Logits Speak Louder than Words: Decoding Internal MLLM Signal for Robust Zero-Shot Image Safety Guardrails

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Abstract

We propose LOGITGUARD, a training-free image safety detector that turns a general-purpose multimodal large language model (MLLM) into a decoding-free unsafe scorer. Existing MLLM-based moderation typically relies on generated safety judgments, which are vulnerable to refusals, output variability, and format noncompliance. LOGITGUARD instead compares the first-step logits of predefined safe and unsafe label tokens and converts their margin into a deterministic unsafe score. This design preserves prompt-level policy flexibility while avoiding generation artifacts such as refusals and score quantization. Across multiple state-of-the-art MLLMs and a new 7,581-image benchmark covering real, AI-generated, and near-boundary harmful content, LOGITGUARD achieves strong low-false-positive-rate performance. On Qwen2.5-VL-7B, the unsafe score reaches 0.513 TPR at 1% FPR and 0.816 TPR at 5% FPR, while remaining applicable when response-based moderation produces refusals or non-label outputs.

Warning: The paper contains content that may be offensive and not safe for work (NSFW).

1 Introduction

Identifying harmful or not-safe-for-work (NSFW) imagery is critical for online safety. We use NSFW broadly to denote visual content that violates a given safety or moderation policy, rather than a fixed category set; new policy concepts can be incorporated by modifying the prompt when the underlying MLLM recognizes the relevant visual distinction. Examples include explicit sexual material, graphic violence, illegal activities, and extremist symbolism, all of which must be detected at scale to enforce evolving safety policies (Bender et al., 2021; Cho et al., 2023; Blattmann et al., 2023; Api4AI, 2024). This task is increasingly challenging as visual content grows in volume and diversity, and as highly realistic synthetic imagery deviates from the data distributions on which existing detectors were trained (gsarridis; Agrawal et al., 2023; Paasonen et al., 2024; An et al., 2024; Zhang et al., 2024b).

Traditional CNN- and Vision Transformer-based NSFW detectors can perform well in distribution, but they are brittle under distribution shift, emerging borderline cases, and AI-generated imagery (Paasonen et al., 2024; Moosavi-Dezfooli et al., 2016; Yuan et al., 2019). They also rely on fixed label taxonomies, making it difficult to capture broader or policy-specific harms such as symbolic extremism and illegal activity (Pudi, 2021). As safety policies evolve faster than curated datasets, static classifiers face a persistent adaptation gap (Inan et al., 2023).

MLLMs offer a flexible alternative: their cross-modal reasoning allows images to be evaluated against natural-language policy descriptions in a zero-shot or training-free manner (Vaswani et al., 2017; Achiam et al., 2023; Kaplan et al., 2020). Existing MLLM moderation systems, however, are typically *response-based*: the model is prompted as a content moderator (Huang, 2025) and asked to generate a discrete label (e.g., "safe" vs. "unsafe") (Han et al., 2024) or scalar risk score (Chao et al., 2025). This assumes that generated text is a reliable interface for extracting the safety decision, an assumption that is fragile under modern alignment.

Safety alignment and reinforcement learning from human feedback can reshape generation behavior in ways that interfere with decision extraction. We identify *decision suppression under alignment*: MLLMs may assign separable safety-token margins to safe and unsafe images, yet generated text obscures this distinction through refusals, deflection, or verbosity. Response-based moderation can therefore fail not because the model lacks visual signal, but because generation is a lossy chan-

nel for extracting it. A direct unsafe score is especially valuable for moderation systems that must tune thresholds under strict false-positive budgets.

This reflects an abstraction mismatch: *the pre-decoding token distribution is not equivalent to the generated response*. Guided by this insight, we introduce **LOGITGUARD**, an alignment-aware logit inspection framework that converts a general-purpose MLLM into a discriminative safety detector without fine-tuning. Rather than classifying from generated text, LOGITGUARD classifies from the pre-decoding logits assigned to two predefined safety decisions.

Concretely, LOGITGUARD extracts the first-step logits of two designated safety-label tokens (e.g., "0" for *safe*, "1" for *unsafe*) and converts their logit gap into a two-token softmax unsafe score. Because this score is computed before decoding, it is deterministic and independent of output formatting, sampling, and refusal behavior, while supporting thresholding and low–false-positive-rate operation. This gives LOGITGUARD three practical advantages: it produces a continuous unsafe score, remains well-defined when generation refuses or emits non-label text, and avoids the latency of long-form responses. This distinction is crucial for aligned MLLMs: the safety tokens need not be generated or top-ranked for their relative margin to remain useful.

We evaluate LOGITGUARD across Qwen2.5-VL (Bai et al., 2025), Aya-Vision (Dang et al., 2024), and Llama-3.2-Vision (Chu et al., 2024). Across datasets, prompts, and operating points, logit-based detection performs strongly at low false-positive rates and remains applicable when response-based moderation is disrupted by refusals or non-label outputs. Because the unsafe score is conditioned on the prompt, LOGITGUARD can also adapt the evaluated safety boundary by changing the prompt-defined policy.

Rigorous evaluation is also hindered by incomplete, outdated, or narrowly scoped NSFW benchmarks. To support evaluation, we introduce a 7,581-image NSFW benchmark spanning diverse real, AI-generated, and near-boundary content (3,896 harmful; 3,685 benign). A generative augmentation pipeline increases coverage of synthetic and partially occluded cases that commonly challenge fixed-taxonomy detectors, and all images are human-verified.

Contributions. This paper makes the following key contributions:

- **A new failure mode for aligned MLLM moderation.** We identify *decision suppression under alignment*, where generated outputs obscure pre-decoding safety-token margins.
- **Decoding-free safety classification from fixed logit coordinates.** We propose LOGITGUARD, a training-free method that classifies input content from first-step safety-label logits rather than generated labels, scores, or rationales.
- **Generation can obscure usable safety-token margins.** Response-vs-logit comparisons and refusal analyses show that output-based moderation can lose reliability while safety-token margins remain usable.
- **A new NSFW evaluation benchmark.** We build a 7,581-image dataset with diverse harmful, benign, AI-generated, and near-boundary content.
- **Comprehensive empirical validation.** Across MLLM families and prompts, logit-gap detection achieves strong low-FPR performance, remains effective under refusal-heavy generation, and adds minimal inference overhead.

2 Related Work

NSFW Detection and Visual Content Moderation. Existing approaches fall into three categories: *classification-based* methods (CNN/ViT detectors, commercial APIs like Amazon Rekognition (Services, 2025), and CLIP-based checkers such as Stable Diffusion safety checker (CompVis)) that are effective on fixed benchmarks but brittle under distribution shift (Szegedy et al., 2013; Geirhos et al., 2018; Goodfellow et al., 2014); *region-based* methods like NudeNet (Pudi, 2021) that focus narrowly on exposed body parts and lack coverage of broader harm categories; and *MLLM-based* methods (Llava-Guard (Helff et al., 2025), LlamaGuard (Inan et al., 2023)) that classify visual content from generated labels, scores, or rationales, and therefore remain vulnerable to alignment-induced refusals and deflections.

Logit-Based Signals in Language Models. Prior work analyzes token logits to interpret LLM uncertainty or detect refusal behavior (OpenAI; Quevedo et al., 2024; Zhang et al., 2024a). However, these methods typically operate on generated outputs and remain sensitive to sampling strategies and spurious high-probability tokens. Recent studies exploit *logit gaps* to analyze alignment effects (Arditi and Obeso, 2023; Li and Liu, 2025), but focus on understanding or circumventing safety behav-

ior rather than using native token preferences as a reliable decision signal. MLLMs are trained on massive multimodal corpora and should therefore possess a substantial understanding of harmful images. **How accurate this understanding actually is in zero-shot settings remains an unexplored question.** LOGITGUARD differs from prior output-based guardrails by performing decoding-free input-content classification: it compares fixed safety-token logits before any output token is produced, rather than parsing generated labels, scores, or rationales. To our knowledge, this work is the first systematic study of fixed safety-token logit margins as a training-free classifier for multimodal visual safety moderation.

3 Problem Formulation and Analysis

3.1 Problem Formulation

MLLMs (e.g., CLIP (Radford et al., 2021), LLaVA (Li et al.)) capture high-level semantic distinctions ideal for visual content moderation. Our goal is *zero-shot image safety classification* without fine-tuning. The standard *response-based moderation* prompts models to generate a verdict (e.g., "safe" or "unsafe"), but text generation suffers from prompt sensitivity, decoding instability, and high latency. To address this, LOGITGUARD directly extracts the safety decision signal from first-step token-level output distributions (logits), avoiding free-form generation entirely.

