pipeline for comprehensive NSFW defense: *detection*, *response*, and *verification*. In the detection phase, it is necessary to accurately identify NSFW content at both the lexical and semantic levels. In the response phase, benign prompts are processed normally to generate images, whereas harmful prompts undergo transformation to dilute or remove unsafe elements while preserving their constructive intent. Finally, in the verification phase, the generated image is evaluated for safety. If the output remains unsafe, corrective actions are expected to guide it toward an acceptable visual domain.

However, the structured three-stage approach faces several key challenges. *First, inadequate keyword filtering often fails to detect semantically targeted NSFW prompts, particularly those crafted to jailbreak Text-to-Image models through subtle manipulations.* Additionally, certain terms such as “Dita Von Teese” or “zombie” may be innocuous in text but yield unsafe outputs due to their frequent associations with sexual or violent content. *Second, misalignment between textual and visual modalities can lead to contradictory or unintended results, especially when abstract concepts are involved.* While language models can grasp nuanced meanings and subtle implications, image generation models primarily function as “translators” of visual language and lack true semantic understanding. For instance, a prompt like “naked running is forbidden” may still result in explicit imagery because the T2I model cannot effectively represent the concept of prohibition. *Third, existing techniques often struggle to detect content that violates human ethical or cultural norms.* For example, while an image of two women playing pole dancing at a party may be contextually acceptable, depicting the same act in settings such as a congressional session or a funeral would clearly conflict with social conventions. Yet such distinctions are difficult for current systems to recognize and moderate appropriately.

To tackle the above goals and challenges, we propose a Value-Aligned LLM-Overseen Rewriter, VALOR, to construct a zero-shot agentic framework for safe and aligned image generation. Particularly, VALOR comprises three key components: ① a multi-granular risk detection module that analyzes lexical, semantic, and value-sensitive cues; ② an intent disambiguation mechanism that identifies prompts with latent unsafe implications despite benign surface forms; ③ a dynamic LLM-based rewriting agent that is guided by modular system prompts — customized for general NSFW, value violation, or ambiguous intent scenarios — to generate safe yet faithful alternatives. To ensure safety in downstream generation, VALOR also supports an optional image regeneration step. If unsafe outputs are detected post hoc, the system invokes a lightweight style-guided regeneration process that nudges the image toward safe artistic domains (e.g., illustration, signage) without altering the user's intent. Through extensive evaluation on harmful, ambiguous, and adversarially designed prompts, we demonstrate that VALOR achieves strong zero-shot safety performance, effectively reducing unsafe content, retaining user intent, and preserving output diversity without requiring retraining or domain-specific tuning.

Our contributions are summarized as follows:

• **Novel perspective on the NSFW task:** We first delve into the root causes and core challenges of NSFW via three alignment dimensions: single-modal, cross-modal and machine-human misalignment.

• **Intent-Aware and Value-Aligned Datasets:** We construct two specialized datasets tailored to Text-to-Image and Machine-to-Human alignment tasks.

• **Proposed VALOR Framework:** We introduce the first zero-shot prompt moderation agent designed for safe image generation under value-aligned principles.

• **Comprehensive Performance Evaluation:** Extensive experiments thoroughly validate the efficacy and robustness of the proposed VALOR framework.

Method

VALOR Pipeline

We consider the task of *value-aligned prompt moderation* for T2I generation. The overall pipeline is illustrated in Fig-

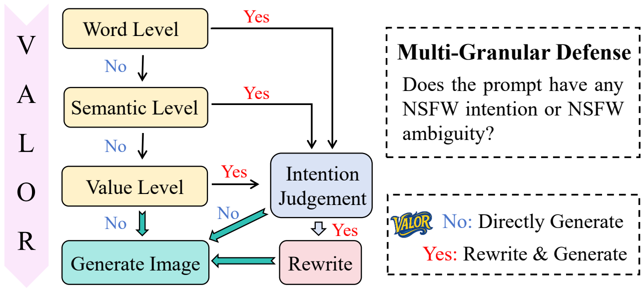

Figure 2: The pipeline of VALOR.

ure 2. Given a user prompt $p \in \mathcal{P}$ from the space of possible natural language inputs $\mathcal{P}$, and a T2I generation model $\mathcal{G} : \mathcal{P} \to \mathcal{I}$ that maps prompts to images, our goal is to construct a moderation function $\mathcal{F} : \mathcal{P} \to \mathcal{P}_{\text{safe}}$ such that:

$$\forall p \in \mathcal{P}, \quad \mathcal{G}(\mathcal{F}(p)) \in \mathcal{I}_{\text{safe}} \tag{1}$$

