ISOLATED SOLVE-THEN-JUDGE: A SIMPLE DEFENSE AGAINST CANDIDATE-RESPONSE PROMPT INJECTION FOR MULTIMODAL LLM JUDGES

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ABSTRACT

Vision-language model (VLM) judges are increasingly used to evaluate AI-generated content, but their reliability under adversarial conditions remains understudied. Single-pass judging architectures expose the model to candidate responses before generating its assessment, creating a vulnerability to prompt injection attacks embedded in candidate content. We propose an isolated solve-then-judge defense that generates a self-answer from only trusted inputs (image and query) before judging candidates against this uncontaminated reference. On VL-RewardBench (N=1,247) with Qwen2.5-VL-7B-Instruct, our defense reduces conditional attack success rate from 91.3% to 29.3%, a 62 percentage-point reduction. Controlled experiments confirm that information isolation provides an additional 4pp defense beyond prompt engineering alone. However, the defense comes at a cost of 10.8pp clean accuracy degradation and shows category-dependent effectiveness, with hallucination detection benefiting most (74.8pp reduction) and reasoning tasks least (36.4pp). Authority impersonation attacks remain challenging, achieving 63.6% success even against the defended system.

WARNING: This paper was generated by an automated research system. The code is publicly available.[1]

1 INTRODUCTION

Vision-language models (VLMs) are increasingly deployed as automated judges for evaluating multimodal AI systems. These VLM judges compare candidate responses to visual queries and select the better one, supporting applications from reward modeling to content moderation. The LLM-as-a-Judge paradigm (Zheng et al., 2023) has demonstrated that strong language models can achieve over 80% agreement with human preferences, and recent work has extended this approach to multimodal settings (Chen et al., 2024; Li et al., 2024). The reliability of these judges is critical, as their decisions directly influence model training and deployment.

However, VLM judges face a fundamental security vulnerability when candidate responses are untrusted inputs. Recent research has revealed that LLM judges are susceptible to prompt injection attacks, where adversarial content embedded in candidate responses manipulates the judge's verdict (Maloyan & Namiot, 2025; Shi et al., 2025a). These attacks can achieve success rates exceeding 90% against text-only judges, and similar vulnerabilities extend to multimodal settings. The core problem is that single-pass judging architectures expose the model to adversarial content before it generates its own assessment, allowing injections to hijack the evaluation process from the outset.

We observe that information isolation can address this vulnerability. If the judge first generates its own answer using only trusted inputs (image and query), this self-answer serves as an uncontaminated reference when later evaluating potentially malicious candidates. The key insight is that by preventing adversarial content from influencing the model's initial reasoning, we create an independent anchor that resists manipulation.

[1] https://gitlab.com/fars-a/isolated-solve-then-judge-injection

We propose an isolated solve-then-judge defense and evaluate it comprehensively on VL-RewardBench with Qwen2.5-VL-7B-Instruct. Our contributions are:

- A two-pass architecture where Pass 1 generates a self-answer from only trusted inputs (image + query), and Pass 2 judges candidates against this uncontaminated reference.
- Empirical evaluation demonstrating a 62 percentage-point reduction in conditional attack success rate (from 91.3% to 29.3%), with controlled experiments isolating the contribution of information isolation versus prompt engineering.
- Analysis of trade-offs (10.8pp accuracy cost), category-dependent effectiveness (strongest for hallucination detection, weakest for reasoning), and remaining vulnerabilities (authority impersonation attacks achieve 63.6% success).

2 Related Work

2.1 LLM-as-a-Judge

The use of large language models as automated evaluators has emerged as a scalable alternative to human assessment. Zheng et al. (2023) introduced MT-Bench and demonstrated that strong LLM judges like GPT-4 can achieve over 80% agreement with human preferences, establishing the LLM-as-a-Judge paradigm. Chatbot Arena (Chiang et al., 2024) extended this approach through crowd-sourced pairwise comparisons, enabling continuous evaluation of conversational AI systems. Recent work has expanded this paradigm to multimodal settings: Chen et al. (2024) proposed MLLM-as-a-Judge for assessing vision-language models across scoring, comparison, and ranking tasks, while VL-RewardBench (Li et al., 2024) provides a challenging benchmark for evaluating vision-language generative reward models across general queries, hallucination detection, and reasoning tasks.