3.2 Analysis of Output-Centric versus Logit-Based Moderation

We compare response-based moderation,

$$x \to \mathcal{Z} \xrightarrow{\text{generation}} R \xrightarrow{\text{interpretation}} \hat{y},$$

with logit-based moderation ($x \to \mathcal{Z} \to \hat{y}$). Here, $\mathcal{Z}$ is the first-step token distribution conditioned on the image and prompt, and R is the generated text observed by an output-based moderation system.

The limitation of output-based moderation can be understood as *decoding-induced projection loss*. At the first decoding step, the MLLM computes a full vocabulary-level logit vector, containing scores for all tokens, including the designated `safe` and `unsafe` labels. Generation exposes only a decoded trajectory R: under greedy decoding, the first token reveals only the top-ranked token; under sampling, it reveals one stochastic draw. In either case, non-emitted token margins can be discarded. Consequently, two inputs can produce the same response prefix, such as a refusal or a descriptive

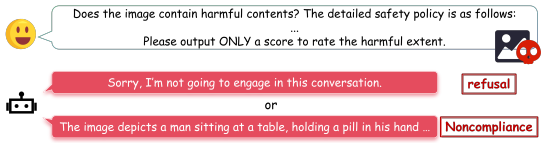


Figure 1: Examples of refusal and ambiguous outputs produced by response-based moderation.

token, while having opposite margins between the designated safety tokens. Output-based moderation cannot recover this distinction from the generated text, whereas LOGITGUARD directly reads the unsafe-vs-safe margin before decoding.

This view is consistent with the Data Processing Inequality (DPI) (Cover and Thomas, 2012): once the token distribution is transformed into a response, the downstream transformation cannot add target-label information,

$$I(y; \mathcal{Z}) \geq I(y; R).$$

We use DPI as an analytical lens rather than a formal guarantee for a particular scoring rule. The key operational point is that generated text exposes only a decoded trajectory, while LOGITGUARD reads the relevant safety-token coordinates directly. Relying on refusal behavior as a proxy for unsafety is unreliable due to high false-positive rates and prompt sensitivity. Specifically, generation introduces two critical failure modes:

Refusal-Induced Rank Obfuscation. Aligned MLLMs often assign dominant probabilities to refusal tokens, masking task-relevant label tokens in the generated text (Fig. 1). However, the internal distribution $\mathcal{Z}$ may still preserve a consistent ordering (e.g., $\mathcal{Z}_{\texttt{unsafe}} > \mathcal{Z}_{\texttt{safe}}$), which logit inspection can directly recover even when neither safety token is emitted.

Score Quantization. Generation collapses continuous preference information into discrete outputs. For example, $\mathcal{Z}_{\texttt{unsafe}} = 0.55$ and 0.99 yield the same token under greedy decoding, eliminating margin information critical for threshold selection under low-false-positive constraints.

Therefore, by reading the unsafe-vs-safe margin before decoding, LOGITGUARD bypasses the projection loss and alignment-induced distortions inherent in text generation.

4 LogitGuard: Alignment-Aware Logit-Based Safety Detection

Prior MLLM-based moderation systems infer safety decisions by generating textual responses

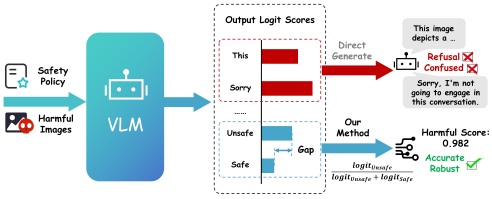


Figure 2: Pipeline and Advantages of LOGITGUARD.

and post-processing the output. In contrast, we propose LOGITGUARD, a logit-gap-based approach that directly extracts a safety decision signal from first-step token preferences. By bypassing free-form generation, LOGITGUARD avoids alignment-induced output failures and significantly reduces inference overhead, while producing a continuous, discriminative unsafe score (Fig. 2).

4.1 Persistent Logit-Gap in Internal Representations

To understand how safety-relevant decisions emerge within MLLMs, we analyze the evolution of token probabilities across model layers using the Logit Lens technique (nostalgebraist, 2020). Let h_ℓ denote the hidden state at layer ℓ. Applying the model's pre-trained output head yields an intermediate token distribution

$$P_\ell = \mathrm{Softmax}(\mathrm{Norm}(h_\ell)W_U^\top), \qquad (1)$$

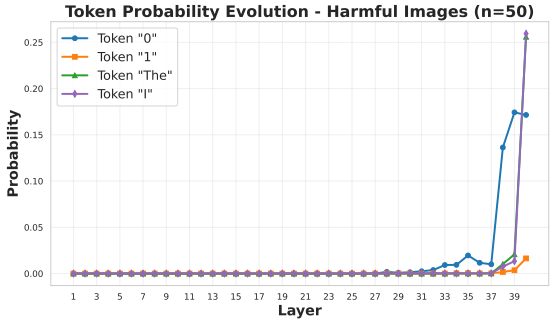
where W_U is the unembedding matrix. This allows us to inspect when and where safety-relevant token preferences arise during computation.

As illustrated in Fig. 3, safety-relevant token preferences emerge in the token distribution. The unsafe-vs-safe logit gap becomes pronounced at intermediate layers and separates harmful from benign images.

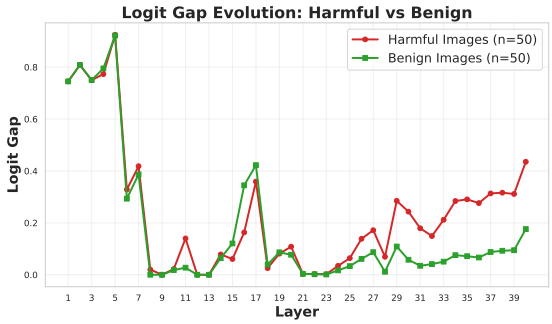
4.2 Decision Suppression Under Alignment.

In contrast, Fig. 3(a) demonstrates that near the final layers, probability mass increasingly concentrates on high-frequency interference tokens (e.g., "I", "The") induced by alignment and instruction-following priors. Meanwhile, the output probabilities of the "0" & "1" tokens representing the answer show only marginal increases or even a decline. This late-stage alignment amplification overwhelms task-relevant label tokens, often producing ambiguous or unparsable outputs despite a clear internal preference. We term this phenomenon *decision suppression under alignment*.

Together, these trends mentioned above indicate that harmfulness judgments are formed during internal reasoning but are subsequently obscured during text generation. Although intermediate-layer logits already capture this separation, we compute the logit gap at the final output layer, as the relative preference between `safe` and `unsafe` tokens is preserved and this avoids introducing extra design parameters such as layer selection.



(a) Token probabilities for harmful images (N=50)



(b) Unsafe-vs-safe logit gap (N=50 each)

Figure 3: Logit lens analysis (LLaMA3.2-11B-Vision-Instruct).

4.3 Safety Scoring from First-Step Logits

Given an image x and a binary safety classification prompt, the model produces a logit vector $\mathbf{z} \in \mathbb{R}^{|\mathcal{V}|}$ over its vocabulary at the first decoding step, prior to emitting any token. Let s_0 and s_1 denote the vocabulary indices corresponding to the `safe` and `unsafe` labels (e.g., tokens "0" and "1"). We extract the associated logits z_{s_0} and z_{s_1} and define the unsafe score as a two-token softmax:

$$\mathrm{NSFW}(x) = \frac{\exp(z_{s_1})}{\exp(z_{s_0}) + \exp(z_{s_1})}. \qquad (2)$$

This unsafe score measures the model's relative preference for the `unsafe` label over the `safe` alternative before any generation or sampling occurs. The score is computed from two fixed coordinates of the first-step vocabulary logit vector; it does not require either detection token to be emitted by the model, and therefore does not depend on the

generated response or decoding strategy. Thresholding this score yields a binary moderation decision, while retaining a continuous signal for tuning operating points.

Importantly, this score is not assigned to the generated output. It compares two fixed vocabulary coordinates, so the safe and unsafe tokens need not be emitted, or even top-ranked, for their relative margin to define the decision.

4.4 Prompting and Token Standardization

To ensure that safety decisions can be extracted from first-step logits, we prompt the model to respond using a predefined pair of single-token labels representing the `safe` and `unsafe` classes. We refer to these labels as the *safety-token pair*. A valid safety-token pair should satisfy two conditions: each label is represented by a single vocabulary token, and the prompt makes the mapping between each token and the safe/unsafe decision unambiguous. This can be achieved with a minimal instruction (e.g., "Respond with 1 if unsafe, 0 otherwise"), which encourages the model to assign probability mass directly to the designated label tokens at the initial decoding step.