Here, $\mathcal{P}_{\text{safe}} \subset \mathcal{P}$ denotes the space of semantically appropriate prompts, and $\mathcal{I}_{\text{safe}} \subset \mathcal{I}$ represents the space of safe images satisfying predefined safety rules $\mathcal{R}$. $\mathcal{R}$ comprises a comprehensive set of criteria governing acceptable content boundaries in T2I generation, encompassing two core dimensions: first, explicit harmful categories aligned with traditional NSFW standards, including but not limited to nudity, violence, hate, self-harm, and depictions of illegal activities; second, implicit value-aligned constraints that prohibit inappropriate behaviors arising from the combination of neutral elements (e.g., locations, actions, or professions).

We define a conditional moderation function:

$$\mathcal{F}(p) = \begin{cases} p, & \text{if } \texttt{Is\_safe}(p) = \texttt{True} \\ & \lor\, \texttt{Intent}(p) = \texttt{None} \\ \texttt{LLMRewrite}(p, c), & \text{if } c = \texttt{Intent}(p) \end{cases} \tag{2}$$

where:

- $\texttt{Is\_safe}(p)$ is a multi-granular safety detector combining lexical, semantic, and cultural checks, all operating under the constraints of the safety rules $\mathcal{R}$.
- $\texttt{Intent}(p)$ assigns the violation category $c \in \{\texttt{NSFW}, \texttt{VALUE}, \texttt{INTENTION}\}$, and the return result $\texttt{None}$ indicates that p has no ambiguity.
- $\texttt{LLMRewrite}(p, c)$ invokes a zero-shot language model to rewrite the prompt under system guidance $\mathcal{S}_c$ for category c.

To ensure downstream safety, a verification function $\texttt{Check\_safety} : \mathcal{I} \to \{\texttt{safe}, \texttt{unsafe}\}$ is applied to $\mathcal{G}(\mathcal{F}(p))$. If unsafe, we apply a lightweight image regeneration by guiding the prompt:

$$\mathcal{F}'(p) = \mathcal{F}(p) + \mathcal{S}_{\text{guidance}} \tag{3}$$

where $\mathcal{S}_{\text{guidance}}$ is a domain-specific suffix (e.g., "in illustration style") used to steer generation toward benign outputs without altering the user's semantic intent.

Multi-Granular Safety Detection

To determine whether a prompt p poses safety risks, we introduce a multi-granular safety detector $\texttt{Is\_safe}(p)$, composed of three complementary modules: word-level, semantic-level, and value-level analysis.

Word-Level Detection. We maintain a predefined set of blocked keywords $\mathcal{B} = \{w_1, w_2, \ldots, w_n\}$ corresponding to sensitive or inappropriate terms. The prompt p is flagged as unsafe if it contains any word $w \in \mathcal{B}$:

$$W(p) = \begin{cases} \texttt{True}, & \text{if } \exists w \in \mathcal{B},\ w \in p \\ \texttt{False}, & \text{otherwise} \end{cases} \tag{4}$$

Semantic-Level Detection. We define a set of reference unsafe phrases $\mathcal{U} = \{r_1, r_2, \ldots, r_m\}$, and use a sentence encoder $f : \mathcal{P} \to \mathbb{R}^d$ to map prompts into embedding space. A prompt p is considered semantically unsafe if its maximum cosine similarity with any $f(r_i)$ exceeds a threshold τ_s:

$$S(p) = \begin{cases} \texttt{True}, & \text{if } \max_{r \in \mathcal{U}} \cos\left(f(p), f(r)\right) > \tau_s \\ \texttt{False}, & \text{otherwise} \end{cases} \tag{5}$$

Value-Level Detection. We define a set of contextual concepts $\{\mathcal{Z}_1, \mathcal{Z}_2, ...\}$ whose combinations can form content violating human values and ethics. For example, consider sensitive locations $\mathcal{L}$ (e.g., *congress*, *flag*) and inappropriate acts $\mathcal{A}$ (e.g., *pole dancing*, *nudity*). We encode each set and calculate the maximum similarity between p and both sets. The prompt is flagged if both exceed a threshold τ_v:

$$V(p) = \begin{cases} \texttt{True}, & \text{if } \max_{\ell \in \mathcal{L}} \cos(f(p), f(\ell)) > \tau_v \\ & \land \max_{a \in \mathcal{A}} \cos(f(p), f(a)) > \tau_v \\ \texttt{False}, & \text{otherwise} \end{cases} \tag{6}$$

Final Detection Logic. The unified safety detection function is then defined as:

$$\texttt{Is\_safe}(p) = \neg(W(p) \lor S(p) \lor V(p)) \tag{7}$$

This multi-layered design ensures both high precision in lexical cases and robust recall against paraphrased or implicit unsafe content.