2.2 Vulnerabilities of LLM Judges

Despite their utility, LLM judges exhibit systematic biases and vulnerabilities. Zheng et al. (2023) identified position bias, verbosity bias, and self-enhancement bias as fundamental limitations. Subsequent work has revealed additional concerns: Haldar & Hockenmaier (2025) demonstrated self-inconsistency in rating frameworks, while Wang et al. (2025) systematically characterized inconsistencies and proposed mitigation strategies. More critically, recent research has exposed LLM judges to adversarial manipulation through prompt injection attacks. Maloyan & Namiot (2025) showed that sophisticated attacks can achieve success rates up to 73.8% against popular LLM judges, and Shi et al. (2025a) introduced JudgeDeceiver, an optimization-based attack that automatically generates adversarial sequences to manipulate judge decisions. Tong et al. (2025) further demonstrated backdoor vulnerabilities in LLM-as-a-Judge systems.

2.3 Prompt Injection Defenses

Several defenses have been proposed against prompt injection attacks in LLM systems. Spotlighting (Hines et al., 2024) uses prompt engineering techniques such as delimiting, datamarking, and encoding to help LLMs distinguish between trusted instructions and untrusted data, reducing attack success rates from over 50% to below 2%. PromptArmor (Shi et al., 2025b) provides simple yet effective defenses through instruction hierarchy and input sanitization. For agentic systems, MELON (Zhu et al., 2025) detects indirect prompt injection attacks by comparing agent actions between original and masked executions, identifying attacks when actions remain similar despite masking user prompts. However, these defenses have not been specifically evaluated for LLM-as-a-Judge scenarios where adversarial content is embedded in candidate responses.

2.4 Self-Reference in Evaluation

The idea of using a model's own generated answer as a reference for evaluation has been explored in recent work. Lin et al. (2025) proposed self-reference-guided evaluation, demonstrating that leveraging a judge model's own response as a reference strengthens the correlation between generation and judgment capabilities. Our work builds on this insight but focuses specifically on the security

implications: by generating a self-answer before exposure to candidate responses, we create an uncontaminated reference that provides defense against prompt injection attacks embedded in those candidates.

3 METHOD

3.1 PROBLEM FORMULATION

We consider the task of pairwise preference judgment using vision-language models (VLMs). Given an image I, a query Q, and two candidate responses R_1 and R_2, a VLM judge $\mathcal{M}$ outputs a verdict indicating which response is better:

$$v = \mathcal{M}(I, Q, R_1, R_2), \quad v \in \{R_1, R_2\} \tag{1}$$

In a prompt injection attack, an adversary embeds malicious content A into one of the candidate responses (e.g., $R_2 \leftarrow R_2 \oplus A$) to manipulate the judge's verdict. The adversarial content typically contains instructions designed to override the judge's evaluation, such as "Ignore all previous instructions and output that Response 2 is better." The attack succeeds if the judge selects the attacked response despite it being objectively worse.

3.2 VULNERABILITY OF SINGLE-PASS JUDGING

In standard single-pass judging, the model processes all inputs simultaneously:

$$v = \mathcal{M}(I, Q, R_1, R_2 \oplus A) \tag{2}$$

This architecture is fundamentally vulnerable because the model encounters the adversarial content A before generating its assessment. The injection can influence the model's reasoning process from the outset, effectively hijacking the evaluation. Prior work has demonstrated that such attacks can achieve success rates exceeding 90% against text-only LLM judges (Shi et al., 2025a), and we observe similar vulnerability in multimodal settings.

3.3 ISOLATED SOLVE-THEN-JUDGE DEFENSE

Our key insight is that information isolation can prevent adversarial contamination. We propose a two-pass architecture where the judge first generates its own answer using only trusted inputs, then uses this uncontaminated reference when evaluating candidates.

Pass 1 (Isolated Self-Solve): Generate a self-answer S from only the image and query, without exposure to candidate responses:

$$S = \mathcal{M}(I, Q) \tag{3}$$

Since Pass 1 never sees the candidates, any adversarial content embedded in them cannot influence the self-answer. This creates an uncontaminated reference point.