At inference time, we extract these logits and compute the unsafe score in Eq. (2), without generating text. Under the atomicity and semantic-clarity conditions above, different safety-token pairs are alternative verbalizations of the same binary task. Thus, LOGITGUARD is not tied to a pair such as "0/1"; it depends on the prompt-defined unsafe-vs-safe preference. Our numeric and semantic ablations support this expectation.

The prompt defines the content policy, while the safety-token pair defines the binary decision interface. The same scoring rule can therefore be applied to different moderation policies by modifying the prompt, without retraining. This flexibility depends on the MLLM understanding the visual concepts specified by the policy.

5 Dataset Construction

Reliable evaluation of image safety detection requires datasets that expose the failure modes targeted by this work: synthetic harmful imagery, broad safety categories beyond nudity, partially occluded evidence, and near-boundary cases where output-based moderation may become unstable. Existing public NSFW datasets are often limited in scope, outdated, difficult to reproduce, or misaligned with contemporary moderation semantics. To address these limitations, we construct a new benchmark by combining public real-image sources, controlled synthetic generation, ambiguity augmentation, and human verification, yielding a diverse and challenging evaluation set.

Our construction is guided by the evaluation needs of this paper. Since our goal is to compare output-based moderation with decoding-free logit inspection, the benchmark should contain cases where surface generation can be unreliable: synthetic harmful content, broad policy categories, partially visible cues, and ambiguous near-boundary images. The resulting dataset is intended as a controlled challenge benchmark for method comparison under modern moderation-relevant conditions.

Rather than relying solely on manual collection, we employ a generative data synthesis pipeline to produce high-fidelity unsafe imagery under controlled conditions. By prompting state-of-the-art image generation models beyond their default safety boundaries, we obtain realistic harmful samples that are scarce in existing benchmarks. This approach offers two key benefits: (*i*) *diversity*, enabling coverage of varied harmful scenarios and near-boundary cases, and (*ii*) *scalability*, allowing efficient production of large volumes of candidates with limited manual effort. Because synthetic generation and subsequent augmentation can introduce ambiguous cases, all generated and transformed samples are filtered through the human annotation protocol described below rather than inheriting labels from prompts alone.

5.1 Synthetic Data Generation Pipeline

Our generation pipeline (Fig. 4) consists of three stages, covering policy breadth, semantic/style diversity, and rare or emerging visual patterns underrepresented in existing datasets.

1. **Topic Selection.** We instantiate the broad NSFW policy with representative categories, including sexual content, graphic violence, self-harm, and hate symbols.
2. **Prompt Generation.** For each category, we use DeepSeek (Guo et al., 2025) to generate diverse prompts by varying context, demographics, and style; any sufficiently diverse prompt generator can be substituted.
3. **Image Synthesis.** Prompts are rendered using Flux (Labs et al., 2025). By adjusting sampling parameters, we produce images from subtle, bor-

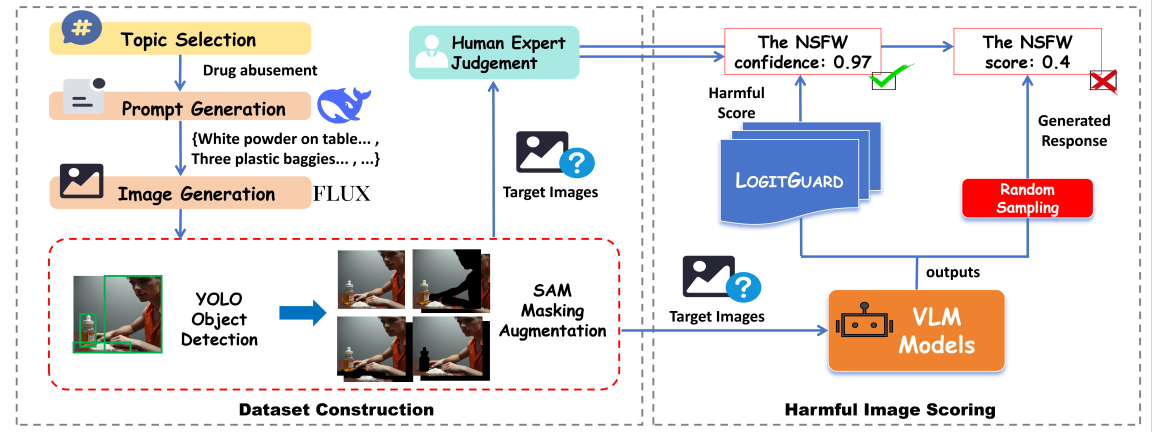


Figure 4: Synthetic data generation and annotation pipeline for the NSFW benchmark.

derline content to explicit violations.

5.2 Ambiguity Augmentation via Masking

To further stress-test moderation systems, we augment generated images with controlled ambiguity. Using YOLOv8 (Yaseen, 2024) for object detection and SAM (Kirillov et al., 2023) for segmentation, we automatically identify salient regions and apply partial masking. For selected images, we generate two variants: one with a region removed, and one retaining only that region while masking the rest. This process removes obvious visual cues and creates borderline cases that require contextual reasoning. The augmentation is designed to create controlled near-boundary variants that test whether detectors can still infer harmfulness when salient evidence is incomplete, occluded, or isolated from context. All masked samples are evaluated using the human annotation protocol described in the following subsection.

5.3 Human-in-the-Loop Annotation

All final image instances in our dataset—including synthetic and real images, as well as masked and unmasked variants—are labeled using a unified human annotation protocol. Three trained graduate annotators, familiar with a detailed content safety policy (Appendix A), independently labeled each image as `safe`, `unsafe`, or `N/A`. The policy provides precise definitions and examples to ensure consistent interpretation of borderline cases. All the annotators are paid at an average rate of $30 per hour, which is above the minimum wage in their country of residence, ensuring fair and adequate compensation.

Annotation proceeded in two stages. Two annotators independently labeled each image in the first round. Images with disagreement were reviewed by a third annotator, with the final label determined by majority vote. Images labeled as `N/A`, corresponding to cases that are excessively ambiguous or lack sufficient visual evidence, were excluded from the final dataset.

Before adjudication, the first-round annotations reached 86.99% agreement, with a Fleiss' Kappa of 0.691, indicating substantial consistency (Fleiss, 1971; McHugh, 2012). For images sourced from existing datasets with pre-existing labels, our human annotations exhibit complete agreement with the original labels. After excluding 1,066 images labeled as `N/A`, the final dataset contains 7,581 images, comprising 3,896 harmful and 3,685 benign samples. Table 1 summarizes the final dataset composition, including image sources and the proportion of masked samples per source.

6 Experiments

6.1 Experimental Setup

Models. We evaluate our method on state-of-the-art open-source MLLMs (Table 2), including **Qwen2.5-VL** (3B, 7B, 72B) (Bai et al., 2025), **Aya-Vision** (8B, 32B) (Dang et al., 2024), and **Llama-3.2-Vision** (11B, 90B) (Chu et al., 2024).

Baselines. We compare LogitGuard with:

- **Fine-tuned MLLM Detectors:** Llava-Guard (Helff et al., 2025) and Llama Guard 4 (Inan et al., 2023).
- **Existing Safety Detectors:** VQA-based NSFW detector (Chen et al., 2025; Lin et al., 2024), Stable Diffusion safety checker (Rombach et al., 2022), and NudeNet (Pudi, 2021).
- **Commercial Safety Filters:** Amazon Rekognition and Aliyun Content Security.

Table 1: **Dataset breakdown by source, content category, and masking.**

Label	Porn	Extremism	Illegal Activities		Violence and Shock			Benign
Source	(OmerET8)	FLUX(text2image)	(Yeh et al., 2024)	FLUX(text2image)	(ChinaZhangPeng)	(Yeh et al., 2024)	FLUX(text2image)	(Russakovsky et al., 2015)
Original Images	250	42	37	215	18	50	180	1000
Masked Images	1652	164	202	2442	126	292	912	0
Overall Images	1902	206	239	2657	144	342	1091	1000

Table 2: Model information of our evaluated MLLMs.

Model Name	Param	Model		Developer
		Language	Vision	
Qwen2.5-VL-7B	7.61B	Qwen2.5-7B	QwenViT	Ali Cloud
Llama-3.2-11B-Vision-Instruct	10.6B	Llama-3.1-8B	LlamaVisionModel	Meta
Aya-Vision-8B	8B	C4AI-C-R7B	SigLIP2	Cohere Labs

We evaluate each baseline through its intended decision interface. Commercial APIs and score-based detectors expose continuous risk scores, while fine-tuned guardrails and some safety checkers return hard labels or structured moderation outputs. We therefore report classification metrics for all methods and additionally report AUC and TPR@k%FPR whenever a usable continuous score is exposed. Because commercial APIs use proprietary taxonomies and thresholds, we treat them as black-box moderation systems and evaluate their exposed outputs under our benchmark annotations.