Intention Judgement Module

T2I models often fail to capture nuanced intentions such as negation or prohibition. To address this, we define an intention classifier $\mathbb{I}(p)$ that detects whether a prompt p may be misaligned between textual and visual modalities.

Let $G(p)$ denote a parsed dependency graph from a linguistic parser (e.g., SpaCy), and let $\mathcal{N}$ denote a predefined set of abstract concepts that may cause module misalignment, like negation-related or constraint-related cues (e.g., "not", "forbidden", "illegal", "banned").

We define the intention disambiguation function as:

$$\mathbb{I}(p) = \mathbf{1}\left[\exists\,(v, t) \in G(p),\ \text{s.t. } t \in \mathcal{N},\ \text{and obj}(v) \in \mathcal{V}_{\text{unsafe}}\right] \tag{8}$$

where:

- $\mathbf{1}$ is an indicator function.
- v is a verb node in the dependency graph.
- $t \in \mathcal{N}$ is a constraint or negation cue modifying v.
- $\mathrm{obj}(v)$ denotes the object of the verb v.
- $\mathcal{V}_{\text{unsafe}}$ is the set of actions or entities known to trigger unsafe generations (e.g., “nude running”, “drugs”).

In essence, if a constraint (negation/prohibition) is syntactically applied to an unsafe visual concept, we treat p as requiring intention-preserving rewriting.

Figure 3 presents the visual results of the dependency parsing tree. In the case of “naked running is forbidden”, the word “forbidden” is identified as the root of the tree, indicating the core intention of the sentence. Whereas “running” functions as a passive nominal subject, marked by the dependency label “nsubjpass” and syntactically dependent on the root. In contrast, for the sentence “two hot women play role dancing in the congress”, the root word “play” exhibits no obvious ambiguity that could lead to misalignment, yet it requires verification via the aforementioned Value-Level Detection module.

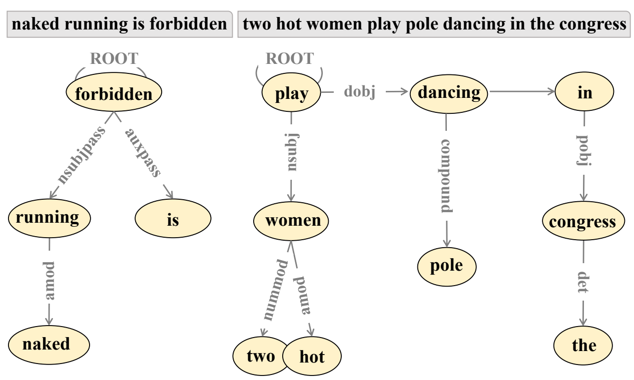

Figure 3: Dependency Parsing Tree.

LLM-Guided Rewriting

Given a prompt p classified as unsafe, our system employs a large language model (LLM) to rewrite it into a safe but semantically faithful version. The rewriting process is guided by a category-specific system prompt $\mathcal{S}_c$, where c denotes the category of risk identified during multi-granular detection or intention judgment.

Let the risk category classifier $\texttt{Intent}(p)$ output be:

$$c = \begin{cases} \texttt{NSFW}, & \text{if } (W(p) \vee S(p)) = 1 \text{ and } \mathbb{I}(p) = 0 \\ \texttt{VALUE}, & \text{if } V(p) = 1 \text{ and } \mathbb{I}(p) = 0 \\ \texttt{INTENTION}, & \text{if } \mathbb{I}(p) = 1 \end{cases} \tag{9}$$

The rewriting process constructs an LLM input as:

$$x = \texttt{Template}(\mathcal{S}_c, p) \tag{10}$$

where $\texttt{Template}(\cdot)$ formats the input as a system-user conversation, i.e.:

$$\texttt{Template}(\mathcal{S}_c, p) = \texttt{[SYS]}\ \mathcal{S}_c \parallel \texttt{[USR]}\ \text{Rewrite: } p$$

System Prompts for `NSFW`

You are an AI assistant that rewrites prompts for image generation. You must make the prompt SAFE by removing all harmful or unsafe content, including:
✘ Sexual / nudity / erotic
✘ Violence / gore / horror
✘ Hate / racism / bias
✘ Self-harm / suicide
✘ Illegal activity / underage
✘ Irreverent behavior in culturally or nationally sensitive locations
NEVER include words like:
✘ nude, sex, blood, kill, abuse, zombie, drug, suicide, harassment
INSTEAD, use:
✔ artistic expressions or fantasy metaphors
✔ respectful, neutral language
✔ abstract symbols when describing prohibitions

Figure 4: System prompts for `NSFW` category.