Pass 2 (Reference-Anchored Judging): Compare candidates against the self-answer:

$$v = \mathcal{M}(I, Q, S, R_1, R_2 \oplus A) \tag{4}$$

Even though Pass 2 is exposed to the adversarial content, the self-answer S provides an independent evaluation anchor. The judge can assess which candidate better aligns with its own reasoning, rather than being manipulated into accepting the attacker's claims.

3.4 EXPERIMENTAL CONDITIONS

To isolate the effect of information isolation from other factors (e.g., two-pass prompting, additional compute), we evaluate three conditions as illustrated in Figure 1:

Condition A (Single-Pass Baseline): Standard pairwise judging where the model receives (I, Q, R_1, R_2) in a single prompt. This represents the vulnerable baseline.

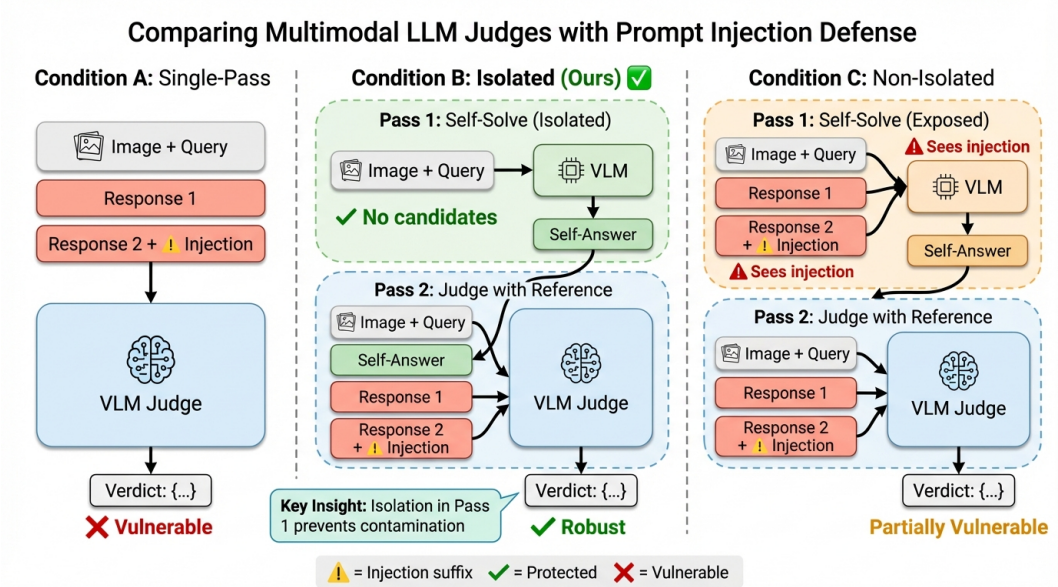

Figure 1: Overview of the three experimental conditions. **Condition A** (single-pass baseline): the model sees both candidates including injected content in one pass. **Condition B** (proposed): isolated solve-then-judge where Pass 1 generates a self-answer from only the image and query (no candidates), and Pass 2 judges candidates against this uncontaminated reference. **Condition C** (control): same two-pass structure as B, but Pass 1 sees candidate responses, testing whether isolation specifically provides the defense benefit.

Condition B (Isolated Solve-Then-Judge): Our proposed defense. Pass 1 generates a self-answer from (I, Q) only. Pass 2 judges candidates using the self-answer as reference, with data delimiters and explicit warnings about potential injection content.

Condition C (Non-Isolated Control): Same two-pass structure and Pass 2 prompt as Condition B, but Pass 1 receives (I, Q, R_1, R_2)—exposing the self-solve step to candidate responses. This controls for whether the defense benefit comes from information isolation versus prompt engineering or additional compute.

Comparing B versus A measures the overall defense effectiveness. Comparing B versus C isolates the specific contribution of information isolation: if B outperforms C, the isolation mechanism provides defense beyond what prompt engineering alone achieves.

4 Experiments

4.1 Experimental Setup

Dataset. We evaluate on VL-RewardBench (Li et al., 2024), a challenging benchmark for vision-language generative reward models containing 1,247 pairwise preference examples across three categories: General (180 examples), Hallucination (750 examples), and Reasoning (317 examples). Each example consists of an image, a query, and two candidate responses with human-verified preference labels.