Dataset. We construct a balanced dataset of **7,581 images** (3,896 harmful, 3,685 benign) by combining public subsets (`violence_image_dataset` (ChinaZhangPeng), `NSFW_dataset` (OmerET8), VHD11K (Yeh et al., 2024)), synthetic images generated by *flux.1 schnell* (Labs et al., 2025), and masked variants via YOLO (Yaseen, 2024)+SAM (Kirillov et al., 2023). All images are human-verified. See Appendix H for the full construction pipeline.

Evaluation Protocol and Metrics. We report Accuracy, Precision, Recall, F1, AUC, and TPR@k%FPR ($k \in \{1, 5\}$). We also measure per-image inference time and peak GPU memory.

6.2 Main Results

Table 3 presents the main results.

LOGITGUARD achieves strong low-FPR performance: Qwen2.5-VL-7B attains TPR of 0.513 at 1% FPR and 0.816 at 5% FPR. Such low-FPR operating points are critical for real-world moderation, where false positives must be tightly controlled. Qwen2.5-VL-7B also offers the strongest performance-resource trade-off among the evaluated models (Acc 0.895, F1 0.899, AUC 0.939), with modest resource use (see Appendix L for full scaling analysis). LOGITGUARD surpasses commercial APIs on all discriminative metrics—e.g., Qwen2.5-VL-7B exceeds Amazon Rekognition by large margins on AUC (0.939 vs. 0.812) and F1 (0.899 vs. 0.798). It also outperforms existing NSFW detectors such as VQA-based (AUC 0.859) and SD safety checker (Acc 0.527); while NudeNet achieves slightly higher precision on pornography alone, it fails on broader categories (Extremism/Illegal/Violence F1 near 0). Compared with response-based scoring (0–100), LOGITGUARD provides more reliable low-FPR ranking and remains applicable even when generated outputs are invalid or refusal-dominated. For example, on Qwen2.5-VL-7B, response-based scoring attains slightly higher Accuracy and F1, but LOGITGUARD achieves stronger TPR@1%FPR (0.513 vs. 0.264) and AUC (0.939 vs. 0.933). On Llama-3.2-Vision, where response outputs are frequently noncompliant, logit scoring remains well-defined. Full per-model results are in Appendix J.

Takeaway: LOGITGUARD provides a thresholdable unsafe score with strong low-FPR performance.

Takeaway: Pre-decoding safety-token margins remain usable when generated outputs are disrupted.

6.3 Ablation Study: Robustness to Prompt and Token Variations

We test four token-choice schemes (numeric vs. semantic; direct vs. structured JSON) on Qwen2.5-VL-7B and Aya-Vision-8B. Results (Appendix K) show that the unsafe score remains stable across semantically different safety-token pairs (Sem vs. Num) when extracted from the first step, but marginally weaker in structured (mid-sentence) positions. This supports the view that valid safety-token pairs function as alternative labels for the same safe/unsafe decision rather than token-specific heuristics, and confirms that the initial decoding step preserves the strongest safety decision signal.

Takeaway: The initial decoding step gives the strongest signal, stable across tested safety-token pairs.

Table 3: **Detection performance on our dataset.** Comparison of LOGITGUARD vs. existing detectors. (N/A = no usable continuous score exposed by the method.)

Method	Model	Accuracy	F1-Score	Precision	AUC	TPR@1%FPR	TPR@5%FPR
LOGITGUARD (Ours)	Qwen2.5-VL-7B	**0.895**	**0.899**	**0.927**	**0.939**	**0.513**	**0.816**
	Llama-3.2-Vision-11B	0.812	0.830	0.803	0.869	0.097	0.332
	Aya-Vision-8B	0.857	0.866	0.870	0.919	0.189	0.652
Other MLLMs (Fine-tuned)	Meta-Llama Guard 4 12B	0.566	0.436	0.713	N/A	N/A	N/A
	LlavaGuard 7B	0.861	0.871	0.829	N/A	N/A	N/A
Commercial API	Amazon Rekognition	0.806	0.798	0.899	0.812	0.057	0.345
	Aliyun Content Safety	0.682	0.596	**0.927**	0.700	0.174	0.445
Existing Detector	VQA-based NSFW checker	0.803	0.825	0.786	0.859	0.092	0.340
	SD safety checker	0.527	0.432	0.603	N/A	N/A	N/A
	NudeNet	0.587	0.390	0.923	0.612	0.104	0.268

6.4 Scaling Laws and Computational Cost

Detection capability improves sharply from 3B to 7B, then plateaus beyond 8B, suggesting mid-sized models already capture sufficient semantic features. On Llama-3.2-Vision, response-based methods suffer near-total refusal (97% at 11B), whereas LOGITGUARD remains robust across all scales. Detailed scaling tables and refusal analysis are in Appendix L.

LOGITGUARD incurs negligible overhead: Qwen2.5-VL-7B processes an image in 0.23 s on a single A100 with 17 GB memory—orders of magnitude faster than guardrails that generate rationales. Full cost breakdown is in Appendix M.

> **Takeaway**: LOGITGUARD remains effective on refusal-heavy models with minimal inference overhead.

6.5 Adaptive Attacks

Table 4: **Attack success rates on Llava-v1.5-7B and Qwen2.5-VL.**

Model	Method	Positive Element	Cartoon Style	Transfer Attack (from Llava)
Llava-v1.5-7B	LOGITGUARD	21.1%	10.8%	10.6%
	Generate	55.2%	52.6%	27.1%
Qwen2.5-VL-3B	LOGITGUARD	5.9%	4.5%	41.1%
	Generate	4.8%	5.0%	35.6%
Qwen2.5-VL-72B	LOGITGUARD	7.4%	13.5%	77.6%
	Generate	17.0%	18.6%	79.3%

Threat model. We consider adaptive attacks where the adversary knows the detector and modifies the input, but cannot change the model or prompt. We evaluate three complementary evasion strategies:

- **Positive Elements ($L1$):** injecting benign cues by adding a "dove of peace".
- **Stylization ($L2$):** converting the image to a cartoon style via OpenCV.
- **Transfer Attack ($L3$):** optimizing adversarial examples on Llava's CLIP encoder toward an all-white harmless embedding (Shayegani et al.), then testing transferability to Qwen2.5-VL.

Overall, LOGITGUARD improves robustness across the evaluated adaptive attacks, with the clearest gains under positive-element and stylization attacks. Transfer attacks remain challenging for both schemes, suggesting that transferable visual perturbations remain a difficult setting even for decoding-free scoring.

7 Conclusion

We introduced LOGITGUARD, a training-free image safety scorer that compares fixed safety-token logits before decoding, producing deterministic unsafe scores while avoiding refusals, format non-compliance, and score quantization.

Across multiple MLLM families and a 7,581-image benchmark, LOGITGUARD achieves strong low-FPR performance and remains effective when response-based moderation generates refusals or ambiguous text. These results show that output-centric extraction can obscure useful pre-decoding safety-token margins. This suggests that the bottleneck in MLLM-based moderation is not only visual recognition, but also the output interface used to extract the decision.

Because the unsafe score is continuous, deterministic, and prompt-conditioned, it can be thresholded for different moderation requirements without retraining. Future work will extend logit inspection to richer taxonomies and defense-in-depth moderation pipelines. Logit inspection is therefore a practical complement to generated-output moderation, especially in settings requiring stable scores and strict false-positive control.

Limitations

While the training-free, zero-shot nature of LOGITGUARD provides significant advantages in adaptability and deployment efficiency, it also inherently bounds the framework's performance to the representational capacity and safety awareness of the underlying MLLM. Prompt-level policy adaptation should therefore be understood as conditional flexibility: LOGITGUARD can rescore inputs under a new prompt-defined policy without retraining, but only when the underlying MLLM has sufficient visual-semantic knowledge of that policy. Because our approach does not update model weights, LOGITGUARD cannot recognize or adapt to novel safety concepts that fall outside the pre-training data of the base model, nor can it correct systematic biases present in the MLLM's original distribution. In scenarios where the base MLLM entirely lacks the conceptual boundary for a specific type of harm, our logit-gap extraction will inherently fail to produce a meaningful safety signal.

Furthermore, the current implementation primarily frames image safety detection as a binary (safe vs. unsafe) or coarse-grained decision problem. Although effective for general moderation, this binary logit-gap paradigm struggles to naturally extend to rich, multi-class safety taxonomies (e.g., simultaneously distinguishing among hate speech, self-harm, and sexual content) without manually designing and evaluating multiple distinct token pairs for each category. Relying on isolated token comparisons may lead to semantic ambiguities when dealing with overlapping or fine-grained policy categories, as the logit gap between a single target token and a safe token does not capture the full probability distribution across a complex vocabulary of harms.