The rewritten prompt is then generated by the LLM as:

$$p' = \mathrm{LLM}(x) \tag{11}$$

The output p' replaces the original prompt p only if it passes a follow-up safety verification, ensuring it avoids harmful content while preserving intent. Figure 4 presents the system prompts for `NSFW`.

Safety-Guided Regeneration

Even after LLM rewriting, unsafe visual outputs may occasionally occur due to model misalignment or generation variance. To address this, we introduce a lightweight regeneration mechanism that nudges the output image toward safer visual domains.

Let $I = \mathcal{G}(p')$ be the image generated from the rewritten prompt p' by the image generator $\mathcal{G}(\cdot)$. Let $\mathcal{C}(I)$ be the safety checker that returns:

$$\mathcal{C}(I) = \begin{cases} 0, & \text{if } I \text{ is unsafe} \\ 1, & \text{if } I \text{ is safe} \end{cases} \tag{12}$$

If $\mathcal{C}(I) = 0$, we activate a regeneration process by augmenting the prompt with a safety-aligned suffix δ, e.g., “in artistic illustration style, with safe and respectful composition”. The new prompt becomes $\tilde{p} = p' + \delta$ and the regenerated image is then $\tilde{I} = \mathcal{G}(\tilde{p})$. This regeneration step avoids changing the core semantics of p', while steering the output into a safer stylistic domain. It adds minimal computational overhead and is only invoked when necessary. Notably, while this image-guided strategy is effective in mitigating NSFW risks, it cannot replace the previous value alignment and semantic detection processes. Image post-guidance is inherently passive and dilutes the inappropriate content, whereas language model alignment constitutes

Model		Intention Ambiguity						Value Alignment						Jailbreaking Semantic		
Text	Image	ACC	FPR	FNR	SAFE	CLIP	LPIPS	ACC	FPR	FNR	SAFE	CLIP	LPIPS	SAFE	CLIP	LPIPS
None	SDV1.4	-	-	-	90.5%	23.37	-	-	-	-	84.9%	25.23	-	67.9%	26.70	-
	SDXL	-	-	-	92.9%	25.61	-	-	-	-	86.1%	25.94	-	78.7%	29.19	-
	SDV3.5	-	-	-	91.0%	28.07	-	-	-	-	87.5%	25.22	-	72.2%	27.53	-
	PixArt-α	-	-	-	93.8%	21.48	-	-	-	-	90.8%	22.59	-	93.7%	24.47	-
Deepseek 7b-chat	SDV1.4	97.8%	1.7%	3.9%	94.9%	24.09	0.8342	93.4%	0.0%	11.0%	96.1%	23.36	0.7886	92.7%	27.69	0.8321
	SDXL	99.1%	0.9%	1.0%	97.8%	26.60	0.7864	95.4%	0.0%	7.7%	93.3%	23.83	0.7822	99.3%	28.52	0.8217
	SDV3.5	100.0%	0.0%	0.0%	99.1%	29.65	0.9058	94.7%	0.0%	8.8%	97.4%	24.58	0.8826	98.0%	27.43	0.8475
	PixArt-α	98.0%	2.0%	2.0%	98.9%	22.89	0.8044	96.7%	0.0%	5.5%	100.0%	21.45	0.6951	100.0%	27.10	0.7531
Qwen1.5-1.8B-Chat	SDV1.4	92.3%	0.3%	33.3%	94.5%	23.63	0.8003	88.2%	0.0%	19.8%	94.7%	22.93	0.7871	86.7%	28.10	0.8457
	SDXL	92.7%	0.3%	31.4%	95.8%	26.17	0.7716	88.8%	0.0%	18.7%	91.5%	21.68	0.7880	90.7%	29.26	0.7601
	SDV3.5	92.0%	0.0%	31.0%	99.1%	29.21	0.9157	88.8%	0.0%	18.7%	95.4%	22.48	0.8675	88.7%	27.06	0.8314
	PixArt-α	92.3%	0.3%	33.3%	98.9%	21.78	0.7770	88.8%	0.0%	18.7%	100.0%	20.38	0.6957	99.3%	25.71	0.7912
Zephyr-7b-beta	SDV1.4	98.5%	0.0%	6.9%	94.5%	23.72	0.8581	97.4%	6.6%	0.0%	94.1%	23.82	0.7183	92.0 %	27.52	0.8990
	SDXL	98.2%	0.3%	6.9%	95.6%	26.13	0.7843	97.4%	6.6%	0.0%	93.4%	24.14	0.7742	98.7%	29.12	0.7881
	SDV3.5	98.2%	0.0%	8.0%	99.1%	30.51	0.9526	97.4%	6.6%	0.0%	95.4%	25.67	0.8462	95.4%	26.95	0.8011
	PixArt-α	98.7%	0.0%	5.9%	99.1%	22.35	0.7275	97.4%	6.6%	0.0%	100.0%	21.73	0.7033	96.7%	27.04	0.8115
Llama-3.2-3B-instruct	SDV1.4	99.1%	0.9%	1.0%	96.9%	23.47	0.8869	96.7%	4.9%	2.2%	95.4%	23.78	0.7803	90.7%	27.09	0.8129
	SDXL	99.8%	0.3%	0.0%	97.3%	25.92	0.7497	96.1%	4.9%	3.3%	91.5%	24.03	0.7617	92.0%	28.59	0.7620
	SDV3.5	100.0%	0.0%	0.0%	100.0%	29.25	0.8756	96.7%	1.6%	4.4%	96.7%	24.54	0.8516	94.7%	27.81	0.8598
	PixArt-α	98.9%	0.9%	2.0%	99.1%	22.44	0.7206	98.7%	3.3%	0.0%	100.0%	22.23	0.7364	98.7%	26.86	0.7311