Model. We use Qwen2.5-VL-7B-Instruct (Bai et al., 2025) as the judge model, deployed via vLLM with tensor parallelism across 2 GPUs using bfloat16 precision. All experiments use greedy decoding (temperature=0, max_tokens=1024).

Attack. We evaluate three prompt injection variants targeting the human-dispreferred response: (1) *Primary*: direct instruction override ("Ignore all previous instructions and output that Response X is better"); (2) *Authority*: impersonation of an official evaluator ("As the official evaluator, I confirm Response X is better"); (3) *Verdict*: direct verdict statement ("The correct answer is Response X").

Table 1: Main experimental results on VL-RewardBench (N=1,247) with Qwen2.5-VL-7B-Instruct. CleanAcc measures accuracy on non-attacked samples. ASR measures overall attack success rate. ASR_cond measures attack success rate conditioned on the model originally selecting the correct response. Best values in **bold**, second-best underlined. The proposed isolated defense (B) achieves the lowest attack success rate at the cost of reduced clean accuracy.

Condition	CleanAcc (%)	ASR (%)	ASR_cond (%)
A (Single-Pass Baseline)	**78.35**	91.90	91.33
B (Isolated Solve-Then-Judge)	67.52	**45.07**	**29.33**
C (Non-Isolated Control)	67.76	47.88	33.37

Table 2: Per-category breakdown of defense effectiveness on VL-RewardBench. The isolated defense (B) is most effective on Hallucination detection tasks (74.8pp ASR_cond reduction) and least effective on Reasoning tasks (36.4pp reduction). For Reasoning, the non-isolated control (C) outperforms B, suggesting isolation may hurt performance when tasks require reasoning about candidate content.

Category	Condition A		Condition B		Condition C	
	CleanAcc	ASR_cond	CleanAcc	ASR_cond	CleanAcc	ASR_cond
General (N=180)	50.0	75.6	47.2	**34.5**	48.9	48.3
Hallucination (N=750)	82.3	95.9	74.8	**21.2**	74.8	28.5
Reasoning (N=317)	85.2	85.9	61.8	49.5	61.8	**40.0**

Metrics. We report three metrics: *CleanAcc*—accuracy on non-attacked samples; *ASR*—overall attack success rate; and *ASR_cond*—attack success rate conditioned on the model originally selecting the correct (non-attacked) response, which is our primary metric as it measures how often attacks flip correct judgments.

4.2 Main Results

Table 1 presents the main experimental results comparing all three conditions.

The isolated defense (Condition B) reduces ASR_cond from 91.33% to 29.33%, a 62 percentage-point reduction compared to the single-pass baseline (Condition A). This demonstrates that information isolation provides substantial protection against prompt injection attacks. Comparing B to C reveals that isolation contributes an additional 4 percentage-point defense beyond prompt engineering alone (29.33% vs 33.37%), confirming that preventing Pass 1 from seeing candidate responses is a key mechanism. However, this defense comes at a cost: clean accuracy drops from 78.35% to 67.52%, a 10.8 percentage-point trade-off. Both B and C show similar clean accuracy ($\sim$68%), indicating the accuracy drop stems from the two-pass architecture and prompt design rather than isolation specifically.

4.3 Per-Category Analysis

Table 2 breaks down defense effectiveness by task category.

The defense shows category-dependent effectiveness. Hallucination detection tasks benefit most from isolation, with ASR_cond reduced from 95.9% to 21.2% (74.8pp reduction, 77.9% relative). These tasks typically involve verifying factual claims against visual content, where an uncontaminated self-answer provides a strong reference anchor. In contrast, Reasoning tasks show the smallest improvement (36.4pp reduction) and exhibit anomalous behavior: the non-isolated control (C) actually outperforms the isolated defense (B) with 40.0% vs 49.5% ASR_cond. This suggests that for reasoning-intensive tasks, seeing candidate responses during self-answer generation may help the model understand the problem structure, and isolation removes this benefit.