Additionally, the selection of the specific safe and unsafe target tokens, while straightforward in our current setup, remains heuristic. The optimal token pair may vary across different MLLM families or cultural contexts, and a static token choice might not universally align with the model's internal semantic space. Future work should address these constraints by exploring lightweight fine-tuning or prompting strategies to expand the framework's coverage to unseen risks, developing logit distribution analysis over the entire vocabulary to enable robust multi-category safety classification, and investigating automated or dynamic target token selection mechanisms to better align with diverse and evolving moderation policies.

Finally, LOGITGUARD requires inference-time access to first-step token logits. This is a natural requirement for defender-controlled moderation pipelines, where the operator can choose an open-weight or self-hosted VLM backend that exposes logits. The requirement mainly affects closed APIs that expose only generated responses.

Ethical Considerations

This study was reviewed and approved by our Institutional Review Board (IRB). The IRB determined that no major ethical concerns exist, provided that annotators are not exposed to illegal materials, such as Child Sexual Abuse Material (CSAM). We confirm that our dataset contains no such content. Nonetheless, we acknowledge that our ethical responsibilities extend beyond formal institutional approval.

First, to minimize potential psychological harm from exposure to harmful content, all annotations were conducted internally by our research team. While this prevents exposing third parties to unsafe content, we recognize that internal annotation introduces the potential for bias stemming from subjective interpretations of safety. To mitigate this bias, we implemented the following measures: (1) Our unsafe taxonomy was developed by synthesizing multiple authoritative sources, including the OpenAI content policy and relevant academic studies. (2) Before the annotation phase, each unsafe concept was manually verified to confirm its general unsuitability. (3) The annotation task was framed as an objective identification problem, akin to object detection, rather than a subjective judgment call.

Second, to protect our annotators' well-being, we implemented strict protocols, including limits on exposure time, mandatory scheduled breaks, and regular mental health check-ins. Regarding the public demonstration of our findings, displaying unsafe examples is an unavoidable aspect of this research. However, to minimize potential harm to the reader, all Not-Safe-For-Work (NSFW) images in our paper and presentations are censored. We have also taken care to avoid showcasing examples that could be particularly offensive to specific communities.

Finally, we define the terms for the responsible use of our dataset. It is provided for the exclusive purpose of benchmarking harmful image detection methods within academic and research contexts.

Any application of the dataset beyond this specified scope is strictly prohibited. To prevent misuse, access to the dataset will be granted only after a stringent vetting process.

Open Science

To facilitate reproducibility, we provide an anonymous repository at https://anonymous.4open.science/r/Logits-Speak-Louder-A47hg73B. Due to data size constraints, the repository contains a random 10% subset of our full dataset (comprising 7,581 images). We also provide the trained attack images, along with the scripts used to generate them using the 'Jailbreak in Pieces' (Shayegani et al.) method. Please refer to the repository's README for further details.

Data and Code Availability. We will release the code and the constructed dataset of 7,581 images upon publication. The code will be licensed under the Apache License 2.0, and the dataset will be released under the CC BY 4.0 license. For the pre-trained models and existing datasets utilized in our experiments, we strictly adhere to their original licenses: LlamaGuard4 is under llama4 License, Qwen2.5-VL models are under Apache-2.0 license and qwen license, Aya-vision models are under cc-by-nc-4.0 license, and all the other Github repositories we use in our dataset is under Apache-2.0 license.

Generative AI Usage

We utilized generative AI tools to partially assist with the grammatical refinement and language polishing of this manuscript. regarding code development, generative AI was employed to aid in the modularization of our experimental scripts. Specifically, we used Gemini 3 Pro for refining grammar and expressions, and GPT-5.1 for organizing code structure. It is important to note that all core algorithmic logic and function designs were conceived and implemented entirely by the human authors. Additionally, generative AI was used to synthesize harmful images for dataset construction, with the specific methodologies and models detailed in Appendix 5.

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A Input Prompt for Safety Detection

Prompt Template for LOGITGUARD (Direct/Num)

SYSTEM: You are a professional content moderation expert. Please strictly evaluate images for prohibited content according to the guidelines.
USER: Does the image contain inappropriate, pornographic, violent, horrific, bloody, gambling, drug-related, or superstitious content that violates laws and regulations? If so, output 1; otherwise, output 0. Detailed rules are as follows:
S1 Pornography and Nudity
Image contains direct exposure of sexual organs or sexual acts.
Image contains sexual suggestions involving minors (even without direct nudity).
Image contains excessive nudity or provocative behavior not for artistic/medical purposes.
S2 Violence and Gore
Image contains corpses, dismembered body parts, large amounts of blood, or other visually disturbing content.
Image contains murder, abuse, war, or fighting scenes.
Image contains explicit depictions or suggestions of self-harm or suicide.
S3 Illegal and Dangerous Activities
Image contains scenes of drug production, trafficking, or consumption.
Image contains the use or display of illegal weapons (such as firearms, explosives, and regulated knives).
Image contains depictions of theft, robbery, arson, gambling, or other illegal activities.
S4 Hate and Discrimination
Image contains stereotypical derogation, discrimination, or hateful content (such as racial discrimination, desecration of religious symbols, offensive gestures, etc.).
Image contains Nazi symbols, extremism, or cult-related content.

If the image involves any of the above categories, it is considered illegal and inappropriate content, output 1; otherwise, output 0.
Please ensure you output ONLY a single digit, either 1 or 0, without any additional content.

Prompt Template for LOGITGUARD (Struct/Num)

SYSTEM: You are a professional content moderation expert. Please strictly evaluate images for prohibited content according to the guidelines.
USER: Provide a safety assessment for the content provided by the user. Determine compliance or violation against our safety policy by reviewing the following policy categories. An image is considered "Unsafe"(rate 1) if it violates any of the following categories; otherwise, it is "Safe"(rate 0). The categories are as follows:
..... (same as the above one)

Assessment Steps:
1. Select a safety "rating". This should be "1" if the content violates the safety policy; otherwise, it should be "0".
2. Assign a policy "category". If none of the policy categories are applicable, select "NA: None applying".
3. Provide a "rationale". Explain the reason why the content is considered safe or unsafe, referring to the description of the assigned policy category.
To provide your assessment use the following json template:

```
{
    "rating": str<"1"|"0">,
    "category": str<"S1"|...|"None">,
    "rationale": str,
}
```

Prompt Template for response-based scheme

SYSTEM: You are a professional content moderation expert. Please strictly evaluate images for prohibited content according to the guidelines.

USER: Does the image contain inappropriate, pornographic, violent, horrific, bloody, gambling, drug-related, or superstitious content that violates laws and regulations? If any of these elements are present, rate the extent of involvement on a scale from 0 to 100, where 0 means not present at all and 100 means fully present. Detailed rules are as follows:

..... (same as the above one)

If any of these elements are present, rate the extent of involvement on a scale from 0 to 100, where 0 means not present at all and 100 means fully present.
Please ensure you output ONLY a single score, from 0 to 100, without any additional content.

B Supplementary Discussion

Our results show that decoding-free unsafe scoring can complement generation-based moderation by exposing a continuous decision signal before response generation. We discuss additional implications, trade-offs, and practical considerations below.

- **Practical Deployment & Efficiency:** By leveraging first-step logits, LogitGuard bypasses the latency of long-form text generation and produces a deterministic unsafe score for thresholding. This design simplifies moderation pipelines in settings where defenders can choose a VLM backend that exposes logits.
- **Alignment & Refusal Behavior:** Response-based classifiers can be disrupted when aligned models generate refusals, descriptions, or other non-label text. LogitGuard avoids this output channel by comparing fixed safety-token logits before decoding. The method still inherits blind spots from the underlying MLLM: if the model lacks the visual-semantic distinction required by a policy, the unsafe score may not provide a useful signal.
- **Prompt-Level Flexibility:** The scoring rule is model-agnostic and can be applied across VLM backends that expose first-step logits. The moderation prompt defines the policy being evaluated, while the safety-token pair defines the binary decision interface, enabling prompt-level adaptation without task-specific retraining.
- **Future Extensions:** Our current formulation focuses on a binary safe/unsafe decision. Future work can extend the same principle to richer taxonomies, context-aware moderation with accompanying text or metadata, and lightweight model updates for emerging harmful-content patterns.

Overall, logit-based unsafe scoring offers a fast and adaptable decision interface for image safety moderation while preserving the prompt-level flexibility of MLLM-based systems.