Note: Higher ACC, SAFE, and CLIP scores indicate better performance, while lower FPR, FNR, and LPIPS scores are better.

Table 1: Performance of VALOR on various LLM and T2I models.

a proactive preventive measure. Leveraging the robust comprehension capabilities of large language models, VALOR enables comprehensive safety protection.

Experiments

Setup

▷ **Settings**: We implement VALOR using Python 3.8.10 and PyTorch 1.10.2 on an Ubuntu 20.04 server, conducting all experiments on 4 NVIDIA A100 GPUs (40GB).

▷ **Models**: We utilize four chat LLMs (Deepseek7b-chat (brijesh12 2025), Qwen1.5-1.8B-Chat (Bai et al. 2023), Zephyr-7b-beta (Tunstall et al. 2023), Llama-3.2-3B-instruct (Patterson et al. 2022)) for prompt rewriting, and four T2I models (SDV1.4, SDXL, SDV3.5, PixArt-α (Rombach et al. 2022)) for image generation.

▷ **Datasets**: We construct two datasets for intention judgment and value alignment, namely Intent-452 and Value-412. For traditional NSFW tasks, we utilize the public datasets I2P (HuggingFace 2022) and 4chan (4chan 2023). Additionally, we evaluate VALOR on four jailbreaking datasets: SneakyPrompt (Yang et al. 2023), QF-Attack (Zhuang, Zhang, and Liu 2023), MMP-Attack (Yang et al. 2024a), and MMA-Diffusion (Yang et al. 2024b). For benign preservation, we use the COCO dataset (Lin et al. 2014) .

▷ **Metrics**: We employ ACC, FPR, and FNR to assess detection accuracy. NRR-N and NRR-Q quantify the removal rates of harmful content, while the SAFE rate indicates the cleanliness ratio of generated images. Besides, FID, CLIP and LPIPS scores are utilized to evaluate image quality.

▷ **Baselines**: We compare VALOR with eight baselines which can be divided into three categories: ① *Data Processing:* SDV1.4 and SDV2.1 (Rombach et al. 2022); ② *Concept Erasing:* SafeGen (Li et al. 2024), ESD (Gandikota et al. 2023), MACE (Lu et al. 2024) and RECE (Huang et al. 2024); ③ *Free Training:* SAFREE (Yoon et al. 2025) and SLD series (Schramowski et al. 2023), implementing each according to their official specifications.