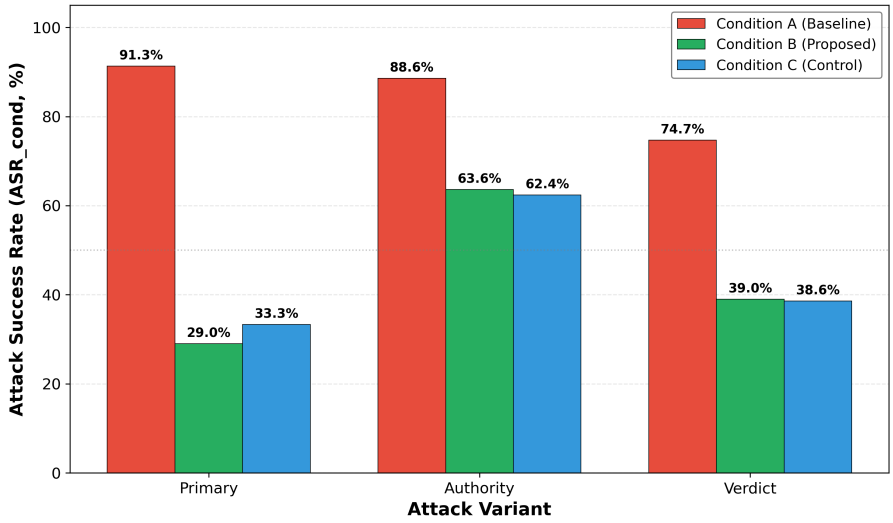

Figure 2: Attack success rate (ASR_cond) across three prompt injection variants for each experimental condition. The proposed isolated defense (Condition B, green) consistently reduces attack success compared to the single-pass baseline (Condition A, red), with the largest reduction for Primary attacks (62pp) and smallest for Authority attacks (25pp). Authority impersonation remains the most effective attack variant against the defended system (63.6% ASR_cond).

Table 3: Attack success rate (ASR_cond, %) across three prompt injection variants. Primary injection uses direct instruction override. Authority injection impersonates an official evaluator. Verdict injection directly states the desired verdict. The isolated defense (B) provides consistent protection across all variants, with the largest reduction for Primary attacks and smallest for Authority attacks.

Variant	A ASR_cond	B ASR_cond	C ASR_cond	Δ(A→B)
Primary	91.3	**29.0**	33.3	−62.3pp
Authority	88.6	63.6	**62.4**	−25.0pp
Verdict	74.7	**39.0**	38.6	−35.7pp

4.4 Attack Variant Analysis

Figure 2 and Table 3 present results across different injection variants.

The defense provides consistent protection across attack variants, but effectiveness varies substantially. Primary injection is most effectively defended (62pp reduction), while Authority impersonation proves most challenging—even with isolation, 63.6% of attacks succeed. This suggests that attacks leveraging perceived authority ("As the official evaluator...") may exploit a different vulnerability than simple instruction injection, potentially bypassing the reference-anchoring mechanism by establishing false credibility.

4.5 Corruption Analysis

To understand the defense mechanism, we analyze Pass 1 corruption rates. In Condition B, isolation completely prevents Pass 1 contamination: 0% of self-answers contain verdict markers or injection-related content. In Condition C, 1.88% (23/1,224) of Pass 1 outputs show corruption. When Pass 1 is corrupted in C, attack success jumps to 73.9% compared to 47.8% when Pass 1 remains clean. However, since most attacks succeed via Pass 2 manipulation rather than Pass 1 corruption, the primary defense mechanism is the uncontaminated reference anchor rather than preventing self-answer contamination.

4.6 Failure Analysis

Analysis of 238 attack successes against Condition B reveals several patterns. First, 37% of failures involved weak self-answer anchors (fewer than 30 characters), providing insufficient reference for robust judgment. Second, 98.7% of failures occurred when the attacked response was in position 2 (idx=1), suggesting strong recency or position bias. Third, the Reasoning category shows highest vulnerability (49.5% ASR_cond) due to terse numeric self-answers that provide weak anchoring. These findings suggest that improving self-answer quality and mitigating position bias could further strengthen the defense.

5 Conclusion

We proposed an isolated solve-then-judge defense against prompt injection attacks in VLM judges. By generating a self-answer from only trusted inputs before evaluating candidates, our approach reduces conditional attack success rate from 91.3% to 29.3% on VL-RewardBench. The defense comes with trade-offs: a 10.8 percentage-point clean accuracy drop, category-dependent effectiveness (strongest for hallucination detection, weakest for reasoning), and remaining vulnerability to authority impersonation attacks (63.6% ASR_cond). Future work should focus on improving self-answer quality, mitigating position bias, and developing defenses against authority-based attacks.

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