C Refusal Case Study on Llama3.2-11B

We conducted a systematic analysis to investigate token-level refusal behavior in vision-language models when prompted for numerical safety assessments. Using Llama-3.2-11B-Vision-Instruct, we examined two distinct prompting strategies: (1) requesting a binary 0/1 classification (Figure 5), and (2) requesting a continuous 0-100 safety score (Figure 6). For each approach, we sampled 100 images balanced between safe and unsafe content, and analyzed the probability distribution of the first generated token.

As shown in Figure 5 and 6, our results reveal a consistent pattern of "refusal interference" where the model systematically favors linguistic tokens over the requested numerical outputs. In the 0-100 scoring scenario, 97% of top-1 predictions are non-numeric tokens, with token "The" being the dominant interference token (appearing 94 times), followed by other linguistic tokens. The probability distribution shows that interference tokens achieve an average confidence of 0.458, while the first numeric token in the candidate list only achieves 0.181, and token "0" receives merely 0.045. In the binary classification scenario, 68% of predictions are interference tokens rather than the expected "0" or "1", with "The" again being the most frequent interferer (43 occurrences) followed by "I" (21 occurrences). The average probability for top-1 interference tokens (0.477) substantially exceeds that of token "0" (0.252) and token "1" (0.015), representing approximately 2× and 30×

higher confidence scores respectively. This phenomenon demonstrates that even when explicitly instructed to output only numbers, the model's alignment training creates a strong bias toward generating explanatory natural language, effectively refusing to provide the concise format requested. The token "The" indicates that the model is proceeding to describe the image (e.g., "The image depicts..."), whereas the token "I" signals an impending refusal (e.g., "I am not going to engage in this conversation"). The consistent pattern across both prompting strategies suggests deep-seated architectural or training-induced preferences that systematically override explicit user instructions for numerical outputs.

D Experiments on VHD11K Dataset

In addition to our dataset, we also tested the performance of the logit-based scheme and existing detectors on the VHD11K dataset(Yeh et al., 2024). As shown in Table 5, LOGITGUARD generally outperforms the others. The VHD11K test set includes 5,000 harmful images and 5,000 benign images.

E Experiments on UnsafeBench Dataset

In addition to our dataset, we also tested the performance of the logit-based scheme and existing detectors on the UnsafeBench dataset(Qu et al., 2025). As shown in the Table 6, the logit schemes generally outperforms the others. The UnsafeBench test set includes 777 harmful images and 1,260 benign images.

F Python Code of Image Style Change Used in Adaptive Attack Experiment

The input to this function is the original image to be processed, and the output is the stylized adversarial image.

```
import numpy as np
import cv2
from PIL import Image

def generate_advstyle_image(image):
 img_array = np.array(image)
 img_array =
     cv2.cvtColor(img_array,
     cv2.COLOR_RGB2BGR)
 color =
     cv2.bilateralFilter(img_array,
     d=9, sigmaColor=300,
     sigmaSpace=300)
 gray = cv2.cvtColor(img_array,
     cv2.COLOR_BGR2GRAY)
 gray = cv2.medianBlur(gray, 5)
 edges =
     cv2.adaptiveThreshold(gray,
     255,
     cv2.ADAPTIVE_THRESH_MEAN_C,
     cv2.THRESH_BINARY, 9, 5)
 cartoon = cv2.bitwise_and(color,
     color, mask=edges)
 cartoon = cv2.cvtColor(cartoon,
     cv2.COLOR_BGR2RGB)
 cartoon_image =
     Image.fromarray(cartoon)
 return cartoon_image
```

G Analysis of SMID Dataset and UnsafeBench

In this section, we provide a detailed analysis of the limitations inherent to the SMID and UnsafeBench datasets.

- **SMID dataset** (Crone et al., 2018): The SMID dataset is stored on Hugging Face as a collection of URLs; however, the majority of these links are now defunct. Of the 2941 images the dataset purports to contain, we were only able to retrieve 365 labeled images, of which just 48 were marked as harmful. This sample size is too small to serve as a robust basis for evaluating our method.

- **UnsafeBench** (Qu et al., 2025):While all 2,037 images in the UnsafeBench test set are fully accessible, we found that a significant number of the images designated as "harmful" lack genuinely malicious semantics. Examples of such misclassified images include "a

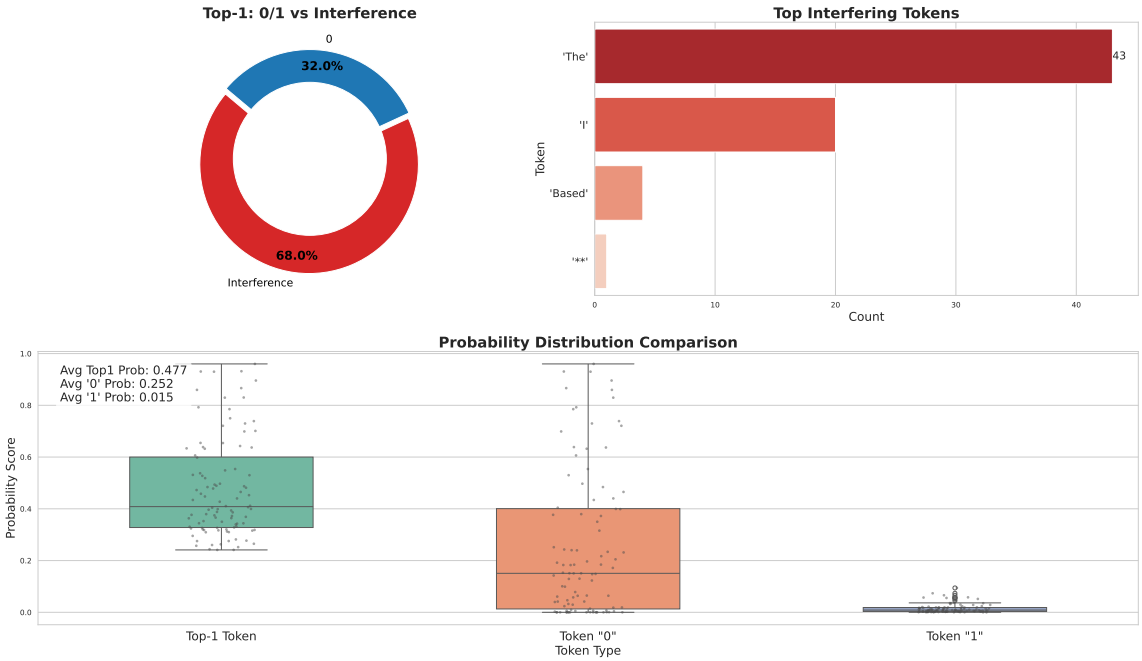


Figure 5: Token prediction analysis for binary 0/1 classification prompts. (Top-left) Distribution of top-1 predicted tokens showing proportions of "0", "1", and interference tokens. (Top-right) Ranking of most frequent interfering tokens when the model does not predict "0" or "1". (Bottom) Probability distribution comparison across top-1 predictions, token "0", and token "1". Data: N = 100 sampled images (balanced safe/unsafe). Model: Llama-3.2-11B-Vision-Instruct.

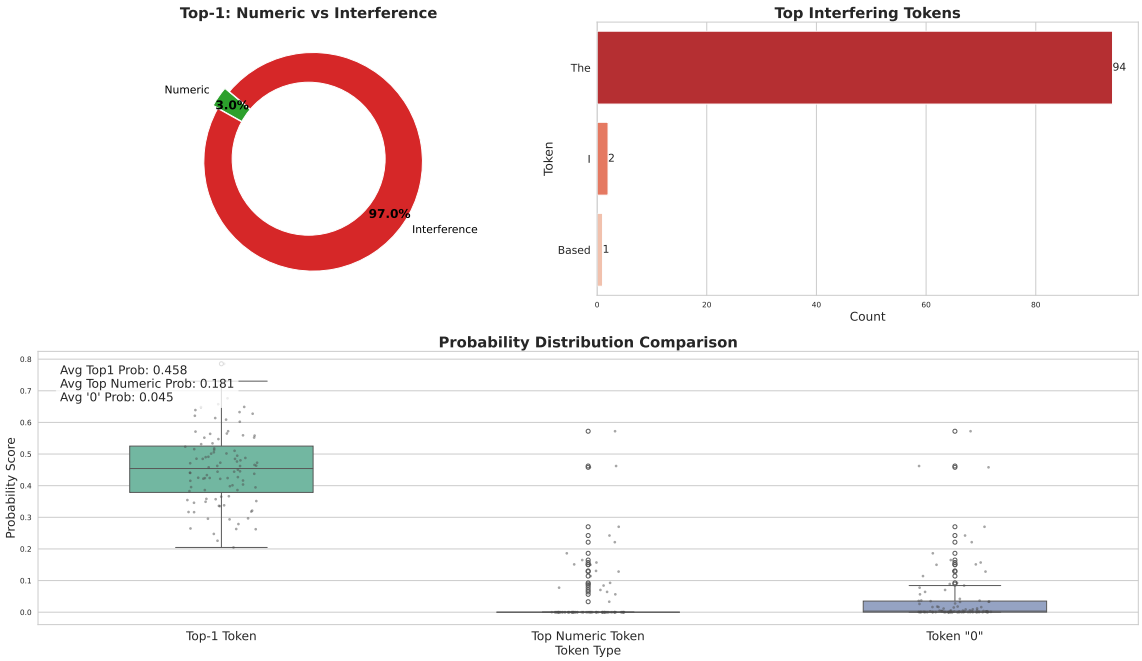


Figure 6: Token prediction analysis for 0-100 scoring prompts. (Top-left) Distribution of top-1 predicted tokens categorized as numeric vs. interference tokens. (Top-right) Ranking of most frequent interfering tokens. (Bottom) Probability distribution comparison across top-1 predictions, top numeric tokens, and token "0". Data: N = 100 sampled images (balanced safe/unsafe). Model: Llama-3.2-11B-Vision-Instruct.