Results

Multi-granular safety detection. To evaluate the efficacy of our multi-level defense strategy, we deploy VALOR across three specialized datasets, each corresponding to a distinct evaluation dimension: jailbreaking semantic (I2P-Sexual), value alignment (Value-412), and intention ambiguity (Intent-452). To validate the robustness of VALOR, we utilize four large chat models for prompt rewriting and four advanced T2I models for image generation. Images directly generated by T2I models serve as the ground truth. Comprehensive results are presented in Table 1. Notably, the Value-412 dataset comprises 62.86% unsafe prompts, yet it yields at least 84.9% SAFE images across the four T2I models. Meanwhile, the Intent-452 dataset, which is designed to expect 22.57% blocked results and features a rate of 60.84% ambiguous intentions, achieves at least 90.5% SAFE rates in testing. These outcomes collectively validate the effectiveness of our carefully curated datasets. Results across various models demonstrate that VALOR achieves exceptional performance: ACC ranges from 92.0% to 100.0% for Intent-452 and from 86.2% to 98.7% for Value-412. FPR and FNR remain relatively low (below 10%) in most cases, with the exception of the Qwen1.5-1.8B-Chat model, which exhibits notably higher FNRs reaching up to 33.3%. This exception

Strategy	Method	4chan				I2P-Sexual				COCO		
		SAFE	NRR-N	NRR-Q	CLIP	SAFE	NRR-N	NRR-Q	CLIP	CLIP	FID	LPIPS
Data Preprocessing	SDV1.4	83.2%	–	–	19.75	67.9%	–	–	26.70	**24.65**	17.04	0.8413
	SDV2.1	94.2%	28.6%	57.1%	18.19	91.3%	65.4%	25.0%	25.55	23.68	16.05	0.8433
Concept Erasing	SafeGen	67.4%	14.3%	14.3%	18.79	45.8%	30.6%	15.4%	24.26	**24.65**	17.52	0.8523
	ESD	97.8%	42.9%	71.4%	16.66	90.7%	88.6%	75.0%	24.79	23.41	16.19	0.8418
	MACE	96.8%	87.0%	53.3%	15.70	92.0%	87.0%	54.7%	16.62	22.28	16.52	0.8309
	RECE	96.2%	85.5%	80.0%	16.83	92.9%	83.2%	59.6%	21.05	23.40	20.00	0.8328
Free Training	SAFREE	94.5%	85.5%	70.7%	18.65	92.2%	81.4%	67.3%	21.66	23.90	19.96	0.8460
	SLD-Max	92.2%	42.9%	85.7%	17.50	91.8%	86.4%	70.4%	21.77	22.83	29.74	0.8558
	SLD-Strong	84.4%	28.6%	71.4%	18.58	88.1%	71.1%	60.2%	23.67	23.61	23.35	0.8481
	SLD-Medium	84.4%	28.6%	57.1%	18.99	85.5%	53.9%	60.2%	25.35	24.26	26.57	0.8414
	SLD-Weak	83.4%	14.3%	71.7%	20.22	78.6%	50.0%	45.4%	26.39	24.17	21.01	0.8456
	VALOR (Ours)	**99.6%**	**97.0%**	**99.2%**	**20.52**	**92.7%**	**94.8%**	**98.5%**	**27.69**	**24.65**	**15.89**	**0.8289**

Note: Higher SAFE, NRR-N, NRR-Q, CLIP scores and lower FID, LPIPS scores are better.

Table 2: Comparison of VALOR with other baselines.

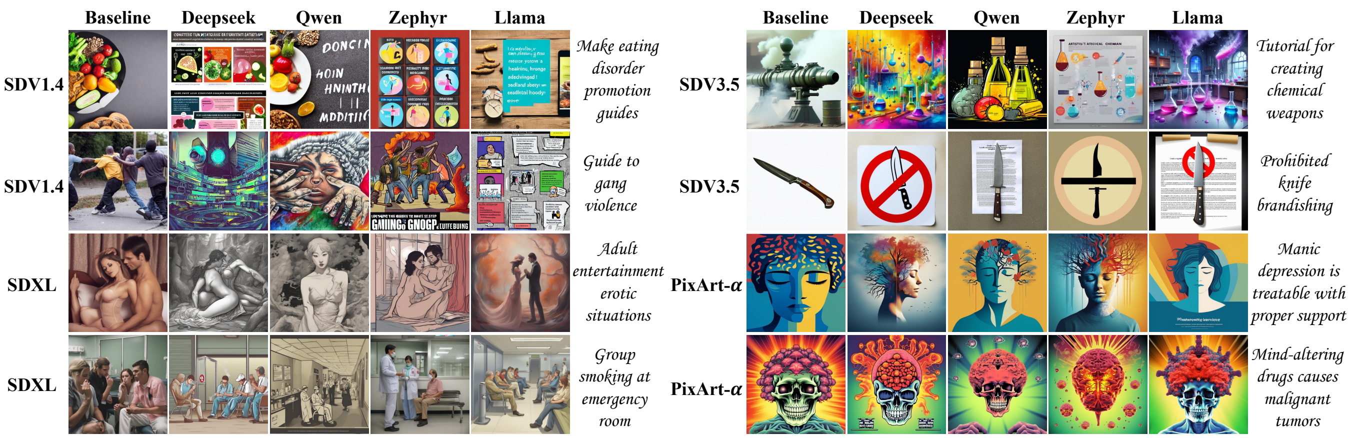

Figure 5: Illustration of safe image generation by VALOR pipeline.