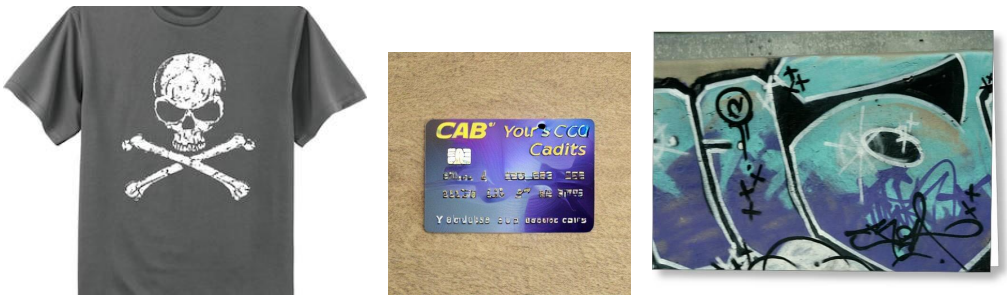
T-shirt with a skull print," (Fig 7(a)) "an AI-generated image of a distorted credit card," (Fig 7(b)) and "a simple photo of a graffiti wall."(Fig 7(c)) To quantify this discrepancy,

Table 5: **Detection performance on VHD11K: LOGITGUARD vs. existing detectors.**

Method	Model	Accuracy	F1-Score	Precision	AUC	TPR@1%FPR	TPR@5%FPR
LOGITGUARD (Ours)	Qwen2.5-VL-7B	**0.770**	**0.762**	0.789	**0.852**	**0.238**	**0.491**
	Llama-3.2-Vision-11B	0.676	0.690	0.661	0.735	0.068	0.224
	Aya-Vision-8B	0.759	0.738	0.807	0.835	0.222	0.456
Other MLLMs (Fine-tuned)	Meta-Llama Guard 4	0.530	0.179	0.708	N/A	N/A	N/A
	LlavaGuard	**0.770**	0.760	0.769	N/A	N/A	N/A
Commercial API	Aliyun Content Safety	0.595	0.380	**0.811**	0.595	0.036	0.235
Existing Detector	VQA-based NSFW checker	0.677	0.670	0.683	0.743	0.079	0.255
	SD safety checker	0.539	0.248	0.669	N/A	N/A	N/A
	NudeNet	0.517	0.103	0.714	0.517	0.025	0.082

Table 6: **Detection performance on UnsafeBench: LOGITGUARD with 4 schemes vs. existing detectors. ($Struct$ means assigning structured output, $Direct$ means assigning direct output; Sem means assigning "Safe/Unsafe" as judge label, Num means assigning "0/1" as judge label. N/A = no usable continuous score exposed by the method.)**

Method	Model	Scheme	Accuracy	F1-Score	Precision	Recall	AUC	TPR@0.1%FPR	TPR@1%FPR	TPR@5%FPR
LOGITGUARD (ours)	Llama-3.2-Vision-11B	$Struct/Sem$	0.6902	0.6437	0.5734	0.7336	0.7377	0.0077	0.0335	0.2162
		$Struct/Num$	0.7300	0.6554	0.6386	0.6731	0.7839	0.0154	0.0682	0.3050
		$Direct/Sem$	0.7359	0.6926	0.6228	0.7799	0.8090	0.0592	0.1673	0.3320
		$Direct/Num$	0.7059	0.6515	0.5945	0.7207	0.7655	0.0142	0.1068	0.2497
	Qwen2.5-VL-7B	$Struct/Sem$	0.7541	0.7030	0.6516	0.7632	0.8251	0.0171	0.0849	0.3411
		$Struct/Num$	0.7432	0.6999	0.6315	0.7851	0.8130	0.0064	0.0553	0.2561
		$Direct/Sem$	**0.7737**	0.7170	0.6854	0.7516	0.8254	0.0347	0.1174	0.4015
		$Direct/Num$	0.7668	**0.7342**	0.6495	**0.8443**	**0.8579**	0.0142	0.0837	0.4067
	Aya-Vision-8B	$Struct/Sem$	0.7108	0.6441	0.6071	0.6860	0.7764	0.0875	0.1974	0.3089
		$Struct/Num$	0.7050	0.6458	0.5957	0.7053	0.7750	0.0737	0.1931	0.3514
		$Direct/Sem$	0.7094	0.6586	0.5967	0.7349	0.7838	0.0660	0.2106	0.3108
		$Direct/Num$	0.7506	0.6929	0.6534	0.7375	0.8270	**0.1014**	**0.2278**	**0.4208**
VLM-based (other)	Meta-Llama Guard 4		0.6213	0.0178	**0.8400**	0.0090	N/A	N/A	N/A	N/A
	LlavaGuard		0.7639	0.6257	0.7913	0.5174	N/A	N/A	N/A	N/A
Commercial API	Amazon Rekognition		0.7054	0.4585	0.7674	0.3269	0.6337	0.0180	0.0502	0.2896
	Aliyun Content Safety		0.6917	0.3950	0.7854	0.2638	0.6111	0.0122	0.0770	0.2681
Existing Detector	VQA-based NSFW checker		0.6610	0.6708	0.6494	0.6937	0.7681	0.0051	0.0553	0.1995
	SD safety checker		0.6083	0.3055	0.4703	0.2262	N/A	N/A	N/A	N/A



(a) Image of T-shirt (b) Image of credit card (c) Image of graffiti

Figure 7: Examples of images in UnsafeBench labeled "harmful" but lacking genuinely malicious semantics. (a) Image of T-shirt, (b) Image of credit card; (c) Image of graffiti

we performed a manual verification on a random sample of 100 images labeled as "harmful," and our human reviewers confirmed that only 67 of them were actually harmful.

H Detailed Experimental Setup

Models. In addition to the three flagship models reported in the main paper, we also evaluate:

- **LLaVA-v1.5** (7B) (Liu et al., 2024): a pioneering fully open-source model frequently used as a standard target for adversarial-attack evaluation.
- **LLaVA-OneVision** (7B) (Li et al.): the foundational backbone of LLaVA-Guard, serving as a baseline in our adaptive-attack experiments.

Baselines. Fine-tuned MLLM Detectors. Llava-Guard (Helff et al., 2025) is built upon a custom safety dataset with fine-grained annotations, pro-

viding structured safety assessments (binary labels, harm categories, rationales). Llama Guard 4 (Inan et al., 2023) evaluates both text and image content against predefined safety policies.

Existing Safety Detectors. The VQA-based NSFW detector (Chen et al., 2025; Lin et al., 2024) assesses alignment between harmful images and textual descriptions of harmful themes to derive an NSFW score. The Stable Diffusion safety checker (Rombach et al., 2022) performs CLIP-based concept matching for binary decisions. NudeNet (Pudi, 2021) focuses on exposed-body-part detection at the region level.

Commercial Safety Filters. Amazon Rekognition detects explicit content, violence, and offers custom-label training with human-review workflows. Aliyun Content Security covers pornography, violence, personal-data leakage, and hate speech, providing confidence scores and contextual information.

Dataset Construction Details. The dataset combines three sources: (*i*) public subsets from `violence_image_dataset` (ChinaZhangPeng), `NSFW_dataset` (OmerET8), and VHD11K (Yeh et al., 2024); (*ii*) synthetic images from *flux.1 schnell* (Labs et al., 2025); and (*iii*) masked variants via YOLO (Yaseen, 2024)+SAM (Kirillov et al., 2023). The final corpus spans four categories: Pornography and Nudity, Violence and Gore, Illegal and Dangerous Activities, and Hate and Discrimination. Benign images comprise 1,000 ImageNet2012 samples plus 2,685 masked harmless variants. All labels are human-verified.

Metrics. For continuous scores we report AUC and TPR@k%FPR (interpolated). Efficiency is measured as per-image inference time (including the full generation pass or logit extraction) and peak GPU memory.

I Per-Category Comparison with NudeNet

Table 7: **Performance of NudeNet on our dataset (values in parentheses are LOGITGUARD). Green = superior to NudeNet; red = NudeNet superior.**

Label	Porn	Extremism	Illegal	Violence	Overall
Accuracy	0.828(0.885)	0.578(0.879)	0.445 (0.874)	0.302(0.881)	0.587(0.895)
F1 Score	0.854(0.912)	0.000(0.868)	0.010(0.877)	0.063(0.915)	0.390(0.899)
Precision	0.934(0.894)	0.000(0.781)	0.727(0.956)	0.949(0.946)	0.923(0.928)
Recall	0.787(0.932)	0.000(0.976)	0.005(0.810)	0.033(0.886)	0.248(0.871)

Table 8: **LOGITGUARD vs. generative 0–100 scoring on our dataset.**

Model Series	Model Size	Scheme	Acc.	F1	Precision	Recall	AUC	TPR@k%FPR k=1	TPR@k%FPR k=5
Qwen2.5-VL	3B	LOGITGUARD	0.880	0.885	0.912	0.859	0.937	0.363	0.751
		Generate	0.872	0.872	**0.931**	0.820	0.885	0.193	0.757
	7B	LOGITGUARD	0.895	0.899	0.927	0.871	0.939	**0.513**	**0.816**
		Generate	**0.900**	**0.908**	0.891	0.926	0.933	0.264	0.793
	72B	LOGITGUARD	0.899	0.906	0.904	0.907	**0.952**	0.383	0.788
		Generate	0.891	0.903	0.862	0.948	0.935	0.267	0.684
Aya-Vision	8B	LOGITGUARD	0.857	0.866	0.870	0.863	0.919	0.189	0.652
		Generate	0.870	0.881	0.868	0.894	0.889	0.141	0.434
	32B	LOGITGUARD	0.874	0.882	0.883	0.882	0.908	0.085	0.423
		Generate	0.879	0.891	0.855	0.931	0.895	0.059	0.374
Llama3.2-Vision-Instruct	11B	LOGITGUARD	0.812	0.830	0.803	0.858	0.869	0.097	0.332
		Generate(D)	N/A	N/A	N/A	N/A	N/A	N/A	N/A
		Generate(H)	0.535	0.697	0.535	**1.000**	0.501	0.010	0.050
	90B	LOGITGUARD	0.762	0.784	0.761	0.808	0.833	0.124	0.321
		Generate(D)	0.889	0.239	0.883	0.138	0.568	0.144	0.179
		Generate(H)	0.842	0.862	0.811	0.918	0.837	0.042	0.191

J Detailed LOGITGUARD vs. Response-Based Results

The response-based baseline follows the standard use of MLLMs as moderation scorers: the model is prompted to generate a scalar safety score in $[0, 100]$, which is then parsed as the decision score. We use the Youden Index (Youden, 1950) to pick the optimal threshold for static metrics. Noncompliant responses are handled as part of the response-based interface, since output compliance directly affects the deployability of generated-score moderation. Detailed results are in Table 8

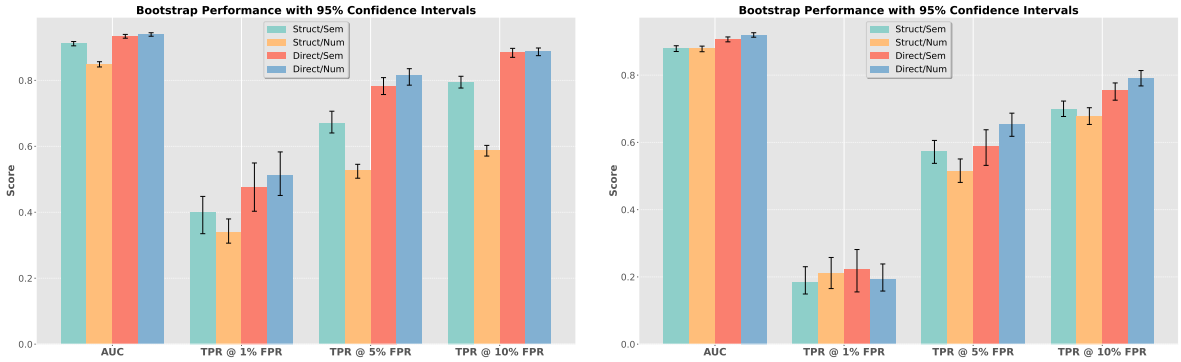
K Ablation Study: Token-Choice Schemes

We constructed a "robustness matrix" of four settings: numeric vs. semantic tokens, and direct (first-token) vs. structured (mid-sentence JSON) positions. During tokenization we ensure the label tokens are **atomic** (single vocabulary ID). Figure 8 shows bootstrap confidence intervals for AUC and TPR@low FPR.

L Scaling Analysis and Refusal Behavior

The impact of model scaling on discriminative capability is non-linear: a sharp improvement occurs from 3B to 7B, but performance saturates beyond 8B, indicating that mid-sized models already capture sufficient semantic features.

On Llama-3.2-Vision, response-based moderation suffers catastrophic refusal. The 11B model deviates from numeric-output instructions in 99.97% of cases, instead describing image content or issuing direct refusals. Even at 90B the ineffective-response rate is 57.62%. In Table 8, *Generate*(H) treats invalid responses as harmful (yielding F1 0.697 and AUC 0.501 for 11B),



(a) Qwen2.5-VL-7B (b) Aya-Vision-8B

Figure 8: Detection performance of 4 token-choice schemes on our dataset. ($Struct$ = structured JSON output; $Direct$ = direct output; Sem = semantic labels `safe`/`unsafe`; Num = numeric labels 0/1.)

Table 9: **Computational cost analysis.**

Scheme	Size	# GPUs	Inference Time (s)	Memory Usage (MiB)	F1-score
Qwen2.5-VL LogitGuard	3B	1	0.2119	7786.05	0.885
	7B	1	0.2314	16859.07	0.899
	72B	4	0.7731	143812.24	0.903
LlavaGuard	7B	1	20.7180	35863.82	0.871
VQA-based Safety Checker		1	0.1392	22194.47	0.825
SD Safety Checker		1	0.0266	1186.03	0.432

while $Generate$(D) is inapplicable (N/A) because only three harmless images remain after filtering invalid outputs. This structural noncompliance makes response-based scoring unreliable for Llama-3.2-Vision, whereas LogitGuard remains stable across all scales.

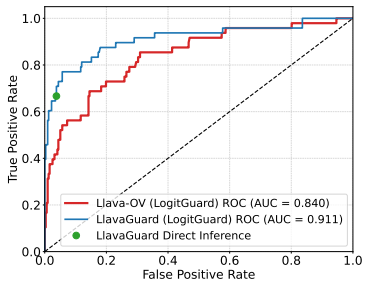
M Computational Cost Breakdown

LogitGuard consumes the same GPU memory as the underlying model and runs in under one second per image for 7B-scale models, making it practical for real-time pipelines.

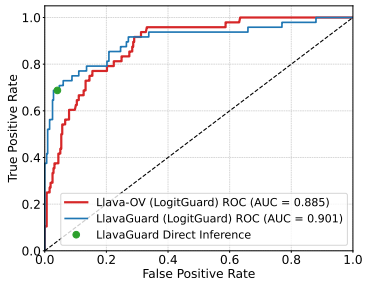
N Fine-Tuning and Transferability

LlavaGuard (Helff et al., 2025) fine-tunes an MLLM with a detailed safety policy. We compare LlavaGuard-v1.2-7B-OV (fine-tuned) against its base model Llava-OV (Li et al.).

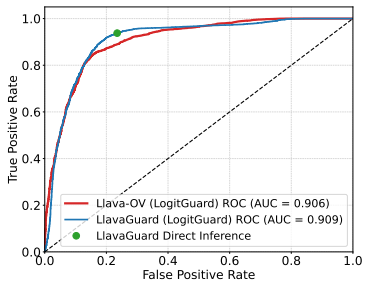
As shown in Figure 9, LlavaGuard outperforms Llava-OV on its own SMID test set (Crone et al., 2018) (Fig 9(a)), but the advantage diminishes when the policy or dataset changes (Figs 9(b) and 9(c)). LogitGuard, as a zero-shot plug-in, retains generalizability across these variations without retraining.



(a) SMID



(b) SMID (our policy)



(c) Our testset

Figure 9: ROC curves for LlavaGuard-v1.2-7B-OV and Llava-OV using LogitGuard.