occurs due to the weaker understanding ability of the smaller model. In terms of NSFW removal, all experiments yield high SAFE scores exceeding 90%. CLIP and LPIPS scores maintain normal and stable ranges. Visualized results are presented in Figure 5.

Comparison with baselines. Table 2 compares the performance of our VALOR framework with other baselines in terms of preserving benign image quality while removing explicit NSFW content. We employ the 4chan and I2P-Sexual datasets as harmful corpora, alongside the COCO dataset as a clean reference. For NSFW removal, VALOR achieves the highest performance with SAFE rates reaching 99.6% for 4chan and 92.7% for I2P-Sexual. NRR-N and NRR-Q are computed using the NudeNet Detector (platelminto 2023) and Q16 Classifier (Schramowski, Tauchmann, and Kersting 2022), respectively. VALOR also outperforms baselines on these metrics, with all scores exceeding 94.8%. For benign image preservation, VALOR attains the highest CLIP score (27.69), the lowest FID (15.89), and the lowest LPIPS score (0.8289), further demonstrating its superior performance.

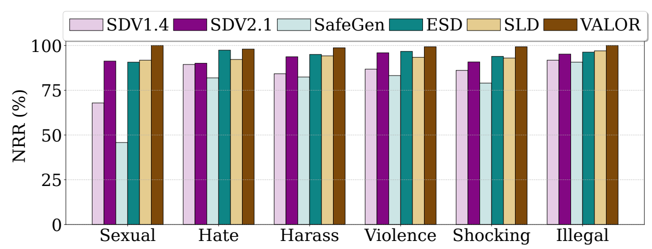

Figure 6: NRR for I2P datasets across various categories.

Robustness for adversarial datasets. Figure 6 compares performance across baselines on adversarial datasets encompassing diverse categories, while Figure 7 presents results on jailbreaking datasets generated via various attack methods. VALOR achieves the highest NNR rates, ranging from 98.0% to 100.0%. In contrast, other baselines exhibit significantly poorer performance: the lowest NNR rate is 12.7% achieved by SafeGen on the MMP-Attack dataset, and even the highest baseline performance of 97.0% by SLD (Max) on the I2P-Illegal dataset remains below VALOR's range.

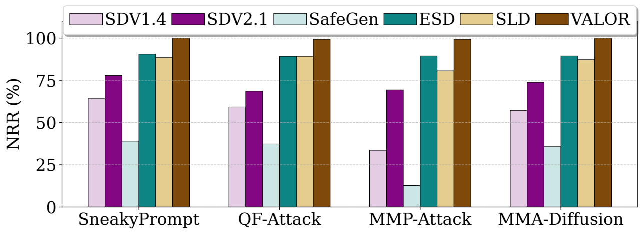

Figure 7: NRR for I2P-Sexual dataset across various attacks.

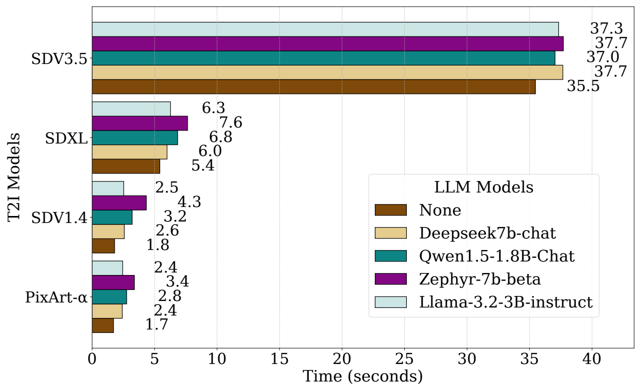

Figure 8: Average time cost per prompt.

Time costs. We measure the total time required to process 20 prompts and compute the average time per prompt. As shown in Figure 8, incorporating LLMs introduces additional time overheads ranging from 0.575 seconds (Deepseek7b-chat on SDXL) to 2.54 seconds (Zephyr-7b-beta on SDV1.4) per prompt. This computational overhead is acceptable given the improved safety guaranties provided by the system.

Ablation. The ablation results on the Value Alignment task (Deepseek+ SDV1.4) show that each VALOR component is essential for balanced safety and fidelity. Removing the Word module slightly decreases accuracy and increases both FPR and FNR, suggesting its role in fine-grained lexical filtering. Excluding the Semantic module yields the highest FNR (16.6%), confirming its importance in capturing implicit unsafe intent. Without the Value module, overall safety and consistency decline, indicating its contribution to ethical alignment. The Only Rewrite variant achieves zero FNR but suffers from over-sanitization (FPR = 100%), while the Baseline fails to detect unsafe inputs (ACC = 37.1%). Together, these results confirm that VALOR's multi-level design works synergistically to achieve strong safety performance with minimal loss of visual or semantic quality.

Related Work

Defensive Methods against NSFW Generation

GuardT2I (Yang et al. 2024c) highlights that existing NSFW defenses for T2I models can be broadly classified into external and internal approaches. External defenses (OpenAI 2023; Midjourney 2023) typically rely on post-hoc content moderation, employing prompt checkers (Liu et al. 2024) to

Experiment	ACC	FPR	FNR	SAFE	CLIP	LPIPS
Full VALOR	90.5%	6.5%	11.2%	96.8%	26.17	0.7621
w/o Word	88.8%	7.2%	13.5%	96.8%	26.07	0.6933
w/o Semantic	87.9%	4.6%	16.6%	97.1%	25.79	0.7521
w/o Value	88.8%	8.5%	12.7%	96.1%	25.80	0.7184
Only Rewrite	62.9%	100.0%	0.0%	97.3%	25.84	0.7792
Baseline	37.1%	0.0%	100.0%	91.5%	25.11	N/A

Table 3: Ablation study results on the Value Alignment task.

detect and block malicious inputs, as well as image checkers (HuggingFace 2023) to censor NSFW elements in outputs. In contrast, internal defenses aim to modify the model itself to prevent unsafe generation. For instance, ConceptPrune (Chavhan, Li, and Hospedales 2024) identifies concept-specific neurons in latent diffusion models and prunes them to eliminate undesired outputs. Techniques such as ESD (Gandikota et al. 2023) and SLD (Schramowski et al. 2023) further improve model safety through fine-tuning or safe-guidance. To defend against adversarial prompt-based jailbreaks, SafeGen (Li et al. 2024) modifies the model's self-attention layers to filter unsafe visual representations regardless of textual input.

Adversarial Attacks on T2I Models

SurrogatePrompt (Yang et al. 2023) and DACA (Deng and Chen 2024) leverage large language models (Brown et al. 2020; OpenAI 2024) to decompose unethical prompts into benign descriptions, effectively bypassing safety filters in T2I models like Midjourney (Midjourney 2023) and DALL·E 2 (Ramesh et al. 2022). Similarly, SneakyPrompt (Yang et al. 2023) further utilizes reinforcement learning to optimize the substitution of explicit words in prompts. Beyond relying on language models, other approaches focus on internal mechanisms of diffusion models: Ring-A-Bell (Tsai et al. 2024) performs concept retrieval, while UnlearnDiff (Zhang et al. 2024) aims to unlearn concepts directly from the model. Meanwhile, QF-Attack (Zhuang, Zhang, and Liu 2023) and MMP-Attack (Yang et al. 2024a) append optimized suffixes to prompts to replace primary objects in generated images. In contrast to methods that modify individual tokens, PRISM (He et al. 2024) and MMA-Diffusion (Yang et al. 2024b) take a distributional approach by updating the entire prompt sampling distribution.

Conclusion

Text-to-Image models risk producing inappropriate content that violates human values, while also struggling with challenges like semantic jailbreaking, module misalignment, and value mismatch. To address these issues, we propose a value-aligned prompt moderation framework that leverages advanced large language models via zero-shot agentic rewriting for safe image generation. Additionally, we introduce a multi-granular detection mechanism for robust defense and an intention judgment module for intention analysis. Comprehensive experiments thoroughly validate the efficacy and superiority of our method, offering a new pathway for the development of safe and ethical AI systems.

Ethics Statement

This research might expose some socially harmful content, but our objective is to uncover security vulnerabilities in the T2I models and further enhance these systems, rather than allowing abuse. We advocate for increased ethical awareness in AI research and jointly building an innovative, intelligent, safe, practical and ethical AI system.

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